Journal of Mechanical Engineering Research and Developments
ISSN: 1024-1752
CODEN: JERDFO
Vol. 43, No. 2, pp. 165-177
Published Year 2020

EMG – based Force Estimation for Dynamic Muscle Contractions in Physical Human-Robot Interaction

Tanat Tanausavaphol[†], Paramin Neranon[†]*, Passakorn Vessakosol[†] & Pornchai Phukpattaranont[‡]

[†]Department of Mechanical Engineering, Faculty of Engineering Prince of Songkla University, Songkhla, Thailand

[‡]Department of Electrical Engineering, Faculty of Engineering Prince of Songkla University, Songkhla, Thailand

*Corresponding Author Email: paramin.n@psu.ac.th

ABSTRACT: Electromyography is a method in the field of electrodiagnostic medicine for monitoring and assessing the electrical activity generated by skeletal muscles themselves. As reviewed, the study of human force estimation based on Electromyographical signals is such a crucial challenge, since it is further complicated by the dynamic nature of the human subject. Consequently, this paper aims to develop an effective algorithm to roughly approximate the human hand applied force during executing rectilinear-motion-machine interaction, in which a test influence variable, namely friction force against the object movement, was additionally exerted. This mathematical algorithm will be further implemented in a newly designed rehabilitation robot using EMG muscle force estimation instead of applying a costly multi-axis force/torque sensor. Artificial neural networks and Support vector machine approaches were successfully applied to distinctly classify the electromyography signals of human's hand muscles detected by eight-channel EMG electrodes. After the set of tests was carried out, root mean square error was individually utilized to evaluate the quantitative performance of each technique. The experimental results illustrated that both approaches were considered acceptable for EMG–based force estimation for dynamic muscle contractions by indicating that the human applied force was validly estimated based on the EMG signals. Additionally, it can be implied that the more the resistant force applied against the object movement, the lower the force model estimated performance.

KEYWORDS: Electromyography; Muscle force estimation; Artificial neural networks; Support vector machine; Human-robot interaction

INTRODUCTION

Robots are being used more frequently in everyday life tasks (e.g., service robots, robots for clinical applications or industrial robots). Robots have been typically programmed by operators to execute a sequence of predefined functions; however, the new generation of smart robots have been designed to further increase flexibility and to share their workspaces with humans in aiming for complex task improvement. The chief requirement of human-robot interaction (HRI) is to facilitate robots to be able to physically interact and work naturally with humans in a safe and reliable manner. Secondly, the robots themselves should be able to decide their task priority or action levels that can allow them to interact with humans in a timely and speedy manner [1–3].

Stroke is a primary cause of death and the leading cause of permanent disability in adults. There are many stroke survivors, who live with a variety of levels of disability and always need rehabilitation activities on a daily basis. Based on the study of HRI, our research group then promoted an upper-limb rehabilitation robot to provide the improvement of physical functions of stroke patient's muscles. The robot can function like therapists, who actively help patients with exercise-based upper limb rehabilitation with two functions consisting of active and passive therapy. However, a multi-axis force/torque sensor is expensive; subsequently, to overcome the limitation, EMG–muscle force estimation for HRI in the robot-assisted rehabilitation task has been carried out and detailed throughout the paper.

The electromyography is often used as input signals for robot control, such as, in the application of robots for rehabilitation or HRI, which requires the assessment of muscle force from human movements. Therefore, finding an algorithm approach to mathematically determine the force caused by muscle under dynamic muscle contractions is a challenge study. Most of the robot-assisted rehabilitation equipment often uses muscle force to stimulate the movement of the device for treatment of patient users. However, as reviewed, the methods for measuring the individual human muscle force almost require costly multi-axis force sensors [4]. Then to overcome this problem, force estimation using EMG signals is one of the best solutions and significantly leads to cost efficiency. The EMG signals reflect the electrical activity of skeletal muscles and contain information about the structure and function of muscles which particularly make different parts of the body move [5]. Therefore, EMG can be used to predict human muscle force in HRI with strong probability. However, due to the complexity of the electromyography investigation in human muscles, various techniques of detecting the EMG characteristics have been introduced in different ways to an effective EMG measuring system [6].

Linear or nonlinear relationships between EMG and muscle force under the isometric muscle contractions were discovered, in which the joint angle and muscle length do not change during contractions, such as contracting, standing, pushing the wall, etc. Research [7–9] conducted the studies which are the significant steps of muscle force estimation relating to the development of intuitive human- assistive robot interface using EMG, prediction of handgrip forces based on forearm muscle EMG signals, or study of effects of muscle length and tension on rapid isometric contractions using frequency response. Nevertheless, the relationship between the electromyography and muscle force is more complex due to muscle properties, such as the different length of muscles, the speed of muscle flexion and extension or the measuring locations to place EMG sensors [10–12]. However, as extensive review, there are few studies relating to the estimation of human muscle force during dynamically performing human-robot interactive tasks due to the complicated muscular skeleton system, and there is no research paper in consideration of the relationship of the EMG – based force estimation for dynamic muscle contractions in a HRI object manipulating task and variable frictions applied against the object movement. This requires kinetics and muscle dynamics data precisely measured by a set of accurate EMG sensors in order to adopt a good way for a muscle force forecasting under dynamic contractions.

The aim of this paper is, therefore, to develop an efficient algorithm to estimate force exerted by human muscles under dynamic muscle contractions from the EMG signals using an artificial neural network (ANN) and support vector machine (SVM). Both techniques were appropriately executed to examine the complex relationship between muscle force applied to the HRI system and the EMG signals in less complicated. As reviewed, the advantages of both algorithms are high performance and can be productively used with error-prone data sets; the SVM scheme also has more advantages in terms of less over-fitting problems. However, both methods still have some disadvantages in the use of time for long training and the parameters used for training are complex [13–16]. Subsequently, this study additionally explains how to achieve a suitable number of the sample size of training data in HRI. The details are organized in the following sections.

SYSTEM DESIGN OF ONE-DOF HUMAN-ROBOT INTERACTION

Conceptual Design and Test Procedure of One-DOF Human-Machine Interaction

In order to achieve the above objective, the HRI experiment has been conducted to mimic the object manipulating in a one-dimensional axis. A set of one-DOF rectilinear motion machine interaction was initially designed and mainly employed in the study of muscle force estimation of the human arm using surface EMG sensors as depicted in Figure 1. A set of ten human samples were randomly selected to undertake the experiments and first asked to naturally move the object placed on the linear rail in a constrained horizontal path along with various frictions against the movement applied. The external friction has been exerted to the object movement, and it can be varied from 2-5 N with 1 N resolution. Since there is a significant difference among the lengths of human upper limbs, then the test rig allows the object to be horizontally moved up to around 40 cm. The research [17] reported that the average length of the right arm ends of the males is approximately in the range of 20 to 30.5 cm and women's arm lengths are in the range between 19 and 31 cm [17].

