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Development of an EMG-based hand prosthesis with machine learning

Opracowanie protezy ręki opartej na EMG z wykorzystaniem uczenia maszynowego

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Abstract: This study describes the design and comparative assessment of an EMG-based hand prosthesis control strategy using three different systems: Artificial Neural Networks (ANN), Fuzzy Logic (FL), and a Threshold-Based (TB) Arduino system as a baseline. Testing of the systems was conducted in accordance with a standardized protocol with ten healthy participants. The testing results showed that the FL system had the highest classification accuracy (91.3±3.5%) and low tracking error (0.11 ± 0.02 rad RMSE); FL also was the most effective system of the three used for handling the complexity and uncertainty of EMG signals with little training data. The ANN system did show the possibility of achieving similar high precision, but, as it experienced low initial classification performance (55.0±5.1%), this suggests that it was limited because of a lack of training data and therefore needs diverse training data in order to realize the full potential of the ANN system. The TB system was the fastest of the three in terms of response latency (150 ± 15ms). Overall, findings from this study suggest that the control strategy should emphasize the type of training data available; with FL being the most robust in limited training data to contest with the complexity of EMG signals, while ANN systems require ample training data for complex control performance.

Keywords: EMG-based hand, fuzzy logic, machine learning, smart prosthetic control

Streszczenie: W niniejszym badaniu opisano projekt i ocenę porównawczą strategii sterowania protezą dłoni opartej na EMG, wykorzystującej jako punkt odniesienia trzy różne systemy: sztuczne sieci neuronowe (ANN), fuzzy logic (FL) i system Arduino oparty na progach (TB). Testowanie systemów przeprowadzono zgodnie ze standardowym protokołem z udziałem dziesięciu zdrowych uczestników. Wyniki testów wykazały, że system FL charakteryzuje się najwyższą dokładnością klasyfikacji (91,3%) i niskim błędem śledzenia (0,11 ± 0,02 rad RMSE); FL był także najskuteczniejszym z trzech systemów stosowanych do radzenia sobie ze złożonością i niepewnością sygnałów EMG przy niewielkiej ilości danych treningowych. System SSN faktycznie wykazał możliwość osiągnięcia podobnej wysokiej precyzji, ale ponieważ charakteryzował się niskimi wynikami klasyfikacji początkowej (55,0%), sugeruje to, że był on ograniczony ze względu na brak danych szkoleniowych i dlatego potrzebuje zróżnicowanych danych szkoleniowych, aby w pełni wykorzystać potencjał systemu SSN. System TB był najszybszy z trzech pod względem opóźnienia odpowiedzi (150 ± 15ms). Ogólnie rzecz biorąc, wnioski z tego badania sugerują, że strategia kontroli powinna kłaść nacisk na rodzaj dostępnych danych szkoleniowych; przy czym FL jest najbardziej odporny na ograniczone dane treningowe, aby stawić czoła złożoności sygnałów EMG, podczas gdy systemy SSN wymagają dużych danych treningowych w celu zapewnienia złożonej wydajności sterowania.

Słowa kluczowe: proteza ręki oparta na EMG, logika rozmyta, uczenie maszynowe, inteligentne sterowanie protezą

Introduction

Amputation of an upper limb significantly reduces the affected person's quality of life. It may be hard to carry out daily tasks including eating, getting dressed, and taking a shower. EMG-based control systems have improved prosthetic control by detecting muscle-gen-

erated electrical signals, which are processed to manage prosthetic data movements. Machine learning improves this process by training on movement and EMG data and allows real-time classification for more reliable and adaptable system. Furthermore, to machine learning, Fuzzy logic can assist the system of prosthetic control to improve by handling uncertainties in EMG signals. Fuzzy logic can improve the transitions and adaptive responses to varying muscle contractions by combination of machine learning and fuzzy logic. This paper reviews recent advancements in EMG-based hand prosthesis and focusing on machine learning and fuzzy system in enhancing control mechanism.

The study focused is for those who lack upper limb function, particularly those who desire a prosthetic hand that is more effective and natural feeling. Inability to control a prosthetic hand naturally and precisely, which frequently results in decreased functionality and quality of life to do some tasks. Conventional prostheses always lack the control and dexterity required for daily tasks, which makes people feel frustrated and alone. It also reduces social involvement and increases dependency on others.

To our knowledge, no systematic framework and prototype system exists for the smart prosthesis hand with machine learning established in recent works. This project goals are to build an EMG-based hand prosthesis control system using machine learning for amputees. Surface EMG sensors will produce muscle signals, and the machine learning will translate and convert the algorithms into prosthetic hand movements. System responsiveness, and ease of use can be evaluated based on potential limitations such as signal variability, training data requirements, sensitivity to external factors and incomplete movements. Engineering challenges in integrating the system and its high cost due to technology are also recognized.

By the advantage of machine learning to investigate EMG-based control of trans humeral prosthesis, highlight the applicability of machine learning in prosthetic control [5]. Their research already shown how machine learning may be used to optimize prosthetic limb control mechanisms, opening the door to more flexible and user-friendly interfaces. Furthermore, as reported in [2], investigate the integration of neuro-musculoskeletal modelling and machine learning for the management of prosthetic limbs.

The capacity of machine learning to setup the specific configuration of each user is one of the main benefits of incorporating it into prostheses. A customized and responsive prosthetic control experience can be achieved by training machine learning algorithms to get particular patterns of muscle activation and user intent [3]. The prosthetic community has a requirement, making adaptation especially important.

