Dynamic Modelling of Hand Grasping and Wrist Exoskeleton: An EMG-based Approach

Mohd Safirin Bin Karis[1], Hyreil Anuar Bin Kasdirin[2], Norafizah Binti Abas[3], Muhammad Noorazlan Shah Bin Zainudin[4], Sufri Bin Muhammad[5], Mior Muhammad Nazmi Firdaus Bin Mior Fadzil[6]
Department of Electrical and Electronic Engineering Technology, Universiti Teknikal Malaysia Melaka, Malacca, Malaysia[1]
Department of Electrical Engineering, Universiti Teknikal Malaysia Melaka, Malacca, Malaysia[2, 3, 6]
Department of Electronic and Computer Engineering, Universiti Teknikal Malaysia Melaka, Malacca, Malaysia[4]
Department of Software Engineering and Information System-Faculty of Science and Information Technology,
Universiti Putra Malaysia Melaka, Serdang, Selangor, Malaysia[5]

***Abstract*—Human motion intention plays an important role in designing an exoskeleton hand wrist control for post-stroke survivors especially for hand grasping movement. The challenges occurred as sEMG signal frequently being affected by noises from its surroundings. To overcome these issues, this paper aims to establish the relationship between sEMG signal with wrist angle and handgrip force. ANN and ANFIS were two approaches that have been used to design dynamic modelling for hand grasping of wrist movement at different MVC levels. Input sEMG signals value from FDS and EDC muscles were used to predict the hand grip force as a representation of output signal. From the experimental results, sEMG MVC signal level was directly proportional to the hand grip force production while hand grip force signal values will depend on the position of wrist angle. It's also concluded that the hand grip force signal production is higher while the wrist at flexion position compared to extension. A strong relationship between sEMG signal and wrist angle improved the estimation of hand grip force result thus improved the myoelectronic control device for exoskeleton hand. Moreover, ANN managed to improve the estimation accuracy result provided by ANFIS by 0.22% summation of integral absolute error value with similar testing dataset from the experiment.**

***Keywords*—Hand grasping; wrist control; ANN; ANFIS; exoskeleton wrist design**

I. Introduction

Dexterous human hand movement completed the routine of human daily activities by providing specific hand gestures for task movements, such as object grasping and posture maintenance [1],[2]. Recognizing that hand movement is changeable, as human grasping requires varying grip force and wrist angles to execute various activities [3]. Moreover, hand movement activities induced by user motion intention involves muscle contractions which can be monitored using surface electromyography (sEMG) data, resulting in force output [4],[5],[6]. However, the variation in wrist angle position associated with results in variation of sEMG signal amplitude, which would have a significant impact on the accuracy of grasp force estimation [7].

However, several diseases, including stroke, can have a negative impact on human hand function. Undeniably stroke is a major public health issue in many countries [8],[9]. In 2020, the World Health Organization (WHO) reported that 21,592 people in Malaysia had died from a stroke, accounting for 12.85% of all deaths in the country [10]. According to the 2013 Global Burden of Disease study, this disease currently ranks third among the most significant contributors to disability-adjusted life years [11], [12]. In general, approximately three-quarters of stroke survivors are still suffer from their post-stroke effects [13]. One of the most prevalent disabling effects of a stroke is upper limbs impairment [14]. Based on statistic values, between 55% to 75% of stroke survivors lost of their hand ability. This hand disability can make their survivors dependent on oth ers for help with activities of daily living, which can lower their quality of life [15], [16]. In the sense of that, since 1952, many researchers have looked at the concept of surface electromyography (sEMG) signals production as a means of improving Human Machine Interaction (HMI) for the benefit of post-stroke survivors [17].

Providing a path to integrate HMI has always triggers a challenge among all the research. In such tasks or activities, the robot should be designed to match the human arm's dexterity and skill [18]. Therefore, it is crucial to examine the biomechanical model of human muscle force and transfer it to the robot control in order to establish smooth interaction between the human and the robot instead of simple stiff interaction [18]. Although it is difficult to estimate grip force from sEMG signals, successful force recognition can aid in the design of a usable interface for natural and accurate EMG-based robot control [19]. The estimation of a generated force from sEMG signals enables the control of robotic equipment such as exoskeletons or prostheses in real time applications [20], [21], [22].

Realizing the importance understanding of sEMG signals, wrist angle and force excitation in forming the hand movement activities, the exoskeleton hand has been created in Solidwork software and converted in visual Matlab 2017a environment to imitate the natural human hand movement. The input designed for exoskeleton hand was the sEMG signals has been analysed at different wrist angle position (flexion and extension) with different Maximum Voluntary Contraction (MVC) level of hand grasping. The output function of sEMG was the estimation of hand grip force as it was needed to improve the myoelectric control system performance [6].