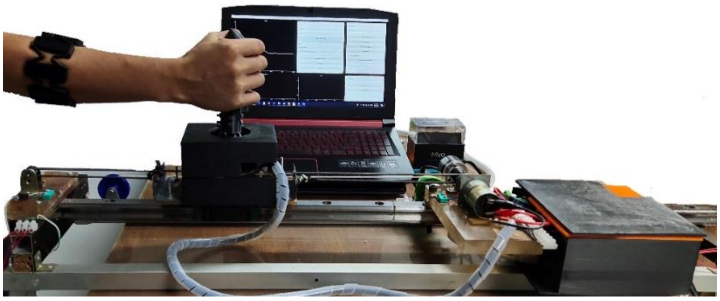


Figure 1. One-DOF rectilinear motion test rig

The schematic block diagram of the test is shown in Figure 2. A one-dimensional force sensor measures the human force applied. A set of grasping force sensors was mounted on the handle in order to detect an individual finger pressing force because the higher the amplitude in grasping force, the inferior the effectiveness of the real-time EMG recording system. The grasping force allowed in the test is between 0.8-1.2 N, and this range of squeezing force was delivered by preliminary tests. If each of the human finger force is higher or lower than the threshold, a buzzer module will be activated to alert the human subject. The speed of object manipulating was strictly set to a constant velocity of 0.1 m/s along with a velocity guide for the human movement measuring by an encoder.

In addition, the HRI experiments also require a linear rail used as a base for the object horizontal movement, two limit switches utilized to limit the object's movement, and a MYO Armband with 8-channel EMG sensors to measure the EMG signals around the human forearm in real-time. Finally, a set of relevant data is used to calculate the set of features shown in Figure 3, consisting of human arm EMG signals, human force applied to the object, grasping force, frictional force, and object displacement and its corresponding velocity were simultaneously captured and monitored under the system control unit. The recorded information (i.e. in samples and out samples) was further used respectively in training and testing the proposed ANN and SVM algorithms. This can be explained using a flowchart diagram illustrated in Figure 4.

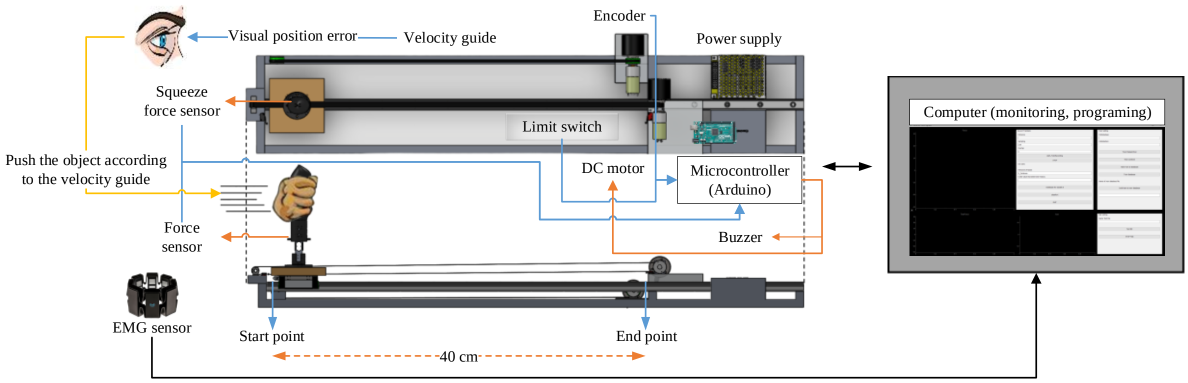


Figure 2. Schematic of experimental structure setup.

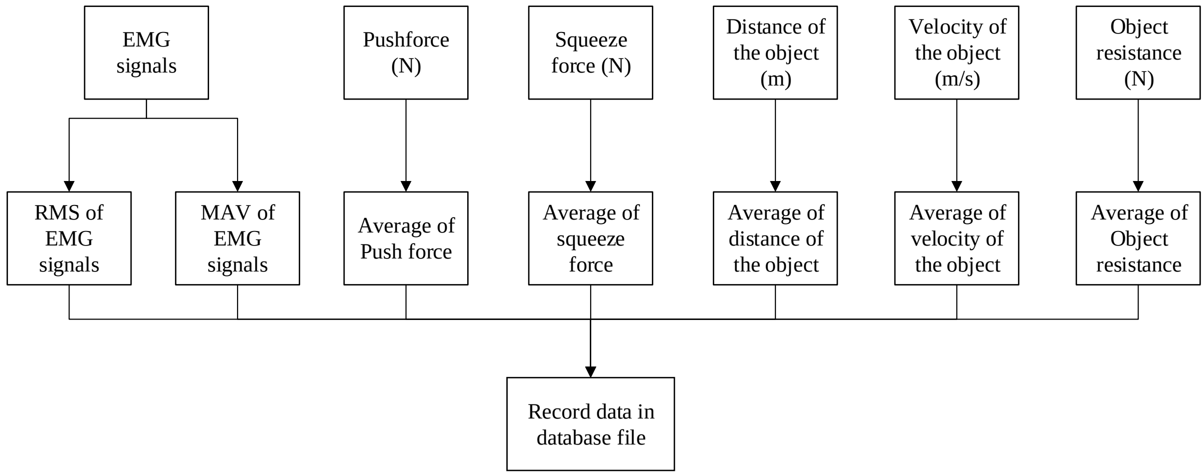


Figure 3. Block diagram of the data set used for calculating the feature set in the experiments.