But it's important to recognize the difficulties and nuances involved in integrating machine learning into prosthetic devices. These challenges include the necessity for substantial and diverse training datasets, as well as strong algorithms that can manage real-time processing and user variability [4]. These obstacles, research and innovation in prosthetics are still being driven by the potential advantages of machine learning, which include more functionality, less cognitive strain on users, and an overall higher quality of life.

Literature review

The field of advanced prosthetic technologies has the potential to significantly improve the lives of people who have lost limbs. Examples of these technologies include machine learning applications, smart prosthetics, and EMG-based control systems. An overview of the diverse field of research and development in this area is given in this introduction, with a focus on how it has the potential to completely transform prosthetic functioning and user experience. In the realm of assistive technology, prosthetic control and electromyography (EMG)-based systems are essential, especially when it comes to the creation of sophisticated prosthetic limbs. The term "prosthetic control" describes the systems and tools used to help people who have lost limbs control and synchronize the movements of their prosthetic limbs so that they function similarly to their natural limbs. On the other hand, EMG-based systems use electrical signals produced when the user's residual limb's muscles contract to control the prosthesis. According to [1], a systematic review that highlights the importance of EMG-driven control in lower limb prostheses has been implemented. The research highlights the significance of electromyography (EMG) as the principal input source for prosthetic control, offering valuable perspectives on its efficiency and feasibility. By concentrating on EMG-based control of trans humeral prosthesis using machine learning methods, [5] also further this understanding. Their study illus-

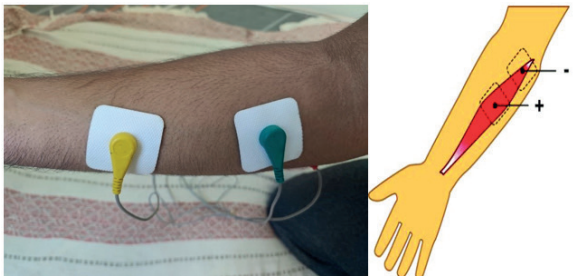


Fig. 1. Real-time EMG Based Prosthetic Hand Controller

trates the increased interest in incorporating artificial intelligence into assistive technology by examining how machine learning may improve the functionality of prosthetic hand.

The topic of myoelectric control of robotic upper limb prosthetics is expanded upon by [3], who offer a thorough analysis of electromyography interfaces, control paradigms, difficulties, and potential future approaches. This review summarises the wide landscape of EMG-based control systems, putting light on the many approaches and interfaces available for prosthetic users. Based on the finding in [7], examine the systematic study of upper limb prosthesis control based on electromyography, providing insights into current developments and patterns in this area.

EMG-based control, although very promising, still has some challenges to face. The main issue is accuracy and reliability, since muscle signals, environmental conditions, and user adaptation can all affect the efficiency of such systems [1]. However, the totality of [8] and [9] continues to recognize that the respective research and development efforts slowly but surely improve the scope and robustness of EMG-controlled prosthetics. To bring about a workable Smart Prosthetic Control: EMG-Based Hand Prosthesis with Machine Learning, the first thing to do is to create a mechanical system that mirrors the human arm's functions very closely. Mechanical design includes not only actuation of joints but also the consideration of the different forces present in the system. The bionic limb design discussed here can be completely made with a 3D printer and easy-to-use tools.

Fusion 360 is a computer design software package made for modelling solid mechanical components and assemblies. Fusion 360 is a popular tool in the engineering industry and has been used extensively in designing and analyzing mechanical components. Every finger is composed of three distinct printed components that are interconnected using polypropylene pins. Based on Fig. 2, the artificial tendon forms a loop around the distal end of the finger, establishing a secure place for tendon immobilization. The tendon traverses the finger's internal channels, creating a closed loop. When the tendon experiences tension, rotational forces are exerted on all the joints, causing the finger to curl up. The presence of a tendon locking point is crucial in order to ensure that when the tendon is under strain, it exerts a force on the fingertip and induces rotation in all the joints. In the absence of tendon locking, the finger would simply slide without any movement occurring when tension is applied. To extend the finger from a flexed posture, tension is exerted on the opposite end of the tendon.

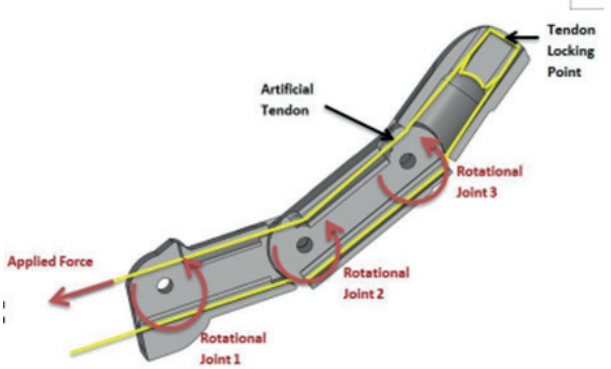


Fig. 2. Index finger with artificial tendon looping through

The thumb has been developed similarly. The main aspiration of both the commercial and research prosthetic hands is to provide at least two degrees of mobility in the thumb. Nevertheless, this thumb is restricted to only one degree of freedom, which means it can just perform a single open/close movement. The configuration of the fingers and thumb comprises guide holes that facilitate tendon alignment and avoid the situation where the tendons get caught on sharp edges, as illustrated in Fig. 3. The usage of high-quality braided fishing line is the preferred option due to its low elasticity while under tension. The elasticity of nylon fishing line would, however, slowly decrease over time, leading to a reduction in tension. This decrease in tension would in turn impair finger movements.