Nicola Secciani et al. proposed a control strategy based on "classification loop" and a "actuation loop" to control the movement of exoskeleton hand for free grasp, spherical grasp, and cylindrical grasp [23]. In 2019, Jing Luo et. al., used Neural Network Based Approach to estimate the force based on received input EMG signals [18]. The research continue as He Mao et. al., and Jiaqi Xue et. al., used EMG signals to estimate force and angle that represent hand movement such as wrist flexion/extension, ulnar/radial deviation, pronation/supination, and grip in 2023 [3],[19]. By recognising the significance of predicting future output results based on EMG input, more opportunities of improvement can be realised, as this relationship can strengthen control area in exoskeleton hands and prostheses section for future development [24].

This paper aims to analyse the relationship between sEMG signals, wrist angle and hand grip force generation at different MVC level using Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) dynamic modelling system for exoskeleton hand. The output of this relationship has been expected to improve the understanding on hand grasping control system strategy and selecting the best dynamic modelling approach for exoskeleton hand.

II. Recent Development

EMG-force relationship always been a highlight in analysing the hand grasping process related with HMI. When using a tool, such as interacting with a robot that requires a high degree of dexterity, the dynamics of a person's arms can have a significant impact on that person's daily activities [18]. Moreover, the dynamic modelling develops for the system always come with an issue of finding the suitable approach to form the relationship between input of EMG signals generated from user motion intention based on muscle contraction towards force generated as an estimated output. Daniele et al. employed a multiple linear regressions strategy to reduce the reconstruction error of exerted endpoint forces from EMG force estimates [5]. Gelareh et al. said that other researchers frequently employ ANN and Support Vector Machines (SVM) to discover mappings processes between EMG and force [4]. Furthermore, Galareh et al. revealed that researchers employed system identification approaches such as polynomial estimation, linear regression, and fast orthogonal search (FOS) to estimate force from sEMG signals [4], [6]. Jiaqi et al. focused on feature design by comparing the performance of EMG linear envelope (ENV) and non-linear EMG to muscle activation mapping (ACT) to obtain optimal force estimate performance [19].

ANN are one of the methods that can be used to define a connection between an input with an output. It acts as a black box model to approximate a complex nonlinear mapping between the sEMG signals towards their wrist angle or force generated equivalent to the signal muscle contractions related to it. ANN can learn from observation of mixture muscle signals and did not require any understanding of biological phenomena of exoskeleton hand system such as mathematical equation to express the relationship between input and output. According to Changmok et al., ANN is computationally efficient and has been implemented in various real-time systems [25]. Numerous similar research publications have demonstrated the effectiveness of neural networks in recognising EMG patterns [26]. Francisco et al., 2020, created a multiclass categorization model using a regression algorithm and neural networks to control an anthropomorphic robotic system with three degrees of freedom that can accurately remote the robot arm to specified positions in a state machine [27].

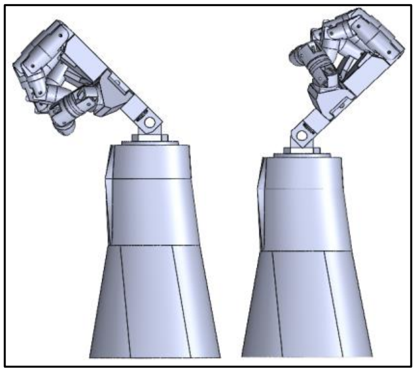
The neural-fuzzy-based myoelectric control system is another scheme for controlling an upper limb exoskeleton-type exoskeleton. Neural fuzzy is defined as the combination of a neural network and fuzzy logic in modern artificial intelligence theory [28]. Kazuo et al. pioneered the neuro-fuzzy myoelectric control system, in which fuzzy logic was comprised of "IF and THEN" statements and the fuzzy modifier was a fully connected neural network [29], [30]. The neural network must tune the fuzzy logic using the EMG signals. Typically, data-driven approaches for ANFIS network synthesis are based on clustering a training set of numerical samples of the unknown function to be approximated. Since then, ANFIS networks have been successfully applied to classification tasks, rule-based process controls and pattern recognition problems [31]. According to Jirui et al., ANFIS can also be used to represent an effective neural network strategy for solving function estimation problems [32]. Moreover, Song Yu et. al., managed to prove the result from ANFIS is better than Tonic Stretch Reflex Threshold (TSRT) approach used for elbow flexors or extensors in their research [33].

Both ANN and ANFIS were established mapping methods that can be used to design a dynamic modelling for exoskeleton hand system. However, to enhance the performance of myoelectric control strategies for exoskeleton hand system, the selection of mapping method to form a dynamic modelling needed to be carefully selected. According to Mao et al., intuitive control that mimics human hand movement as closely as feasible has been greatly praised [3]. When interacting with the external environment, humans typically regulate their force at different wrist angle positions to ensure good operation performance [18]. However, there has been little research into the simultaneous estimation of hand grip force and wrist angles in free space, which mimic the biological functions of human hands.

III. Methodology

A. Mechanical Hand Design

The exoskeleton hand was designed to mimic the natural human hand movement. From ten male subjects ages from 21 to 40 years old, all the anthropometric hand measurement were taken. One degrees of freedom (DoF) of the wrist angle position has been highlighted in this exoskeleton hand designed covered two types of gestures: hand grasping at -45° (flexion) and 45° (extension) showed in Fig. 1. Since the wrist exoskeleton hand can be moved to achieve wrist desired angle, it is completely actuated.