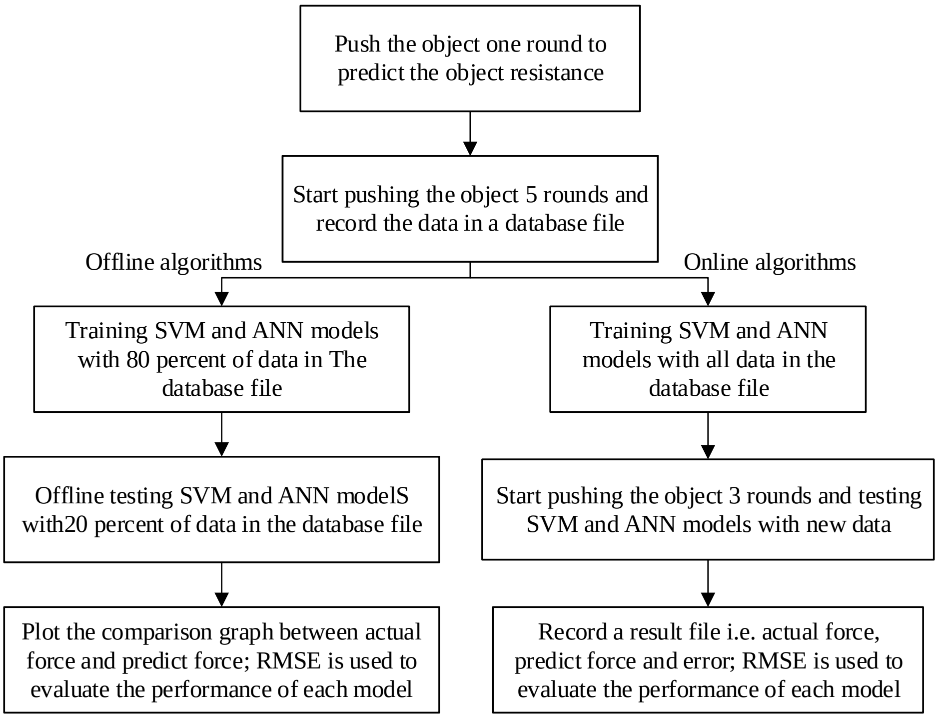


Figure 4. Block diagram of the experimental procedure for data analysis.

According to the experimental procedure, the group of ten participants were randomly selected to perform the HRI tests and initially required to become familiar with the test rig before executing the real tests with 4-5 repetitions. Each human is asked to sit down in comfortable positions in front of the test rig and perform all assigned tasks to the best of their capacity. Only one hand is allowed to grasp the handle with appropriate squeeze force, and twisting or bending the device is not allowed. An individual subject has to push the object towards the endpoint with a constant velocity of 0.1 m/s in the constrained path, according to the movement reference point. To ensure effective data collecting, they have to execute 5 repetition sets of each variable frictional force magnitude applied against the movement. The relevant information was recorded in real-time and divided into two groups made up of an in-sample group (80% of data for online and offline algorithm-training developments) and out-sample group (20% of the data for evaluating the estimated algorithms). Contrastingly, the online feature training was used all measured information. The final step involves the evaluation of ANN and SVM methods in terms of accuracy of the human muscle force estimation using Root Mean Square Error (RMSE) by comparing between the predictive and measured force values based on both on-line and off-line training techniques.

Human muscle force estimation base on ANN and SVM approaches

As mentioned previously, the artificial neural network and support vector machine techniques were used in the prediction of human muscle force. ANN is a mathematical model that mimics biological neural networks, which consists of multiple layers connected together in the model. Each layer has a processing unit which is called a neuron. Layer types are as follows: the input layer which is a layer for importing the initial data into the system for further processing by subsequent layers of artificial, the hidden layer is a layer for learning of artificial neurons by taking in a set of weighted inputs and produce an output through an activation function and, finally the output layer is a layer for produces given outputs [18]. Backpropagation algorithms are a method that is widely used in the training of neural networks (ANNs) effectively according to the gradient descent approach that takes advantage of chain rules. Main features of backpropagation are its iterative, recursive and efficient method for calculating its weights updates to improve the network until it is able to perform the task that has been trained.

The learning algorithm is made up of (1) starting randomly setting the initial network parameters (weights w_{ij} and biases b_j), (2) taking a sample set of input data and then passing them through the designed network to obtain the prediction, (3) comparing these predictions obtained with the target values and calculating the loss function between both of them, (4) performing backpropagation to disseminate this loss to each and every one of the parameters that construct the neural network model, (5) executing this disseminated information to update the model parameters of the ANN using gradient descent in a manner to reduce total loss for the better ANN model, (6) continuing iterating the previous steps until a good model has been successfully adopted [19].

Support Vector Machine (SVM) is a supervised learning algorithm that is widely used for classification or regression challenges. The purpose of the SVM algorithm is to find the hyperplane in the *N*-dimensional space (*N* - number of features) that clearly separates the data point. By separating two classes of data points, there are many possible hyperplanes which can be suitably selected as depicted in Figure 5. The objective of the algorithm is to find the plane with the maximum margin to efficiently distinguish both classes.

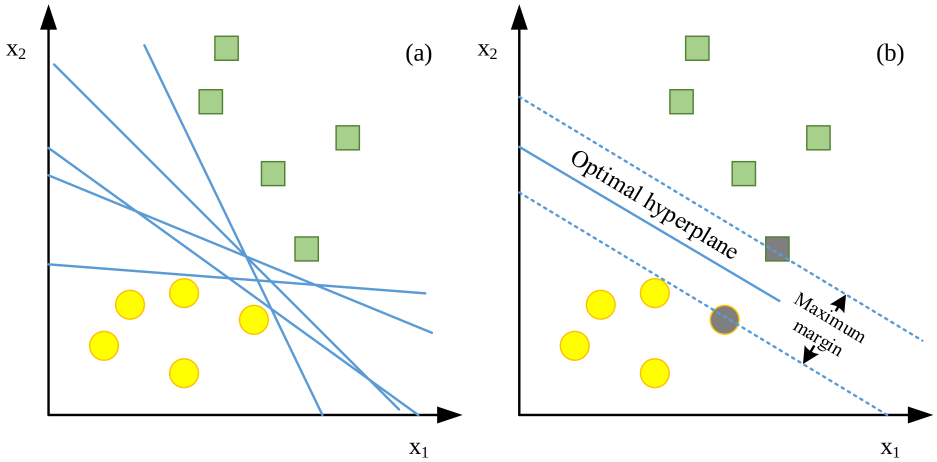


Figure 5: (a) Possible hyperplanes. (b) Optimal hyperplane.

In SVM, it is easy to have a linear hyper-plane between these two classes, but another burning question which arises is, should we need to add this feature manually to have a hyper-plane. SVM has a new technique called the kernel trick. These are functions to transform a low dimensional input space to be a higher-dimensional space. This method is most useful in non-linear separation problems, and engages with complex data transformations, by seeking out the process to significantly separate the data based on the labels or outputs defined.