The tendons in the human hand function similarly, but there is a greater number of tendons connected to various bones, enabling more accurate manipulation of the fingers. The tendons make a closed loop around the special 3D-printed servo horns, which you can see below in Fig. 4. The tendon is pulled tight as the servo motor turns in one direction, which shuts the finger.

To make the finger open, the motor is turned the other way. Amputation can occur anywhere along the arm and is unique in every case. An ideal design facilitates connection to a stump located anywhere along

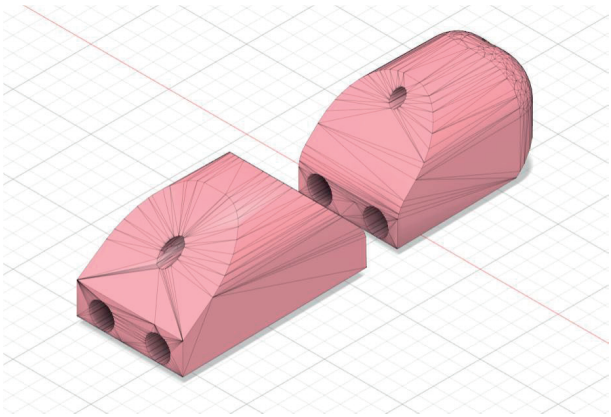


Fig. 3. Thumb Section

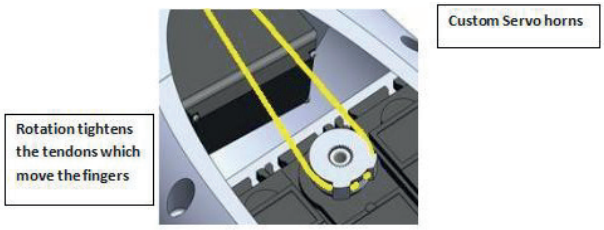


Fig. 4. Tendon actuation system

the arm. The hand and wrist section could now be fitted to a person amputated along their forearm. The full design of the hand prosthesis is shown as in Fig. 5. The creation of intelligent prosthetics is a major development in the field of assistive technology, with the goal of giving people who have lost limbs better physical capabilities as well as increased functionality, connectivity, and user experience. With the addition of sensors, feedback systems, and networking capabilities, smart prosthetics are intended to surpass conventional prosthetic devices by providing the user with increased flexibility, control, and engagement with their surroundings.

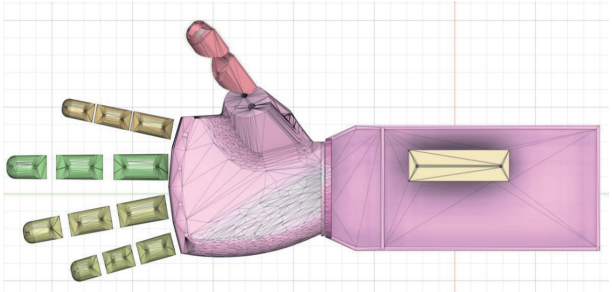


Fig. 5. Assembly of Hand and modular forearm using assisted computer for 3d printer used in this design and development

One of the most important aspects of the development of smart prostheses is the integration of sensors. As discussed in [9], these sensors can include accelerometers, gyroscopes, force sensors, and even touch sensors These sensors record information in real time about the location, orientation, and interactions of the prosthetic limb with surfaces and objects. This data is crucial for giving the user feedback about their surroundings and facilitating more organic and coordinated movements of the prosthetic limb.

Another distinguishing element of smart prostheses is connectivity. Through wireless communication technologies, such as Bluetooth or Wi-Fi, these devices can be synchronized with smartphones, tablets, or other assistive devices. Through specialized apps that provide personalization choices and real-time performance feedback, this connectivity enables users to monitor and manage their prosthetic limbs [9]. It also encourages the possibility of remote diagnoses and modifications, which lessens the need for regular in-person trips to prosthetic clinics.

Previous studies [9] have indicates that to improve the user's proprioception and situational awareness, smart prosthesis development frequently includes feedback methods, such as haptic feedback or visual signals, in addition to sensor integration and networking. These features make using the prosthetic limb easier and safer by giving users a more intuitive understanding of its position and functions. The development of intelligent prostheses extends beyond their hardware components. For these gadgets to reach their full potential, software is essential. As demonstrated by [5] and [2], machine learning algorithms have the capacity to process the massive volume of sensor data produced by smart prosthetics, adjust to the preferences of the user, and enhance the prosthetic's responsiveness over time.