(a) (b)

Fig. 1. Exoskeleton hand designed (a) flexion position (b) extension position.

B. EMG Data Collection

All experiments procedure were approved by the University Ethical Committee or Centre for Research and Innovation Management (CRIM) at University Technical Malaysia Melaka (UTeM) Malaysia. The experiment used a Hand Dynamometer, LabQuest Mini data acquisitions, Vernier EMG sensors, a personal computer with Logger Lite data-collection software, Stopwatch, Protector, and Kendall5400 diagnostic tab electrodes. Ten male subjects signed the researcher's consent form to undertake the hand grip pattern experiment at varying wrist angles at different MVC level. The experiment began after the subjects were fully briefed. Each experiment was repeated three times [34].

Flexor Digitorum Superficialis (FDS) and Extensor Digitorum Communis (EDC) EMG signal values have been employed in this research to represent each hand grasping wrist angle movement at different MVC level [3], [35], [23]. The medial epicondyle has been used to locate the muscles and the palpate scaphoid technique has been employed to determine the position of wrist movement [36], [37]. All subjects were in good health with non-neurological diseases and used their dominant hand for data collection.

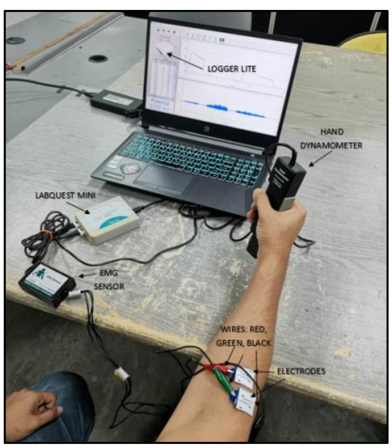
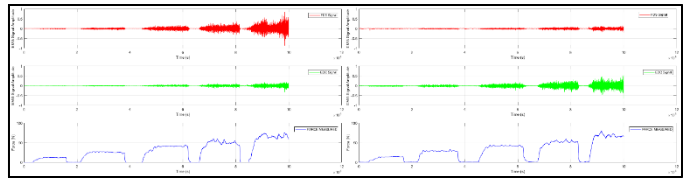


Fig. 2. Experimental set-up [38].

Fig. 2 illustrates how experimental procedures conducted. The maximum force (MVC) of the hand grasp is a measurement of the subject's strongest voluntary contraction Electrode patches are put to the top of the abdominal muscles of FDS and EDC. Samples were instructed to hold the hand dynamometer for five seconds at different hand grip strengths (20, 40, 60, 80, and 100% MVC level [34]. Each grip includes a two-second rest interval. The retrieved raw EMG signals were recorded using the Logger Lite programme. Fig. 3 shows the data collection for flexion and extension hand movement during the experiment.



(a) (b)

Fig. 3. Data collections for FDS, EDC and forces during (a) wrist angle at flexion (b) wrist angle at extension.

C. EMG Signal Processing

This paper adapted time-domain-based features using Waveform Length (WL) approach as it proven itself to be the best feature extraction method among RMS, MAV, IEMG and ZC as shown in Fig. 4 [39], [40], [41]. The sampling frequency was chosen at 1 kHz to suit the EMG signals range. The segmentation of input data was reduced at 50% analysis window increment. A second-order band-pass Butterworth filter was used for this experimental procedure [42]. The MVC method, which was uniquely recorded from each subject, has been used to standardize EMG measurement values. This approach scales the measurement value between 0 to 1 and most used normalization techniques in MVC-normalization [43], [44].

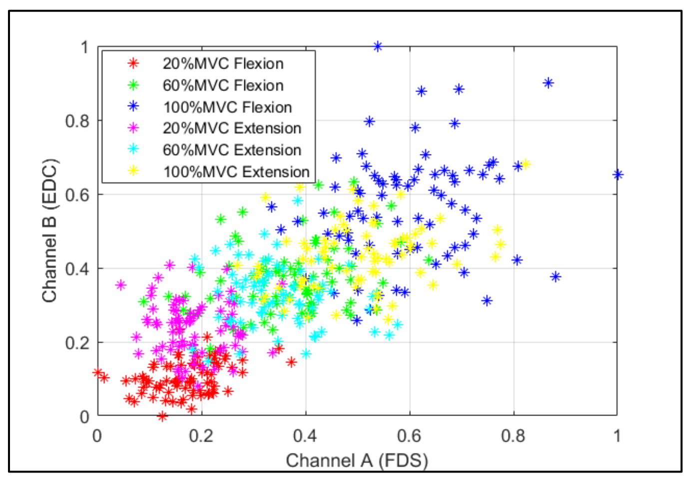


Fig. 4. WL feature extraction for 20%, 60% and 100% MVC at flexion and extension wrist angle.