Pilot Study of the HRI Object manipulating tasks

The pilot study is a small experiment in which the test results and statistical analysis are collected before the appropriate large-scale experiment is conducted. The pilot study in this research consists of two experiments, with the objective to determine the appropriate location for the installation of a sensor to measure the forearm EMG signals and the appropriate sample size to calculate the features. These can be expressed as follows:

1) Amplitudes of EMG signals are regulated relying on many influent factors, and one of the important parameters that makes the difference is the locations of the EMG sensor installation. There are several studies relating electrode sensor locations, such as the research of Chris Jensen et al. [20]. It described the difference in the EMG amplitude when installing electrodes in different positions on the trapezius muscle bundle while stretching arms and bending arms. Therefore, in this experiment, the objective is to determine the appropriate location for the installation of the MYO 8-channel electrode armband by considering the two significant positions of the upper-limb i.e. the forearm muscles and Biceps/Triceps muscles due to both muscle bundles have mainly changed while performing pulling/pushing the object. It displays in Figure 6, and by considering the EMG electrode locations, two preliminary tests have been undertaken and explained below.

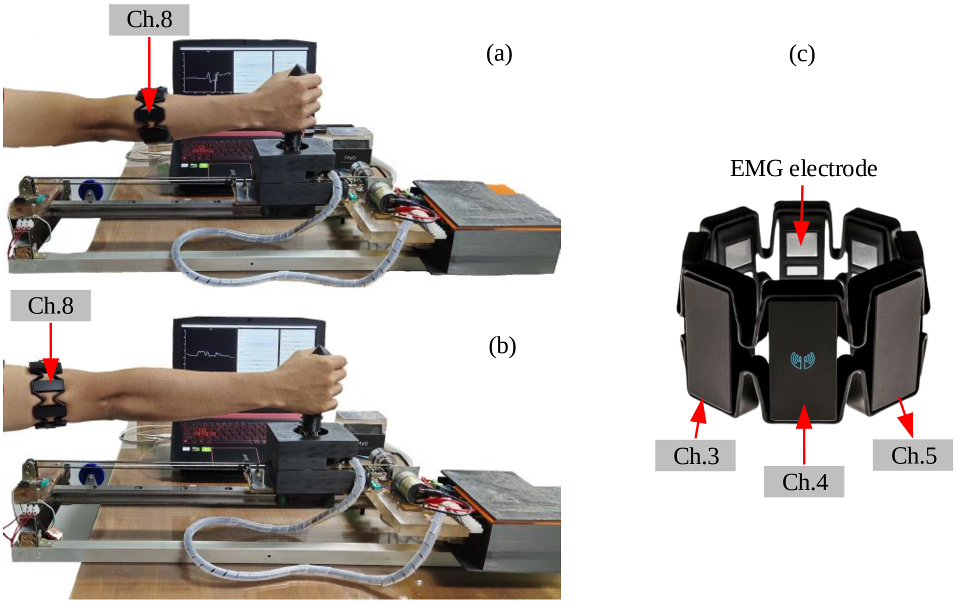
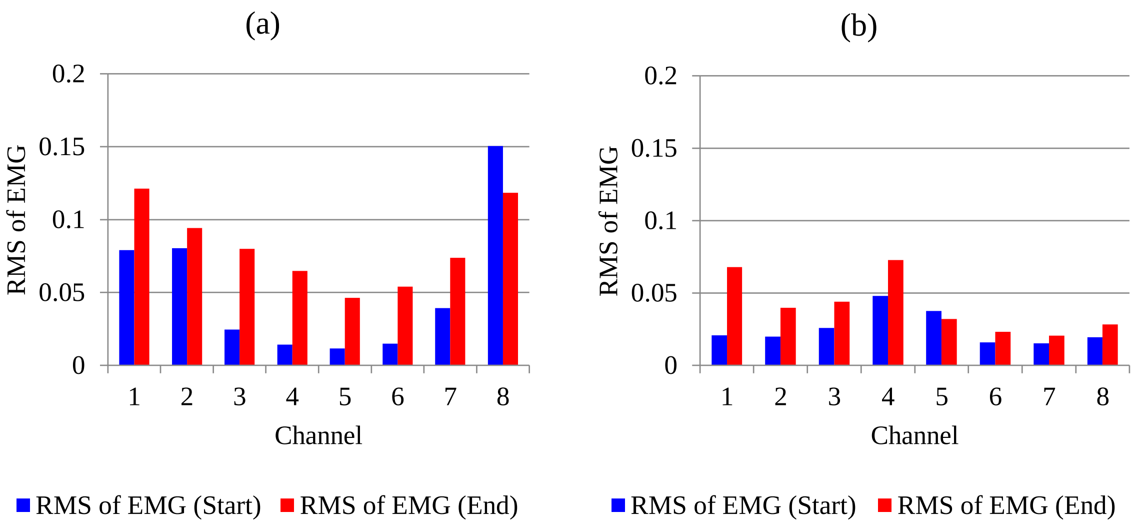


Figure 6. The position of the sensor installation (a) Forearm muscle (b) Biceps/Triceps muscles (c) MYO armband channels position [21].

<u>Preliminary I</u> determines the relations of the different human upper-limb postures preciously influencing though the EMG muscle signals recorded from the human forearm and Biceps/Triceps muscles when the human subject performs pulling and pushing the non-moving object placed on the linear rail of the test rig. The human was initially asked to apply the constant interactive force at10 N throughout the tests. By realizing the various arm's postures based on the elbow flexion and extension, each subject has to be asked to undertake the HRI tests at the start point toward end point respectively. Additionally, to evaluate the distinct EMG signals in each scenario, RMSE was then employed.

The experimental results showed that RMSE values of the 8-channel EMG electrode signals from both forearm and Biceps/Triceps muscles had distinct EMG profiles in different ways. After careful analysis with regard to the results, the RMSE differences captured at the Biceps/Triceps muscles, while pushing and pulling the static object, were slightly represented superior to those of the forearm location as illustrated in Figure 7. As reviewed, it can be claimed that the lower the changes in the EMG magnitudes of several upper-limb postures, the more the qualitative performance of the EMG-based force prediction [22]. This is because the study of the relation between the applied forces directly affecting the muscle EMG measurement, without attention paid to human arm postures, has been primarily investigated. Therefore, the EMG MYO armband was suggested to be specifically installed at the human forearm.



