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A fuzzy inference system for hand injury level classification using surface electromyography signals

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ABSTRACT

The surface electromyography (SEMG) is extensively used in assessing injuries in the musculoskeletal parts of the body. Integrating intelligence in such applications impacted the development of intelligent medical devices. The conventional way of assessing hand injury level is manually and subjectively done by experts to identify the type of rehabilitation program recommended to the patient. This work uses SEMG data to classify hand injury levels through a fuzzy inference system (FIS). Three of the many features of the SEMG signal were selected based on its high distinction levels, namely, the root-mean-square, enhanced mean-absolute value, and the waveform length. Segmentation through a sliding window method is used for feature extraction. The FIS rules were designed based on the assessment guide of the experts. A Mamdani-type FIS classifier was used with membership functions which are a combination of trapezoidal and triangular types. A MATLAB Simulink model was also designed to test the FIS system. The setup effectively identified injury levels through tests with a healthy subject, wherein no muscle activation means an injury, while the full fist, as a full muscle activation or healthy. In between signal values vary with different injury levels. In the future, this setup will be tested on patients in a rehabilitation clinic for validation.

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1. INTRODUCTION

There are different ways on how to assess hand injuries. When a hand injury is diagnosed, it is necessary to determine the extent of the injury. Some of these assessment methods are the Minnesota manual dexterity test (MMDT), the Purdue pegboard test (PPT), and the use of a dynamometer for grip strength quantification. For peripheral nerve injury (PNI), the basic assessment method done by most rehabilitation doctors is the tendon gliding exercises. These exercises are used in assessing mobility, locating the pain or dysfunctional fingers, and the level of injury. Other experts use medical devices such as electromyography (EMG) to detect and measure muscle activities of the body. It comes in two different forms: the needle type and the surface EMG. Needle-type EMGs are invasive as the needle is injected down deep into the muscle of interest to get muscle data. The electronic signals produced by the EMG are analyzed and quantified. This device can also be used to assess damaged muscles. SEMGs, on the other hand, are noninvasive as they are only attached to the surface of the skin. However, it is much preferred to use needle EMG over SEMG for analytical type of assessment of the muscles. SEMGs can be used to determine and assess skeletal muscle activation. It can also be used for monitoring the progress of rehabilitation by tracking muscle activity changes.

EMG signals are found useful in identifying hand movements by works done in [1], [2] to both prosthesis and for assisting physiotherapists (PTs) and occupational therapists (OTs) in assessing patients in their progress during rehabilitation. In some assistive enforcement robots, EMG signal features are selected to classify movement intention necessary for rehabilitation [3]. Common parameters useful in classification are time domain (TD) features, such as moving average value (MAV), root-mean-square (RMS), slope sign change (SSC), waveform length (WL), and enhanced mean-absolute value (EMAV), while others are frequency domain (FRD) features, such as mean frequency (MF), fractal length (FL), and some are in time-frequency domain (TFD).

Hand rehabilitation is the most common least invasive approach in treating injuries of the hand. Carpal tunnel syndrome (CTS) is one of the most common hand injuries which is caused by median nerve compression due to long hours of repeated or complicated posture such as in car and motorcycle driving and in using computers. The common symptoms of CTS are numbness and tingling of fingers, weakness of the hand, and pain in the wrist down to the elbow. Neurodynamic mobilization and exercised-based physiotherapy are two of the common nonsurgical methods in treating carpal tunnel syndrome [4], [5]. It includes exercises moving the wrist, elbow, and head. A case has been presented effective using myofascial stretching to aid the CTS hand rehabilitation [6]. Exercise-based techniques such as tendon gliding and mobilization of the carpal bones and soft tissues have gained their spot as another effective means. The combination of neurodynamic and exercise-based physiotherapy such as tendon gliding exercises has been effectively used for pre-surgical or nonsurgical treatment of CTS. The nerve and tendon gliding exercises are found to be effective when combined with other device-specific therapies such as the laser and ultrasound [7].

Tendon gliding exercises are often used as passive exercises for CTS and stroke patients in the rehabilitation of the hand. It includes the hand formations: straight, hook fist, full fist, straight fist, and tabletop. These exercises need different orientations of the fingers of the hand which increases its range of motion. Aside from the tendon gliding exercises, the activities of daily living (ADL) are also considered to help the hand to become functional. Some designed rehabilitative gloves have very promising results with measured outcomes in aiding hand rehabilitation for post stroke patients [8]. The assessment of the injury level is important in designing the extent of these exercises.

Due to the pandemic, going to rehabilitation facilities has been the least option. In the absence of therapists, wearable rehabilitation devices are much needed. For some passive and active hand exercises, rehabilitation gloves can be useful. A family member can help by putting on wearable devices with the assistance of therapists and rehabilitation doctors online.