D. Mapping Process

Modelling creates a connection between all usage parameters. It establishes a sequential connection between inputs and outputs. This modelling constructs an accurate transfer function to characterize system performance and the measured effectiveness of the selected modelling approach. Modelling, also known as mapping, is a data-based representation of numerous group design types. Since this paper recommended employing two mapping methods, ANN and ANFIS were trained and evaluated using the same data set to ensure that their outputs were comparable.

1) Method 1: Dynamic Modelling of Wrist Movement Using ANN: ANN is one of the methods to generate a dynamic modelling for one's system. Depending on application complexity, neural networks can approximate nonlinear functions using adaptive weights on different layers [45]. From all the collected data set, two of them have been used to generate a training model for ANN approaches. The default setting has been used to generate this model representation as 70% dedicated for training, 15% for validation and 15% for testing. One number of hidden layers was used to connect two inputs with one output consisting of ten neurons shown in Fig. 4. The input were the EMG signals from FDS and EDC and output are the force generated from the hand grasping procedure at different wrist angles. Tangent sigmoid has been selected as ANN activation function and Levenberg-Marquardt has been selected as the training method [24]. The EMG data set taken from selected muscles has been arranged at 20%, 60%, 100% MVC at flexion state and 20%, 60%, 100% MVC at extension state to estimate the force generation at different wrist angle position. Fig. 5 shows architecture for ANN designed to estimate the hand grasping force.

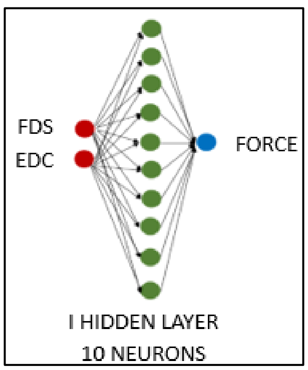


Fig. 5. ANN designed architecture.

2) Method 2: Dynamic Modelling of Wrist Movement Using ANNFIS: ANFIS is another mapping method that can be used to create a dynamic modelling of a system. It has been built up from a combination of ANN and fuzzy logic to create its mapping block. It employs the fuzzification layer to map the input data to fuzzy sets using membership functions. The rule layer applies fuzzy if-then rules (Sugeno method) to capture the relationship between input variables and the output. The adaptation layer adjusts the parameters of the ANFIS model using a learning algorithm, allowing it to continuously improve its performance. For ANFIS setting, three sets of data coming from similar samples were used. two sets of them have been used to form a training block with 70% was dedicated for training, 15% for validation and 15% for checking. One hidden layer was chosen with ten neurons connected to the fuzzy rules to estimate the output value. FDS and EDC muscles sEMG signals have been chosen as an input while hand grasping force at different MVC levels has been selected as an output signal of a system. Number for membership function (mf) of ten neurons with combination of [2 8] and type of "gauss2mf" was set as an input and output selected "constant" as their MF type. 20%, 60% and 100% MVC level for both flexion and extension of sEMG signal level have been arranged to predict the force hand grasping output. Fig. 6 shows an ANFIS designed architecture for the system.

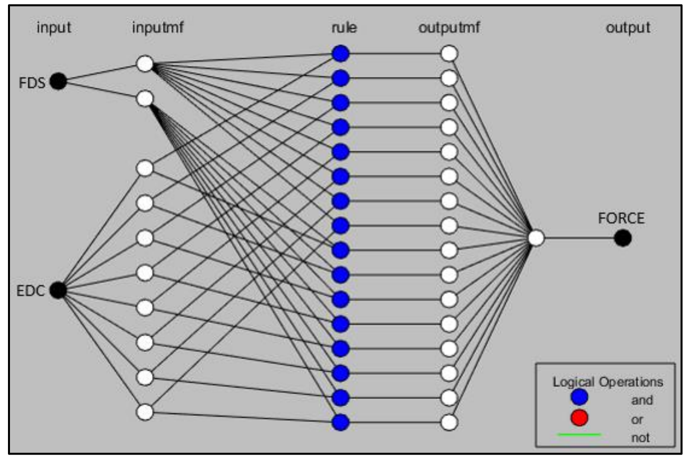


Fig. 6. ANFIS designed architecture.

IV. Results

Fig. 7 depicts an analysis of hand grip forces. Within the same graph, a three-line force graph is plotted. Two of them are line graphs that depict the output from the ANN (magenta) and ANFIS (light blue) mapping processes, while the other (blue) was directly taken from the measurement process during the experimental procedure. As the wrist goes from flexion to extension, the graph is divided into two portions. The first section (wrist angle at flexion position) occurred between 0s and 233s. This section is organized into three subsections to represent the signal levels of 20% MVC, 60% MVC, and 100% MVC. The second part (wrist angle at extension position) existed between 234s and 467s. This section has also been separated into three subsections to represent the signal levels of 20% MVC, 60% MVC, and 100% MVC.