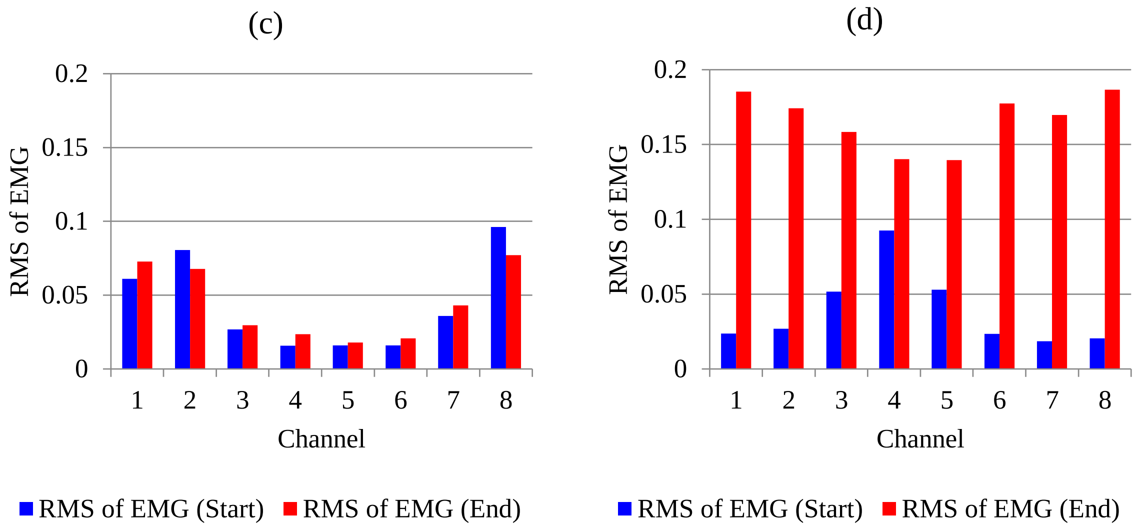


Figure 7. RMS values of the EMG signals when pulling/pushing the object at the start and end points. (a). pushing the object with measuring at the forearm muscles (b). pushing the object with measuring at the Biceps/Triceps muscles (c). pulling the object with measuring at the forearm muscles (d). pulling the object with measuring at the Biceps/Triceps muscles

Preliminary II analyses the effects of hand squeeze force exerted to the handle and the muscle EMG signal regulation can be captured from the human forearm and Biceps/Triceps positions again, while the object is fixed at the endpoint.

Each participant was required to execute the tests by firstly grasp the object with a constant squeeze force of roughly 0.8-1.2 N and loosely grasp the handle. The experimental outcomes reported that there were significant differences while applying the grasping force and without squeeze force in both conditions of mounting the EMG electrodes at the forearm and Triceps/Biceps locations. This can be clearly seen in Figure 8.

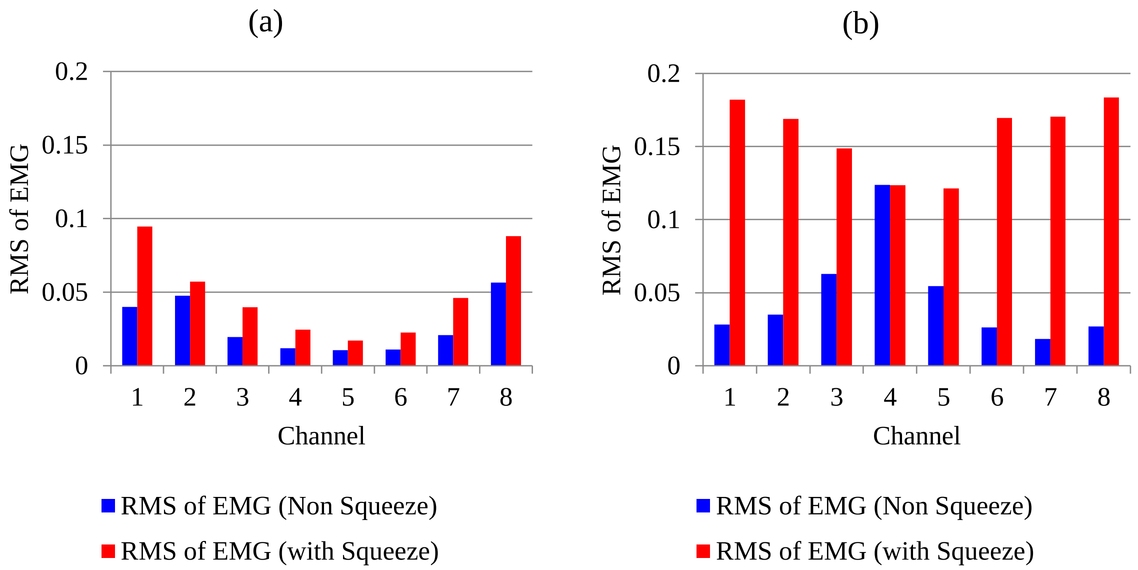


Figure 8. RMS values of the EMG signals when squeezing objects at end point. (a). EMGs measured at the forearm muscles (b). EMGs measured at the Biceps/Triceps muscles

Therefore, the recommendations carried out from the pilot study suggest that the MYO electrode sensors should be mounted around the forearm muscles. It is a crucial aspect to strictly bind the human grasping force as recommended (approximately 0.8-1.2 N). This completely used throughout the substantive main HRI object manipulating tests in order to adopt an effective human muscle EMG magnitudes.

2) In the full-scale experimental design, the number of samplesize for calculating the features of the force prediction algorithms should be sufficient to give effectively significant results. Theoretically, it would be as more as possible, since a higher number of data samples utilized in the feature classification are likely to give a more precise prediction of the date; however, it will take much longer to complete the training process. Therefore, this experiment aimed to determine the sample size which is appropriate for determining the features of the muscle force data in training and testing the ANN and SVM algorithms. By comparing the predictive accuracy at the sample sizes of 50, 100, 150 and 200, again RMSE between the estimated human force and measured force was used to present the investigation of the relationship of the number of samples affecting the model prediction accuracy. The experimental results are shown in Table 1 and graphed in Figure 9

Table 1. The RMSE values of both algorithms at the sample sizes of 50, 100, 150, and 200

Algorithms	Sample size = 50		Sample size = 100		Sample size = 150		Sample size = 200	
	Train80%	Test20%	Train80%	Test20%	Train80%	Test20%	Train80%	Test20%
RMSE_ANN	0.196	0.440	0.088	0.213	0.064	0.130	0.047	0.126
RMSE_SVM	0.202	0.336	0.092	0.173	0.063	0.125	0.048	0.121