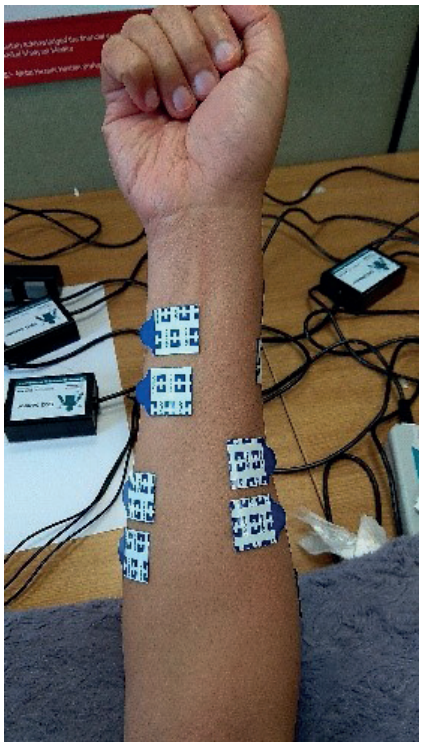


Fig. 6. Examples of electrode placement for EMG extraction from Flexor Carpi Radialis (FCR) and Extensor Carpi Radialis Longus (ECRL) to reflect the movement of each finger joint angle

According to [10], iLimb digits, a product of Touch Bionics, utilize electric motors directly in the prosthetic fingers. This allows for easy integration of the palm into a connecting socket which links the prosthetic fingers to the hand. The images provided show suitable site/s for amputation to accommodate the use of iLimbdigits. Prosthetic devices utilized in research endeavours are specifically engineered to evaluate cutting-edge mechanical designs and intricate control methodologies. Many research prosthetic hands necessitate an external power source, rendering them unsuitable for integration with amputees.

Mechanical Characteristic

As presented in table 1, the bionic limb design was fully fabricated using a 3D printer and designed using Fusion 360 software. The fingers are composed of three distinct printed components connected by polypropylene pins. Movement is achieved via an artificial tendon loop that traverses the finger's internal channels. The system employs high-grade braided fishing line for the tendons due to its minimal elasticity under tension. The thumb possesses a singular degree of freedom (open/close motion).

Table 1 Specification of prosthetic hand

Specification	Value
Total Mass	450 g
Dimension (hand)	200 x 90 x 50 mm
Estimated BOM Cost	$150 USD
Servor Motor	TowerPro MG996r
Stall Torque	9.4 kg/cm (at 4.8V), 11 kg/cm (at 6V)
Max Speed	0.17 sec/60° (at 4.8V), 0.14 sec/60° (at 6V)
Tendon Type	High-grade braided fishing line

Methodology

The surface EMG electrodes were positioned directly on the Flexor Carpi Radialis (FCR) and Extensor Carpi Radialis Longus (ECRL) muscle bellies to record wrist flexion and extension activity, as shown in Fig. 6.

6 male and 6 female participants (N=12) from UTeM students voluntarily agreed to participate in the study. Participants were age 22-30 years and inclusion criteria required participants to be in a state of neurological ailments. The dominant hand was utilized for data collection. All experiments were approved by the University Ethical Committee or Centre for Research and Innovation Management (CRIM) of Universiti Teknikal Malaysia Melaka (UTeM). The experiment employed a Hand Dynamometer, LabQuest Mini for data capture, Vernier EMG sensors, a personal computer equipped with Logger Lite data-collection software, a Stopwatch, a Protector, and Kendall5400 diagnostic tab electrodes.

This study utilized time-domain-based characteristics by employing the Waveform Length (WL) technique. The EMG signal was recorded in time-based mode with a sampling rate of 1kHz (1ms interval) for a total duration of 40 seconds, producing 40,001 samples pre channel shown ad Fig.7. Data collection was manually started and automatically stopped after 40seconds [14] and [15]. This setup provides sufficient temporal resolution for EMG analysis within the 20-450 hz frequency range and ensures high-quality data suitable for feature extraction and controller training (ANN, Fuzzy, PID).

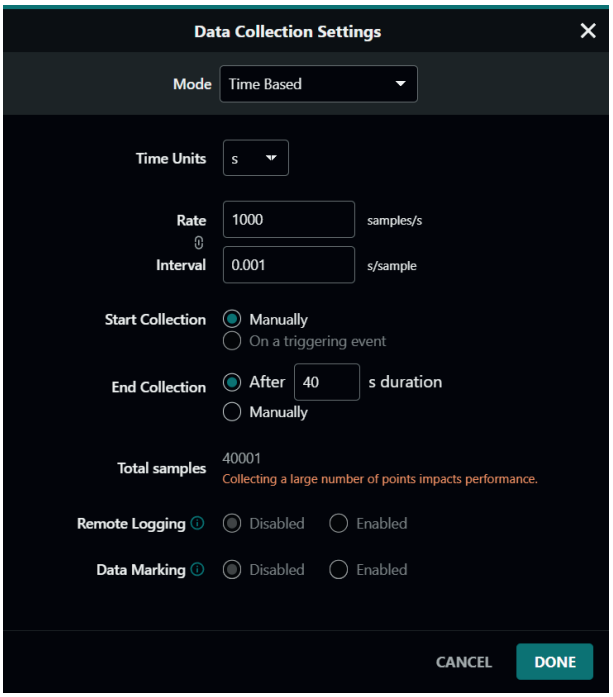


Fig. 7. Time based setting

Experiment 1, the participants will perform repeated hand grasping actions at three different levels of low, moderate and strong grasp for 40 seconds. More precisely, the setting of the low grip will be just the opening and closing of the hand with no resistance at all, the medium grip will be a full grip to the extent of the participant's hand strength but without using a dynamometer, and the strong grip will be the maximum grip possible measured by the use of a dynamometer. Participants took 10 second breaks between tasks to minimize muscle fatigue. Experiment 2, participants will bend their wrist upward (adduction) and downward (abduction) from a fully extended position to a 90-degree angle repeatedly for 40 seconds as shown in Fig.8. Each gesture was performed continuously during the 40-second period following a steady rhythm, not held once.