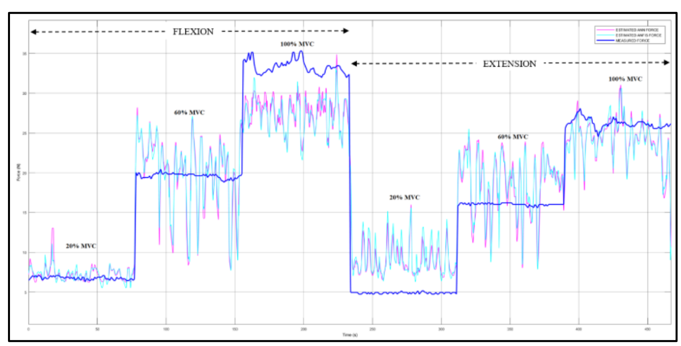


Fig. 7. Hand grip force analysis graph.

Fig. 8 depicts the absolute error for the ANN and ANFIS mapping methods. The magenta line graph is an error graph for the ANN approach, whereas the light blue graph is formed by the ANFIS approach. Both graph line plotting reveals a fluctuation pattern signal generated by both ways, as can be seen. Each method seems to have close estimated hand grip force and error values compare to each other and produce quite a similar graph instead. These graphs were created by deducing the force measured value during the experiment process from the force estimation value obtained from both approaches. The total summation area under each graph representing the total summation error for each approaches used. According to Fig. 8, the sum of absolute error for the ANN technique was 19.33%, while the ANFIS approach was 19.55%. Based on this finding, ANN outperformed ANFIS in force estimation with a similar dataset and parameter settings.

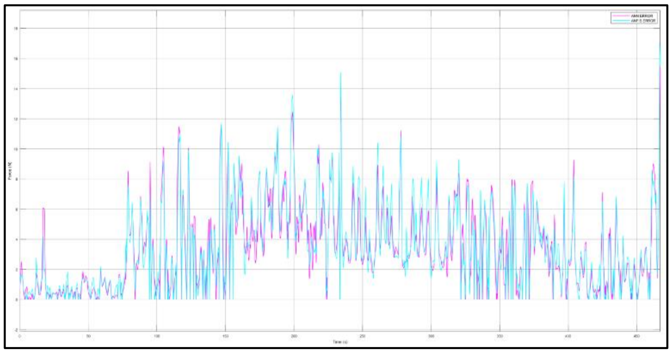


Fig. 8. Absolute error for ANN and ANFIS.

V. Discussions

All of the hand grip forces MVC's plotting in the flexion part have higher values than their identical MVC's opponent in the extension section. The situation happened as referring to the normal human hand grasping movement. As the user motion intention directed the hand wrist angle to move towards human body, FDS muscle (flexion muscle) produce higher sEMG values compared to EDC muscle (extension muscle) signal which causing the flexion hand movement as shown in Fig. 3 [38]. For the flexion hand movement, the measured and estimated force values obviously demonstrated a higher signal level compared to their MVC in the other section. For the extension section, the hand wrist angle was pulled away from the human body, causing the EDC muscle to generate a greater sEMG value than the FCR muscle [3], [39]. As shown in Fig. 7, this extension movement degrades the hand grasp force value in each MVC level compared to the flexion movement.

At 20% MVC flexion section, the estimation graph plotting from both ANN and ANFIS mapping lingering closer to the measured value during the experiment. However, in the extension section, the estimation graph plotting introduced a small gap reading compared to the value from the experimental procedure. This could happen because the sEMG signal values from both muscles are almost the same when they are contracting at a lower level. The wrist angle position doesn't seem to have a big impact on how the signal number is read. Different case happened at 60% MVC level for both sections. Both muscles produce significant values of sEMG signals that causing the estimation force graph plotting for both approaches manage to differentiate between different wrist angle position. The fluctuation of force output graph might be coming from the nonlinearity of sEMG signals muscles contraction and the noise that interrupted during the data collection.

For 100% MVC, the force signals output estimation for the flexion section manages to have a higher value in their estimation but still does not give the same value as the measured one. The explanation for this is because subjects were instructed to flex their hands while grasping the hand dynamometer with 100% strength at 100% MVC of muscle contractions. Hand shaking commonly happened at this stage thus created a noisy environment while the data is being recorded, hence resulting an effect towards sEMG values used in the estimation process. For the extension section, at 100% MVC, the estimation graph for both hand grip force approaches achieves a nearly identical with the measured one due to a favourable environment for muscles contractions and a lower force measured value that allows the subject to perform well in hand grasping experimental procedure.

VI. Conclusion

Hand grasping is one of the most essential hand gestures for humans, including post-stroke patient survivors, to perform daily tasks. To comprehend and control the exoskeleton hand grasping gesture, the relationship between sEMG signal value, wrist angle, and hand grip force production triggered by the user's intention to grasp an object must be clearly understood. WL was chosen for feature extraction method in time domain in this study. To clarify the concept of force generation in both conditions, 20%, 60%, and 100% of the MVC level for flexion and extension wrist joint angle movement were analysed. As a consequence of the experiment procedure and dynamic modelling process, the sEMG MVC signal level was determined directly proportional to the generation of hand grip force. However, the hand grip force signal generated will depend on the wrist angle position. It was also determined that the hand grasp force signal production became greater when the wrist was in flexion as opposed to extension.