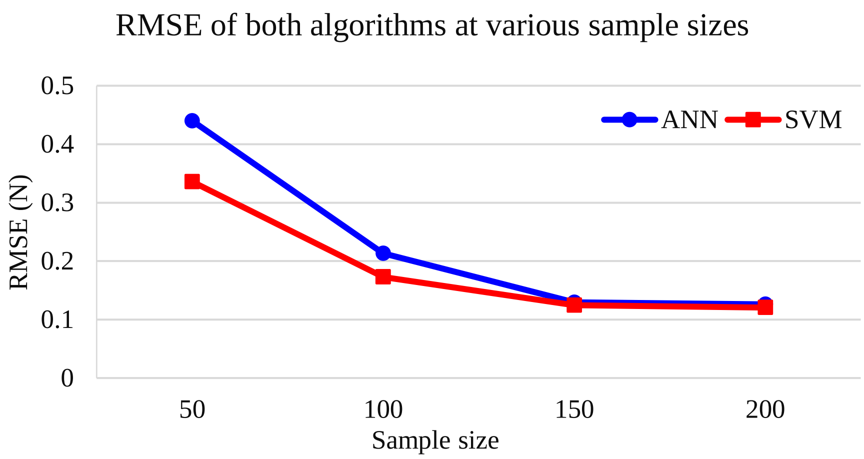


Figure 9. The RMSE line graphs of both algorithms at the sample sizes of 50, 100, 150 and 200.

It can be clearly seen that the ANN and SVM algorithms are more accurate when the sample sizes increase, until the RMSE values of the sample sizes were assigned at 150 and 200 samples which remain rather similar. However, as reviewed, too high sample size could cause the feature extraction process to be slightly delayed. It can be noted that this system has a sampling rate of 100Hz, so the process time of one feature set in each sample size is shown in Table 2. Therefore, as shown in the table, it can be summarized that the most effective point of the test is the samples selection 150, and this is because it offers less processing time than that of the 200 samples. Furthermore as the system has a relatively small sampling rate, the overlapping segmentation technique was used to calculate the features by sliding one data per a feature set to increase the efficiency of the system to work continuously in real time.

Table 2. the process time of one feature set at the sample size of 50, 100, 150, and 200.

Sample size	Process time (second)
50	0.5
100	1

150	1.5
200	2

EXPERIMENTAL RESULTS

ANN and SVM model specifications

Feedforward back-propagation neural network (BPNN) was used in this research to estimate the human exerted forces while interacting with the HRI rectilinear object moving tasks using the muscle EMG signals based on the off-line and on-line algorithm trainings. The BPNN approach requires supervised learning, where the accuracy of a predictive model respects to the training data and the numbers of relative parameters. The following table summarizes the BPNN model configuration. These were strategically achieved and optimized based on a set of trial and error experiments in the range of hidden layer nodes from 15 to 20 by taking benchmarks of the predictive accuracy measurement and processing time.

Table 3. Parameters to be employed in the neural network training

Parameters	Amount / Type
Number of inputs	23
Number of epochs	1000
Number of hidden layers	1
Nodes hidden layer	20
Transfer function of hidden layer 1	Linear (Identify)
Transfer function of output layer	Linear (Identify)

The SVM technique was subsequently implemented for the dynamic muscle force estimation using both off-line and on-line trainings in order to deliver the comparison of the ANN/SVM forecasting performance. The SVM kernel function was initially defined and made up of radial basis functional, linear, and polynomial models for both off-line data training and algorithm testing. However, the on-line algorithm teaching only engaged with the specifically radial basis function model as a result of processing time reduction to be concerned.

Human muscle force estimation results based on ANN and SVM approaches

A set of ten human samples were required to participate with the rectilinear-motion-machine interaction by manipulating the object on the linear rail in the constrained path along with various frictions (2-5 N) exerted. The experimental results are categorized into two main sections, i.e. off-line and on-line training sections. During performing the tasks, the hand grasping force and the object speed were strictly monitored. By evaluating the qualitative performance of the ANN and SVM techniques in terms of accuracy of the human muscle force estimation, Table 4 shows the comparison computed from RMSE values of the ANN and SVM approaches under the frictional forces of 2,3,4 and 5 N, and their corresponding standard deviation were carried out in Table 5. These can be plotted in Figure 10. The blue bar charts indicate the RMSE of the force estimation based on ANN, where the orange, gray and yellow bars show RMSE of the force estimation using the radial basis function-based SVM, linear function-based SVM and polynomial function-based SVM respectively.

By considering the tendency of the algorithm's accuracy, it is clearly seen that the less frictional force levels applied to the test rig offered more accurate estimation carried out by both ANN and SVM. The ANN outcomes under the applied resistance of 2 and 3 N were similar to results calculated using the SVM scheme with the range of 0.05-0.15

N. Contrastingly, at frictions of 4 and 5 N, the SVM algorithm was slightly shown more accurate than the ANN in all scenarios, in which the ranges of the RMSE values based on SVM and ANN were approximately 0.2-0.33 N and 0.34-0.36 N. After being carefully analysed, the quantitative measurement of the performance of both methods can be considered acceptable for the EMG-based force estimation; however, the SVM with the radial basis function kernel optimizely provided the lowest RMSE magnitudes in the conditions of 4 and 5 frictional forces applied.

Table 4. RMSE values of the ANN and SVM approaches using the offline training under the various movement frictional forces

Classifier	friction = 2 N		friction = 3 N		friction = 4 N		friction = 5 N	
	Train80%	Test20%	Train80%	Test20%	Train80%	Test20%	Train80%	Test20%
ANN	0.053	0.087	0.058	0.112	0.108	0.360	0.272	0.345
RBF	0.056	0.087	0.061	0.121	0.135	0.273	0.175	0.200
Linear	0.050	0.078	0.053	0.113	0.122	0.329	0.129	0.328
Polynomial	0.099	0.117	0.076	0.141	0.148	0.275	0.164	0.215

Table 5. Standard deviation of the ANN and SVM approaches using the offline training under the various movement frictional force

Classifier	friction = 2 N		friction = 3 N		friction = 4 N		friction = 5 N	
	Train80%	Test20%	Train80%	Test20%	Train80%	Test20%	Train80%	Test20%
ANN	0.012	0.037	0.007	0.065	0.032	0.188	0.319	0.163
RBF	0.012	0.019	0.008	0.060	0.029	0.078	0.085	0.011
Linear	0.010	0.026	0.010	0.054	0.038	0.135	0.050	0.154
Polynomial	0.020	0.041	0.008	0.065	0.030	0.079	0.071	0.065