The gesture depicted in Fig. 8 was merely employed to set the maximum voluntary contraction (MVC) for each experiment and was consequently excluded from the classification set.

Based on the finding [12], this process system also known as system performance and evaluate the effective of the selected modelling approach.in line with the recommendations of this study, both the ANN and FL method were evaluated utilizing a common dataset to make sure the consistency in output results. Artificial Neural Networks (ANN) technique and Fuzzy Logic

Fig. 8. Experiment 1 and 2

(FL) rules are commonly employed by academics to produce output results when provided with non-linear input. By leveraging the benefits of both methodologies, they have been selected to be incorporated into the mapping technique for predicting the expected required velocity output of the finger, based on EMG input and fingers position. Although artificial neural networks (ANN) are highly effective in processing nonlinear dataset, their performance may be compromised when working with tiny input datasets that are insufficient for constructing an effective network. FL has the capability to process nonlinear inputs and provide estimated outcomes. However, it is crucial to have well-defined ranges of input data in order to prevent inaccurate guesses and minimize substantial errors.

A. Artificial Neural Network (ANN) Controller

The ANN utilized a feed-forward architecture for unidirectional mapping from the dataset. It was trained to predict the desired finger velocity output ($\theta^{\cdot}$). Even though merely 12 subjects participated, the ANN was utilized to verify feasibility with few data, not for statistical generalization purposes.

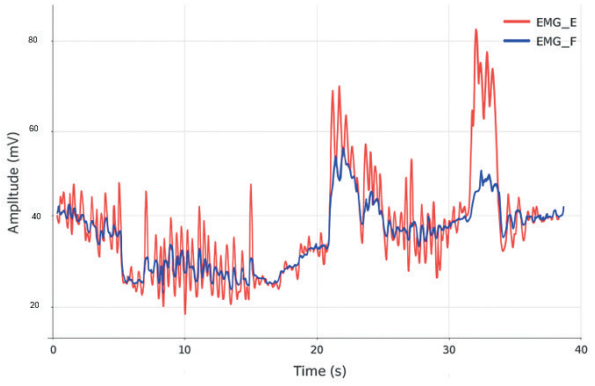
It could be seen that artificial neural networks (ANN) demonstrated great resiliency in recognizing

Table 2 ANN architecture

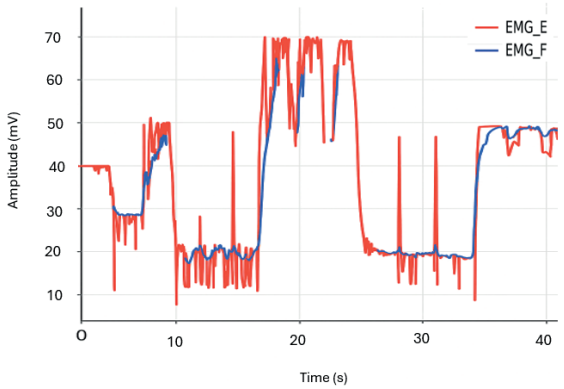
Parameter	Value
Input layer	4 units
Hidden layer 1	8 units
Hidden layer 2	4 units
Output Layer	1 unit
Epochs	100
Train/Test Split	60% Training, 20% Validation, 20% Testing (per-subject)

the motion associated with bio signal patterns while accommodating system nonlinearities with very low computational costs [16]. They also need very low computational capabilities. The ANN technique requires training a network with representatives' input-output datasets.

In this case three sets of data were recorded, and two sets were used to train the ANN model, and the remaining set to test. WL feature extraction technique was used to extract unique characteristics produced by the extensor and flexor muscles of the EMG data. Just the Waveform Length (WL) characteristic was pulled out. The ANN input vector was made up of three values – EMG from FCR, EMG from ECRL, and the finger joint angle. The three inputs employed to predict



(a)



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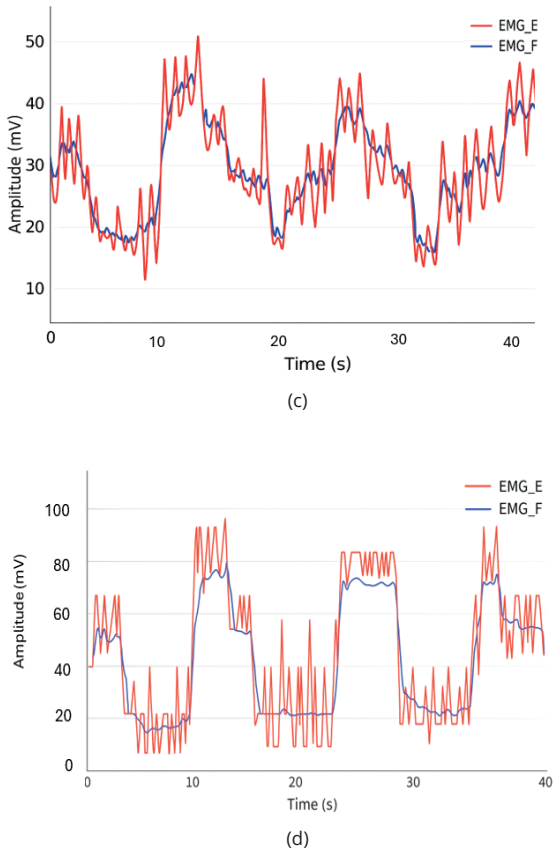

Fig. 9. a) FCR single muscle, b) ECRL single muscle, c) double muscle MVC level (20%), d) double muscle MVC level (60%) [15]

the desired finger velocity output in a single muscle case are EMG_F (EMG value during hand/fingers flexion), EMG_E (EMG value during hand/fingers extension) and finger joint angle position.