ANN and ANFIS were both dynamic modelling method used to analyse the hand grip force estimation. ANN has the capability to interpret unstructured data while, ANFIS used the strength from ANN and fuzzy to adapt with various environments to design a mapping system for exoskeleton hand. For the whole exoskeleton hand system, ANN and ANFIS needs a similar training and testing data set. Both approaches manage to generate its own dynamic model to represent the exoskeleton hand system. When compared to measured hand grip force recorded throughout the experiment process, ANN outperformed ANFIS by 0.22% absolute error with similar settings for both systems. When compared to ANFIS, the ANN technique produces a more accurate estimation of hand grip force output results.

The limitation of this study was the small number of neurons of ten provided for the ANN and ANNFIS methods. Because this paper only focused on a similar number of neurons for output comparison, the value of neurons and their combination can be varied to produce a variety of possible output for the estimation results. Moreover, there are other regression method available thay may need to be considered to improved estimation output results such as Support Vctor Regression (SVR), Linear Regression (LR), Gaussian Process Regression (GPR), ensemble and decision tree.

ACKNOWLEDGMENT

The authors would like to thank the Ministry of Higher Education Malaysia for the financial support. The project is funded under Fundamental Research Grant Support. No (Ref: FRGS/1/2021/TK0/UTEM/02/54). The authors also want to thank Universiti Teknikal Malaysia Melaka for all the support.

REFERENCES

[1] P. A. Banaszkiewicz and D. F. Kader, “Classic papers in orthopaedics,” Class. Pap. Orthop., pp. 1–624, 2014, doi: 10.1007/978-1-4471-5451-8.

[2] T. Tsuji, P. G. Morasso, K. Goto, and K. Ito, “Human hand impedance characteristics during maintained posture,” Biol. Cybern., vol. 72, no. 6, pp. 475–485, 1995, doi: 10.1007/BF00199890.

[3] H. Mao, Y. Zheng, C. Ma, K. Wu, G. Li, and P. Fang, “Simultaneous estimation of grip force and wrist angles by surface electromyography and acceleration signals,” Biomed. Signal Process. Control, vol. 79, no. P1, p. 104088, 2023, doi: 10.1016/j.bspc.2022.104088.

[4] G. Hajian, A. Etemad, and E. Morin, “Generalized EMG-based isometric contact force estimation using a deep learning approach,” Biomed. Signal Process. Control, vol. 70, no. July, p. 103012, 2021, doi: 10.1016/j.bspc.2021.103012.

[5] D. Borzelli, A. D’Avella, S. Gurgone, and L. Gastaldi, “Unconstrained and constrained estimation of a linear EMG-to-force mapping during isometric force generation,” 2022 IEEE Int. Symp. Med. Meas. Appl. MeMeA 2022 - Conf. Proc., pp. 1–6, 2022, doi: 10.1109/MeMeA54994.2022.9856461.

[6] N. Wang, K. Lao, X. Zhang, J. Lin, and X. Zhang, “The recognition of grasping force using LDA,” Biomed. Signal Process. Control, vol. 47, pp. 393–400, 2019, doi: 10.1016/j.bspc.2018.06.011.

[7] 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, 2005, doi: 10.1016/j.jelekin.2004.09.001.

[8] V. L. Feigin et al., “Global and regional burden of stroke during 1990-2010: Findings from the Global Burden of Disease Study 2010,” Lancet, vol. 383, no. 9913, pp. 245–255, 2014, doi: 10.1016/S0140-6736(13)61953-4.

[9] N. H. Omar, N. A. M. Nordin, C. S. Chui, and A. F. A. Aziz, “Functionality among stroke survivors with upper limb impairment attending community-based rehabilitation,” Med. J. Malaysia, vol. 75, no. 2, pp. 146–151, 2020.

[10] Zhou, Yang, and Wang, World health statistics 2020: monitoring health for the SDGs, sustainable development goals, vol. 21, no. 1. 2020.

[11] V. L. Feigin et al., “Update on the global burden of ischemic and hemorrhagic stroke in 1990-2013: The GBD 2013 study,” Neuroepidemiology, vol. 45, no. 3, pp. 161–176, 2015, doi: 10.1159/000441085.

[12] C. J. L. Murray et al., “Global, regional, and national disability-adjusted life years (DALYs) for 306 diseases and injuries and healthy life expectancy (HALE) for 188 countries, 1990-2013: Quantifying the epidemiological transition,” Lancet, vol. 386, no. 10009, pp. 2145–2191, 2015, doi: 10.1016/S0140-6736(15)61340-X.

[13] V. L. Feigin, B. Norrving, M. G. George, J. L. Foltz, G. A. Roth, and G. A. Mensah, “Prevention of stroke: A strategic global imperative,” Nat. Rev. Neurol., vol. 12, no. 9, pp. 501–512, 2016, doi: 10.1038/nrneurol.2016.107.