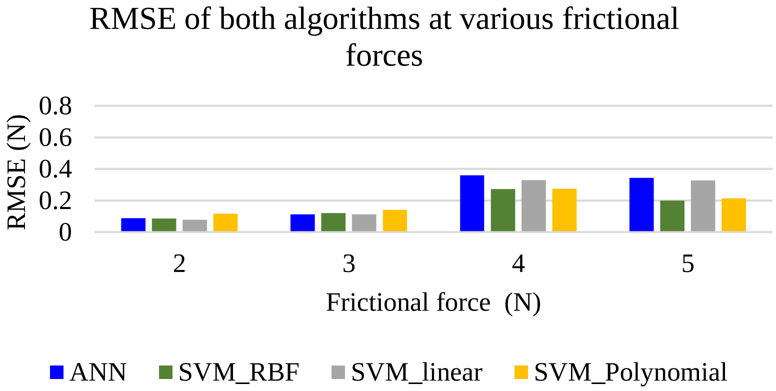


Figure 10. The relationship between the RMSE magnitudes of the force model estimation using ANN and SVM to the frictional forces exerted against the object movement

According to the on-line algorithm training, the same procedure and human participants of the rectilinear object manipulating tasks were again undertaken to provide evaluating of the performance of the ANN and SVM in human force prediction. As the results delivered in the previous substantive tests, in which radial basis kernel-based SVM was reported the most superior performance while having offline training, these tests then allowed only the comparison of the ANN and radial basis function-based SVM strategies. Table 5 illustrates the RMSE values of the ANN and SVM approaches under the several constrained resistances which can be roughly explained in Figure 11. The blue and orange bar charts show the RMSE values by comparing between the predictive and measured force amplituded based on the ANN and SVM using the radial basis function kernel respectively. The results of the on-lining technique show that the qualitative performance of the force prediction techniques is inversely proportional to the magnitude of frictional force applied to the system. Careful observation revealed that the performance of the ANN and SVM with on-line algorithm training are accepted for the human muscle force prediction in the physical HRI test. Additionally, again, after careful analysis with regard to the results, the force prediction based on both schemes contrastingly presented the RMSE values of the ANN is slightly less than those of the SVM method indicating higher capability in dealing with the force estimation of the human muscle in the HRI tasks.

Table 5. RMSE values of the ANN and SVM approaches using the online training under the various movement frictional forces

Algorithms	friction = 2 N	friction = 3 N	friction = 4 N	friction = 5 N
RMSE_ANN (N)	0.113	0.148	0.298	0.423
RMSE_SVM_RBF (N)	0.124	0.175	0.316	0.539

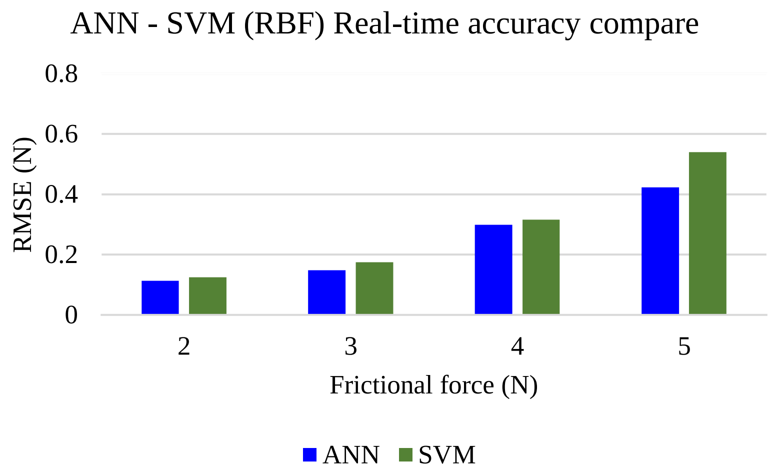


Figure 11. The relationship between the RMSE magnitudes of the real-time force estimation using ANN and SVM to the frictional forces exerted against the object movement

CONCLUSION

This paper examines the use of ANN and SVM for optimizely estimating the human muscle forces based on the human forearm EMG signals during dynamic muscle contractions. The on-line and off-line training algorithms of the ANN and SVM techniques were strategically achieved by dealing with data individually captured from a set of random participants. The qualitative performance of the force prediction based on both methods was assessed using on the root mean square error (RMSE) between the estimated and measured forces during on-line and off-line trainings. The pilot study was conducted to convey the substantive tests. The main results were reported that the quantitative measurement of the performance of ANN and SVM can be considered acceptable for the forces prediction based on the human muscle EMG signals. Additionally, it can be claimed that ANN and SVM have higher capability to estimate the dynamic mathematical model of the EMG based force estimation, and this is in agreement with the parallel test outcomes examined by the researchers [23-25]. After careful analysis, the offline training of the proposed approaches provided similar acceptability for the effective force approximation. Contrastingly, the artificial neural network method was slightly superior to the support vector machine in the online training model. Hence, this study is so advantageous to be further used in a newly designed rehabilitation robot based on the EMG muscle force estimation using the MYO armband instead of a costly multi-axis force/torque sensor in the detection system of human applied force. However, the contributions of in this paper still have a limitation in estimating the force of only one dimensional movement. Even so, this idea is still possible to develop further in order to predict the muscle force in more dimensions, and it can be considered as future work [26-29].

ACKNOWLEDGEMENT

We acknowledge financial support from research grants, research fund from Research and Development Office (RDO) and a 5-year bachelor's-master scholarship program for postgraduate students, Prince of Songkla University. The author would like to thank all the participants in the experiments conducted.

REFERENCES

[1] P. K. Artemiadis and K. J. Kyriakopoulos, "EMG-Based Control of a Robot Arm Using Low-Dimensional Embeddings," *IEEE Trans. Robot.*, vol. 26, no. 2, pp. 393–398, Apr. 2010.

[2] P. J. Xie and J. Haleegoah, "Research on Vision-Based Underwater Robot Positioning and Map Building Technology," p. 6.

[3] Y. T. Oh, "Study of Driving Torque through Analysis of Dynamic Characteristics on Industrial Robot," p. 8.

[4] Fengjun Bai and Chee-Meng Chew, "Muscle force estimation with surface EMG during dynamic muscle contractions: A wavelet and ANN based approach," in *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Osaka, pp. 4589–4592. 2013.

[5] P. Konrad, *The ABC of EMG: a practical introduction to kinesiological electromyography*, Version 1.4. Noraxon USA, Inc, 2006.

[6] W. Kaewboon, P. Phukpattaranont, and C. Limsakul, "Upper limbs rehabilitation system for stroke patient with biofeedback and force," in *The 6th 2013 Biomedical Engineering International Conference*, Amphur Muang, Krabi, Thailand, pp. 1–5. 2013

[7] Tomasz Marek Lubecki, Fengjun Bai, Chee-Meng Chew, and Chee Leong Teo, "Development of intuitive human-machine interface based on Electromyography for assistive robot (KAAD)," in *2011 IEEE/SICE International Symposium on System Integration (SII)*, Kyoto, Japan, pp. 908–913. 2011

[8] M. J. M. Hoozemans and J. H. van Dieën, "Prediction of handgrip forces using surface EMG of forearm muscles," *J. Electromyogr. Kinesiol.*, vol. 15, no. 4, pp. 358–366, Aug. 2005.