The figures (Fig. 9(a) and (b)) illustrate a comparison of signals between EMG_F and EMG_E at different levels of muscle contraction. The level of muscle contraction is the same for both EMG signals. Should lead to minimal hand motion. The other value levels of the MVC should conform to the one that is superior to the others. Through this signal comparison experiment, it is possible to estimate the desired velocity movement of the finger. Nevertheless, the signals from both graphs exhibit fluctuations, which can lead to inaccuracies in finger result velocity.

For the double muscle technique, two input signals have been simultaneously captured from the FCR and ECRL muscle responses, as depicted in Fig. 9 (c) and (d). The expected finger velocity was the predicted output from the trained artificial neural network model. The testing for the desired velocity output of the finger was conducted at two levels: 20% MVC and 60% MVC. When the output reached 20% of the maximum voluntary contraction (MVC), the produced signal exhibited a noticeable fluctuation at 75 seconds and earlier, while the finger was in a neutral posture.

B. Fuzzy Logic (FL) Controller

Function that defines the membership of an element in a fuzzy set. Decisions are made by formulating rules that are grounded in knowledge. The function of inference system that utilizes rules to make decisions. Defuzzification is the process of transforming the conclusion of an inference system into tangible or real-world data, enabling it to interface with the physical system. Fig. 10 illustrates a conceptual configuration of a FL. The Mamdani-type fuzzy logic (FL) controller takes three linguistic variables as input–EMG_F and EMG_E, plus finger joint angle (θ)–and produces an output for hand's desired velocity (θ̇). The inputs EMG_F and EMG_E as normalized muscle activation levels ranging from 0 to 1 (normalized MVC), have three membership functions (MFs) to define them as small (S), medium (M), and high (H) MFs usually as trapezoidal or triangular shape. The finger joint angle (θ) expressed between 0° (fully open) and 90° (fully closed), if defined by three MFs as open, mid, and closed MFs. The output variable, hand's desired velocity (θ̇), defined by five MFs as fast extension (FE), medium extension (ME), zero (Z), medium flexion (FM), and fast flexion (FH) that simultaneously defines the speed (or motion) and direction of the hand. It displays the individual structure of electromyography (EMG) signals originating from the muscles in the forearm. As presented in [16] the FL output, which is the intended velocity of the hand fingers, has been chosen as the selected control theory for exoskeleton hand systems. The activation rate of the EMG signals for extensor and flexor muscles has been continually measured and evaluated while using WL feature extraction technique. A consistent mapping is ensured by using the same dataset for training in the ANN method and in the FL design.

The EMG rules from the table have mapped to the flexion and extension movements of the hand joint, respectively. As per the three base requirements from Table 3, it would be expected that flexion and extension movements would have a desired finger velocity of zero when both signals are at an equal level. The next six base rules looked at how the different EMG signals' stimulations can influence the forecasts of the required velocity of the finger. All of the verbal statements from the rule table have been combined together to form a Mamdani style fuzzy inference process, changing the inputs to get the outputs. The table displayed above, Table 3 and 4, contains a total of IF-THEN rule statements. While the FCR was at the highest signal level during finger flexion, the dataset was developed in this way. The ECRL muscle demonstrated the highest correlation to signal level during hand movement. The signals EMG_F and EMG_E correspond to the flexion and extension move-

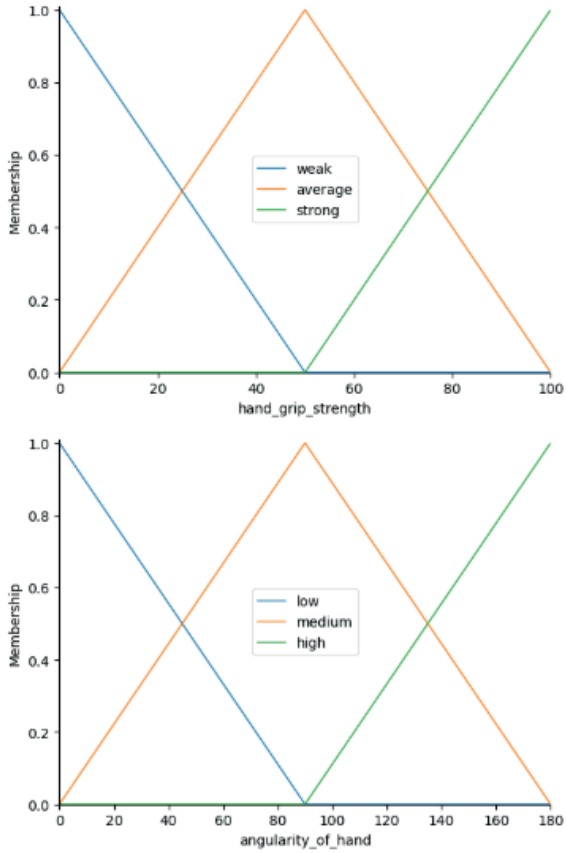

Fig. 10. Mamdani FL configurations

ments of the hand joint, respectively. Based on the initial three fundamental requirements outlined in Table 1, it is expected that both flexion and extension movements will lead to a desirable finger velocity of zero when both signals are at a comparable level. The subsequent six rules examined the impact of different EMG signal stimulations on the forecasts of the required velocity of the finger. In order to fulfil all fifteen criteria, guidelines were implemented to restrict the joint of the fingers angle (Θ) of the device and incorporate safety measures for fingers velocity (Θ/s). All 15 linguistic assertions in the rule table are integrated to create a Mamdani style fuzzy inference method, which translates the inputs into the output. The table displayed as in Table 3 and 4, presents a total of 9 IF-THEN rule statements. The FCR muscle exhibited the highest signal level during finger flexion, leading to the acquisition of parameter data. Conversely, the ECRL muscle displayed the highest signal level during hand movement.