[14] I. Faria-Fortini, S. M. Michaelsen, J. G. Cassiano, and L. F. Teixeira-Salmela, “Upper extremity function in stroke subjects: Relationships between the international classification of functioning, disability, and health domains,” J. Hand Ther., vol. 24, no. 3, pp. 257–265, 2011, doi: 10.1016/j.jht.2011.01.002.

[15] C. De Diego, S. Puig, and X. Navarro, “A sensorimotor stimulation program for rehabilitation of chronic stroke patients,” Restor. Neurol. Neurosci., vol. 31, no. 4, pp. 361–371, 2013, doi: 10.3233/RNN-120250.

[16] R. Teasell, M. J. Meyer, N. Foley, K. Salter, and D. Willems, “Stroke rehabilitation in Canada: A work In progress,” Top. Stroke Rehabil., vol. 16, no. 1, pp. 11–19, 2009, doi: 10.1310/tsr1601-11.

[17] V. T. Inman, H. J. Ralston, J. B. De, M. B. Bertram Feinstein, and E. W. Wright, “Relation of human electromyogram to muscular tension,” Electroencephalogr. Clin. Neurophysiol., vol. 4, no. 2, pp. 187–194, 1952, doi: 10.1016/0013-4694(52)90008-4.

[18] J. Luo, C. Liu, and C. Yang, “Estimation of EMG-Based force using a neural-network-based approach,” IEEE Access, vol. 7, pp. 64856–64865, 2019, doi: 10.1109/ACCESS.2019.2917300.

[19] J. Xue and K. W. C. Lai, “Dynamic gripping force estimation and reconstruction in EMG-based human-machine interaction,” Biomed. Signal Process. Control, vol. 80, no. P1, p. 104216, 2023, doi: 10.1016/j.bspc.2022.104216.

[20] P. Artemiadis, “EMG-based Robot Control Interfaces: Past, Present and Future,” Adv. Robot. Autom., vol. 01, no. 02, pp. 10–12, 2012, doi: 10.4172/2168-9695.1000e107.

[21] R. M. Singh, S. Chatterji, and A. Kumar, “A review on surface EMG based control schemes of exoskeleton robot in stroke rehabilitation,” Proc. - 2013 Int. Conf. Mach. Intell. Res. Adv. ICMIRA 2013, pp. 310–315, 2014, doi: 10.1109/ICMIRA.2013.65.

[22] N. Parajuli et al., “Real-Time EMG Based Pattern Recognition Control Challenges and Future Implementation,” Sensors (Basel), vol. 19, no. 20, p. 4596, 2019.

[23] N. Secciani, M. Bianchi, E. Meli, Y. Volpe, and A. Ridolfi, “A novel application of a surface ElectroMyoGraphy-based control strategy for a hand exoskeleton system: A single-case study,” Int. J. Adv. Robot. Syst., vol. 16, no. 1, pp. 1–13, 2019, doi: 10.1177/1729881419828197.

[24] I. Chihi, L. Sidhom, and E. N. Kamavuako, “Hammerstein–Wiener Multimodel Approach for Fast and Efficient Muscle Force Estimation from EMG Signals,” Biosensors, vol. 12, no. 2, pp. 1–15, 2022, doi: 10.3390/bios12020117.

[25] C. Choi, S. Kwon, W. Park, H. dong Lee, and J. Kim, “Real-time pinch force estimation by surface electromyography using an artificial neural network,” Med. Eng. Phys., vol. 32, no. 5, pp. 429–436, 2010, doi: 10.1016/j.medengphy.2010.04.004.

[26] J. Huang, G. Li, H. Su, and Z. Li, “Development and Continuous Control of an Intelligent Upper-Limb Neuroprosthesis for Reach and Grasp Motions Using Biological Signals,” IEEE Trans. Syst. Man, Cybern. Syst., vol. 52, no. 6, pp. 3431–3441, 2022, doi: 10.1109/TSMC.2021.3069084.

[27] F. Pérez-Reynoso, N. Farrera, C. Capetillo, N. Méndez-Lozano, C. González-Gutiérrez, and E. López-Neri, “Pattern Recognition of EMG Signals by Machine Learning for the Control of a Manipulator Robot,” Sensors, vol. 22, no. 9, 2022, doi: 10.3390/s22093424.

[28] J. Vieira, F. Dias, and A. Mota, “Neuro-fuzzy systems: a survey,” … Neural Networks Appl. Udine …, pp. 1–6, 2004, [Online]. Available: http://dme.uma.pt/people/faculty/fernando.morgado/Down/483-343.pdf

[29] K. Kiguchi, T. Tanaka, and T. Fukuda, “Neuro-fuzzy control of a robotic exoskeleton with EMG signals,” IEEE Trans. Fuzzy Syst., vol. 12, no. 4, pp. 481–490, 2004, doi: 10.1109/TFUZZ.2004.832525.