[9] C. Disselhorst-Klug, T. Schmitz-Rode, and G. Rau, "Surface electromyography and muscle force: Limits in sEMG–force relationship and new approaches for applications," *Clin. Biomech.*, vol. 24, no. 3, pp. 225–235, Mar. 2009.

[10] N. Ali, S. Ahmad, S. Aziz, G. Zaman. "The Adomian Decomposition Method For Solving Hiv Infection Model Of Latently Infected Cells". *Matrix Science Mathematic*, vol. 3, no. 1, pp. 05-08.

[11] E.C. Jekwu, A.G. Precious, A.B. Evans. "Evaluating The Impact Of Unsteady Viscous Flow And Presence Of Solid Particles On Pipeline Surfaces During Crude Oil Transport", *Acta Mechanica Malaysia*, vol. 2, no. 2, pp. 20-27, 2019. DOI: 10.26480/amm.02.2019.20.27

[12] S.H. Gian, S. Kasim, R. Hassan, Z. Zakaria, H. Mahdin, A.A. Ramli, M.F. Md Fudzee, M.A. Salamat. "Online Activity Duration Management System for Manufacturing Company". *Acta Electronica Malaysia*, vol. 3, no. 2, pp. 01-08, 2019.

[13] K.S. Shazwan, R. Shahari, C.N.A. Che Amri, N.S. Mohd Tajuddin. "Figs (Ficus Carica L.): Cultivation Method And Production Based In Malaysia". *Engineering Heritage Journal*, vol. 3, no. 2, pp. 6-8, 2019.

[14] S. Karlsson, Jun Yu, and M. Akay, "Time-frequency analysis of myoelectric signals during dynamic contractions: a comparative study," *IEEE Trans. Biomed. Eng.*, vol. 47, no. 2, pp. 228–238, Feb. 2000.

[15] D. Staudenmann, I. Kingma, D. F. Stegeman, and J. H. van Dieën, “Towards optimal multi-channel EMG electrode configurations in muscle force estimation: a high density EMG study,” *J. Electromyogr. Kinesiol.*, vol. 15, no. 1, pp. 1–11, Feb. 2005.

[16] D. Staudenmann, I. Kingma, A. Daffertshofer, D. F. Stegeman, and J. H. vanDieen, “Improving EMG-Based Muscle Force Estimation by Using a High-Density EMG Grid and Principal Component Analysis,” *IEEE Trans. Biomed. Eng.*, vol. 53, no. 4, pp. 712–719, Apr. 2006.

[17] U. J. Naeem, C. Xiong, and A. A. Abdullah, “EMG-muscle force estimation model based on back-propagation neural network,” in *2012 IEEE International Conference on Virtual Environments Human-Computer Interfaces and Measurement Systems (VECIMS) Proceedings*, Tianjin, China, pp. 222–227. 2012

[18] C. Castellini and R. Koiva, “Using surface electromyography to predict single finger forces,” in *2012 4th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, Rome, Italy, pp. 1266–1272. 2012

[19] F. Xiao, Y. Wang, Y. Gao, Y. Zhu, and J. Zhao, “Continuous Estimation of Elbow Joint Angle by Multiple Features of Surface Electromyographic Using Grey Features Weighted Support Vector Machine,” *J. Med. Imaging Health Inform.*, vol. 7, no. 3, pp. 574–583, Jun. 2017.

[20] Y. Gao, Y. Luo, Q. Li, and J. Zhao, “Continuous Joint Angle Estimation by Least Support Vector Machine from Time-Delayed sEMG Features,” in *Proceedings of the 2018 10th International Conference on Bioinformatics and Biomedical Technology - ICBBT ’18*, Amsterdam, Netherlands, pp. 13–17. 2018

[21] N. Zarzycka and S. Załuska, “[Measurements of the forearm i inhabitants of the Lublin region],” *Ann. Univ. Mariae Curie Sklodowska [Med.]*, vol. 44, pp. 85–92, 1989.

[22] M. Mishra and M. Srivastava, “A view of Artificial Neural Network,” in *2014 International Conference on Advances in Engineering & Technology Research (ICAETR - 2014)*, Unnao, India, pp. 1–3. 2014

[23] C. Keattisak and N. Supot, “A Comparison of Prediction Palm Oil Time Series Using Polynomial Artificial Neural Network and Artificial Neural Network,” presented at the The 12th National Graduate Research Conference (GRC-2011).

[24] C. Jensen, O. Vasseljen, and R. H. Westgaard, “Estimating maximal EMG amplitude for the trapezius muscle: On the optimization of experimental procedure and electrode placement for improved reliability and increased signal amplitude,” *J. Electromyogr. Kinesiol.*, vol. 6, no. 1, pp. 51–58, Mar. 1996.

[25] H. J. Kim, Y. S. Lee, and D. Kim, “Arm Motion Estimation Algorithm Using MYO Armband,” in *2017 First IEEE International Conference on Robotic Computing (IRC)*, Taichung, Taiwan, pp. 376–381. 2017

[26] N. Jiang, S. Muceli, B. Graimann, and D. Farina, “Effect of arm position on the prediction of kinematics from EMG in amputees,” *Med. Biol. Eng. Comput.*, vol. 51, no. 1–2, pp. 143–151, Feb. 2013.

[27] T. M. Bafitlhile and Z. Li, “Applicability of ε-Support Vector Machine and Artificial Neural Network for Flood Forecasting in Humid, Semi-Humid and Semi-Arid Basins in China,” *Water*, vol. 11, no. 1, p. 85, Jan. 2019.

[28] Electrical Engineering, King Fahd University of Petroleum and Minerals, Saudi Arabia, K. O. Akande, T. O. Owolabi, S. Twaha, and S. O. Olatunji, “Performance Comparison of SVM and ANN in Predicting Compressive Strength of Concrete,” *IOSR J. Comput. Eng.*, vol. 16, no. 5, pp. 88–94, 2014.

[29] B. Yu, Y. T. Wang, J. B. Yao, and J. Y. Wang, “A Comparison Of The Performance Of Ann And Svm For The Prediction Of Traffic Accident Duration,” *Neural Netw. World*, vol. 26, no. 3, pp. 271–287, 2016.