C. Threshold-Based (TB) Arduino Controller (Baseline)

Threshold-based (TB) Arduino Controller (Baseline) utilized a traditional Arduino system based on simple threshold methods. An activation threshold, T(act), was set 0.3 as a normalized MVC. A deadband region of ±0.05 was implemented around a lower threshold T(zero) 0.015 to prevent oscillation. T(act) and T(zero) were calibrated per-subject by observing the signal level corresponding to reliable, conscious muscle activation.

Table 3. IF-THEN Rule Statement

RULES					RESULT
	EMG_F		EMG_E		
IF	S		S	=	Z
IF	M		M	=	Z
IF	H		H	=	Z
IF	M	and	S	=	FM
IF	H	and	M	=	FM
IF	H	and	S	=	FH
IF	S	and	M	=	EM
IF	M	and	H	=	EM
IF	S	and	H	=	EH
IF	M	and	S	=	Z
IF	H	and	S	=	Z
IF	S	and	M	=	Z
IF	S	and	H	=	Z
IF	H	and	M	=	Z
IF	M	and	H	=	Z

Table 4. IF-THEN Rule Statement

RULES					RESULT
	EMG_F		EMG_E		
IF	M	and	M	then	Z
IF	H	and	H	then	Z
IF	M	and	S	then	FM
IF	S	and	S	then	Z
IF	H	and	S	then	FH
IF	M	and	H	then	EM
IF	S	and	H	then	EH
IF	H	and	M	then	FM
IF	S	and	M	then	EM

Results and Discussion

The example of achievable movements is shown in Fig. 11 and Fig. 12. The prosthesis hand developed was able to imitate the hand movement as it configures the signal received for the user. This shows the capabilities with specific accuracy of the prosthesis control using this technique. The results achieved demonstrate the prosthetic hand's ability to imitate human hand move-

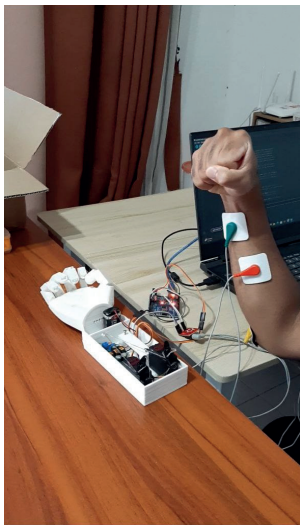

Fig. 11. Grasping movements initiated by the user and imitate by the EMG based prosthetic hand model

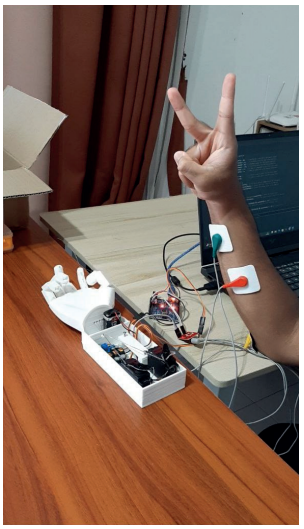
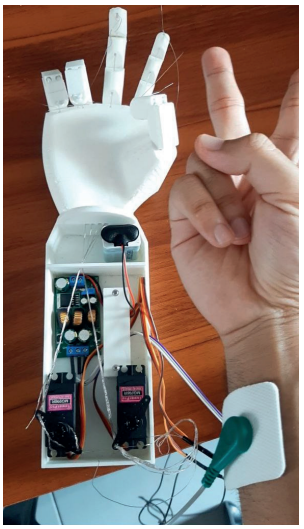

Fig. 12. Peace movements initiated by the user and imitate by the EMG based prosthetic hand model

ments effectively. Specifically, the developed prosthesis could configure the received signals from the user to replicate hand movements such as a "Grasp" (Fig. 11) and a "Peace" sign (Fig. 12). The “Grasp” and the “Peace” gestures were only derived from FCR and ECRL EMG signals, respectively. They were utilized to illustrate the extent of the system's ability to replicate real hand movement, and not for extra training data.

The fuzzy logic control performance was compared to a threshold value Arduino-based system in the study. The Fuzzy system utilized typical input intervals for hand grip force (0-100), hand angularity (0-180), and muscle signal (0-240), and they were classified as low, medium, high-level.

In testing, the fuzzy controller properly transferred these inputs to output signals accordingly. A grip of 100 degrees of angularity of 0, for instance, resulted in a muscle signal of 100, and a grip of 60 degrees of angularity of 0 resulted in a muscle signal of 80. Such results reflect a precise and adaptable behavior of a system for a changing set of input conditions.