[30] K. Kiguchi, R. Esaki, and T. Fukuda, “Development of a wearable exoskeleton for daily forearm motion assist,” Adv. Robot., vol. 19, no. 7, pp. 751–771, 2005, doi: 10.1163/1568553054455086.

[31] J. Addeh, A. Ebrahimzadeh, and H. Nazaryan, “A Research about Pattern Recognition of Control Chart Using Optimized ANFIS and Selected Features,” J. Eng. Technol., vol. 3, no. 1, p. 6, 2013, doi: 10.4103/0976-8580.107095.

[32] J. Fu, R. Choudhury, S. M. Hosseini, R. Simpson, and J. H. Park, “Myoelectric Control Systems for Upper Limb Wearable Robotic Exoskeletons and Exosuits—A Systematic Review,” Sensors, vol. 22, no. 21, pp. 1–31, 2022, doi: 10.3390/s22218134.

[33] S. Yu, Y. Chen, Q. Cai, K. Ma, H. Zheng, and L. Xie, “A Novel Quantitative Spasticity Evaluation Method Based on Surface Electromyogram Signals and Adaptive Neuro Fuzzy Inference System,” Front. Neurosci., vol. 14, no. May, pp. 1–12, 2020, doi: 10.3389/fnins.2020.00462.

[34] F. Xu, Y. Zheng, and X. Hu, “Estimation of joint kinematics and fingertip forces using motoneuron firing activities: A preliminary report,” Int. IEEE/EMBS Conf. Neural Eng. NER, vol. 2021-May, pp. 1035–1038, 2021, doi: 10.1109/NER49283.2021.9441433.

[35] J. M. Ochoa, D. G. Kamper, M. Listenberger, and S. W. Lee, "Use of an electromyographically driven hand orthosis for training after stroke," IEEE Int. Conf. Rehabil. Robot., 2011, doi: 10.1109/ICORR.2011.5975382.

[36] A. D. Sobel, K. N. Shah, and J. A. Katarincic, "The Imperative Nature of Physical Exam in Identifying Pediatric Scaphoid Fractures," J. Pediatr., vol. 177, pp. 323-323.e1, 2016, doi: 10.1016/j.jpeds.2016.06.086.

[37] V. Mendez, L. Pollina, F. Artoni, and S. Micera, "Deep learning with convolutional neural network for proportional control of finger movements from surface EMG recordings," Int. IEEE/EMBS Conf. Neural Eng. NER, vol. 2021-May, pp. 1074–1078, 2021, doi: 10.1109/NER49283.2021.9441095.

[38] M. S. Karis, H. A. Kasdirin, N. Abas, W. H. M. Saad and M. S. M. Aras, "EMG BASED CONTROL OF WRIST EXOSKELETON," vol. 24, no. 2, pp. 391–406, 2023, https://doi.org/10.31436/iiumej.v24i2.2804..

[39] N. Abas, W. M. Bukhari, M. A. Abas, and M. O. Tokhi, "Electromyography Assessment of Forearm Muscles: Towards the Control of Exoskeleton Hand," 2018 5th Int. Conf. Control. Decis. Inf. Technol. CoDIT 2018, pp. 822–828, 2018, doi: 10.1109/CoDIT.2018.8394906.

[40] J. Lara, N. Paskaranandavadivel, and L. K. Cheng, "HD-EMG Electrode Count and Feature Selection Influence on Pattern-based Movement Classification Accuracy," Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS, vol. 2020-July, pp. 4787–4790, 2020, doi: 10.1109/EMBC44109.2020.9175210.

[41] A. Neacsu, J. Pesquet, and C. Burileanu, "ACCURACY-ROBUSTNESS TRADE-OFF FOR POSITIVELY WEIGHTED NEURAL NETWORKS Speech and Dialogue Laboratory University Politehnica of Bucharest , Bucharest , Romania Universit ´ e Paris-Saclay , CentraleSup ´ elec , Inria Centre de Vision Num ´," ICASSP 2020 - 2020 IEEE Int. Conf. Acoust. Speech Signal Process., pp. 8384–8388, 2020.

[42] H. Hayashi, T. Shibanoki, and T. Tsuji, "A Neural Network Based on the Johnson SU Translation System and Related Application to Electromyogram Classification," IEEE Access, vol. 9, pp. 154304–154317, 2021, doi: 10.1109/ACCESS.2021.3126348.

[43] A. Subasi and S. M. Qaisar, "Surface EMG signal classification using TQWT, Bagging and Boosting for hand movement recognition," J. Ambient Intell. Humaniz. Comput., vol. 13, no. 7, pp. 3539–3554, 2022, doi: 10.1007/s12652-020-01980-6.

[44] D. Copaci, D. Serrano, L. Moreno, and D. Blanco, "A high-level control algorithm based on sEMG signalling for an elbow joint SMA exoskeleton," Sensors (Switzerland), vol. 18, no. 8, 2018, doi: 10.3390/s18082522.

[45] J. Schmidhuber, "Deep Learning in neural networks: An overview," Neural Networks, vol. 61, pp. 85–117, 2015, doi: 10.1016/j.neunet.2014.09.003.