The fuzzy logic system demonstrates how the amplitude of the hand muscle signal relates to the rules and membership functions. By comparing the output muscle signal levels in these two instances, the fuzzy logic system assesses the effects of using more grip strength on the muscle signal. Fig. 13 and 14, presents the fuzzy logic system output when the grip strength = 100, and angularity = 0°. The resulting muscle signal output is 100, this indicates a moderate grip with no corresponding angle change. In this second example

Figures 15 and 16 present the grip strength = 60 and angularity = 0°. The resulting muscle signal output is 80 which denotes a stronger grip with the same angle condition. Therefore, with the changes in muscle signal output from the comparison of these two examples, it demonstrates how varying grip strength affects the resulting muscle signal amplitude. The results from the fuzzy logic system demonstrate that it accurately reinforces its ability to adjust how high or low the muscle signal output is, based on the grip strength and altered input of conditions provided.

A. Discrete Gesture Classification

All controllers were evaluated using a standardized protocol across the twelve participants. The protocol included four discrete gestures for classification accuracy and a continuous tracking task for tracking error. Each of the twelve subjects performed all gestures (grip low, grip medium, grip strong, wrist abduction, wrist adduction), and each was repeated in three sets. The figures in Table 5 signify the mean performance throughout all the trials. In total, 144 gesture trial were collected from the volunteers.

The highest average accuracy (91.3%) was achieved by the Fuzzy Logic (FL) controller, with low False-Trigger Rate (FTR) and was able to reliably extract the non-linearity between the movement intention and the EMG features, despite the very short, limited training protocol [15].

The ANN controller, on the other hand, had the worst accuracy (55.0%) and highest FTR. It is the worst performing, as the data collected under the lim-

Table 5 Comparison of classification accuracy

Metric	TB (Threshold)	FL (Fuzzy Logic)	ANN (Neural Network)
Overall Accuracy (%)	85.5±4.2	91.3±3.5	55±5.1
False-Trigger Rate (per min)	3.1±1.1	1.5±0.7	5.5±1.5
Time-to-Complete (s)	1.15±0.20	1.35±0.25	1.45±0.30

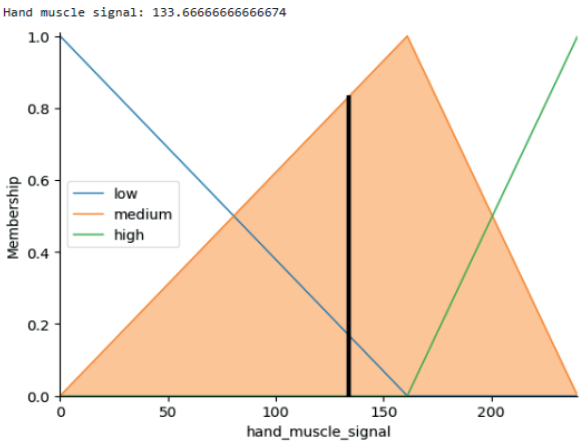

Fig. 13. Output graph for FL rule-base system (Test 1)

Fig. 14. Serial Plotter (Grip)

ited, regular protocol (10–15 minutes per subject) was insufficient to properly train the high-dimensional, complex data that the ANNs are best suited to model. Although ANNs are optimal theoretically for modeling high-dimensional, complex data, they have the tendency to overfit or generalize poorly when the training dataset fails to capture the full variability of the input space. TB system had a mediocre baseline accuracy (85.5%) but had the highest FTR as the system lacks signal smoothing and has simple decision criteria.

B. Continuous Tracking Performance

The ANN controller exhibited the lowest tracking error (RMSE). The FL system also offered smooth, adaptive transitions by handling uncertainty effectively, resulting in low overshoot. The TB system provided the fastest response latency due to its direct, simplified nature.

Table 6 Comparison of continuous tracking performance

Metric	TB (Threshold)	FL (Fuzzy Logic)	ANN (Neural Network)
Tracking Error (RMSE, rad)	0.15±0.03	0.11±0.02	0.08±0.01
Response Latency (ms)	150±15	175±18	180±20
Overshoot (%)	12.5±4.1	5.2±2.8	3.1±2.0

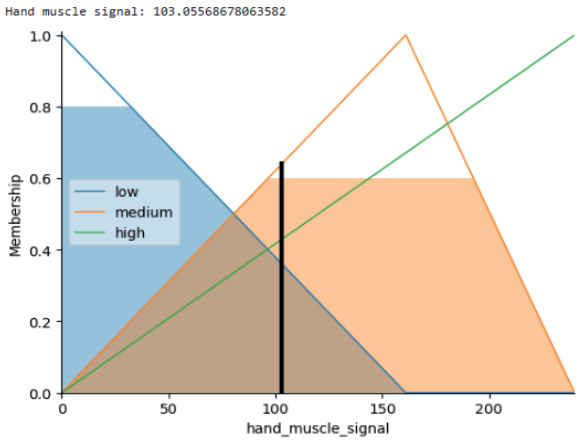

Fig. 15. Output graph for FL rule-base system (Test 2)

Fig. 16. Serial Plotter (Peace)

Conclusions

The findings indicate that the Fuzzy Logic (FL) controller achieved the strongest and best control for discrete gesture classification with restricted training data. This reinforces the known advantage FL has with noisy inputs and the ability to use smooth, adaptive control with minimal reliance on the dataset.

While the Artificial Neural Network (ANN) showed great potential for continuous, proportional control (lowest RMSE), it failed on the discrete classification. This underscores the already established limitation of data-driven methods: ANNs are significantly complex with complex data sets but heavily depend on large, comprehensive well labeled datasets to stimulate generalization, which was clearly absent in the current procedure. The TB system is certainly useful and applicable for fast speed low accuracy.

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