Tendon gliding exercises are used by physicians for both assessment and rehabilitation. It has a varying formation of the hand in which the hand is tested for its mobility, flexion, and extension. The common tendon gliding exercises are listed and presented in Figure 1. Figure 1(a) is the relaxed position and Figure 1(b) is the straight position doing the extension. Other positions are the platform, straight fist, and full fist presented in Figures 1(c) to (e).

(a) (b) (c) (d) (e)

Figure 1. Tendon gliding exercises (a) relax position (b) straight (c) platform (d) straight fist and (e) full fist

The hand muscles are very significant in assessing the hand as compared to the forearm in terms of dexterity based on the study conducted by [9]. The placement of the SEMG electrodes to a certain muscle group is necessary for assessing the hand condition and rehabilitation [10]. In flexor tendon injuries of the hand, the flexor pollicis (FP) and flexor digitorum (FD) are the tendons that affect the mobility of the hand [11]. The attachment of these muscles to the tendons was observed by [12], [13] which is significant in muscle group selection. The motor unit action potential (MUAP) was observed using EMG by [14] as the muscles move during finger movement which led to determining the muscular problems. EMG can be used for classifying hand movements and intentions as displayed by the work of [15], [16]. However, an intelligent system that could do hand injury level assessment is yet to be studied. These intelligent systems are necessary in the development of soft robotic gloves for rehabilitation [17], [18].

In this work, SEMG signals were used to collect the musculoskeletal data of the hand. Three healthy subjects were tested and collected with SEMG signals. Different hand exercises are done by the subjects to observe and record data. These signals are processed and selected features are extracted for classifying hand injury levels. A fuzzy inference system is designed and set up as the classification system used in this work. The hand injury level rules are based on the experts' opinion.

2. METHODOLOGY

2.1. EMG data processing

The specific target muscles that will be used for the evaluation of hand injury are those that lie in the tendons FD, FP, and lumbrical. The signals transmitted through the electrodes are processed through the SEMG module which filters, amplifies, and conditions signals that are compatible with the Arduino microcontroller as shown in Figure 2. It is necessary to identify the regions of interest in processing SEMG signals [19]. The processed signal will be used for feature extraction. Using the sliding window method, the three identified features, namely, the RMS, WL, and EMAV are computed. These features will be used as inputs to the fuzzy inference system (FIS). The membership functions are defined based on the experts' opinions. In this work, it is classified as levels 1-5. The intervention and rehabilitation exercises are described in Table 1 for flexor tendon injuries [20]–[27]. This will also be used for defining the membership functions for the fuzzy inference to be developed.

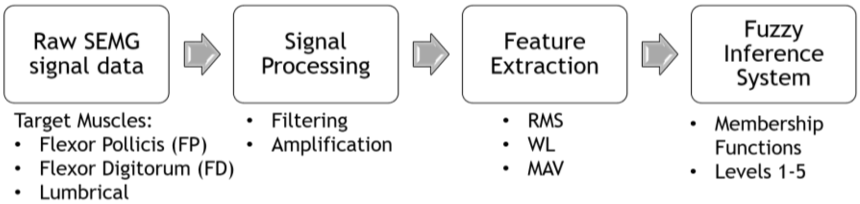


Figure 2. SEMG data processing and classification

Table 1. Flexor tendon injury assessment guide and intervention program

Level	Symptoms	Rehabilitation/Intervention Program
1	Mild pain, minor swelling, minimal loss of motion.	Early Phase (0-4 weeks): Rest, ice, compression, and elevation (RICE). Splinting to prevent further injury. Gentle passive range of motion (PROM) exercises.
2	Moderate pain, noticeable swelling, reduced motion, possible partial tendon tear.	Intermediate Phase (4-8 weeks): Splinting continues, initiating gentle active range of motion (AROM) exercises. Begin tendon gliding exercises. Monitor for signs of adhesion formation.
3	Severe pain, significant swelling, loss of motion, partial tendon tear confirmed by imaging.	Late Phase (8-12 weeks): Progressive resistance exercises. Continue tendon gliding exercises. Functional activities to enhance tendon strength and flexibility. Monitor for complications such as rupture or excessive scarring.
4	Extreme pain, substantial swelling, total loss of motion, complete tendon rupture confirmed.	Post-Surgical Phase (0-6 weeks): Post-operative splinting in a flexed position. Controlled passive motion protocols. Close supervision by a hand therapist. Gentle PROM exercises within safe limits as advised by surgeon.
5	Post-surgical recovery phase, adherence issues, secondary complications (e.g., infections).	Rehabilitation Phase (6+ weeks): Intensive hand therapy focusing on restoring full range of motion, strength, and functionality. Scar management techniques (e.g., massage, silicone gel). Progressive strengthening and functional use of the hand.

2.2. SEMG experimental setup

Three features were used in classifying the level of injury of the hand, namely, the RMS (1), WL (2), and EMAV (3) with their equations, respectively. The sliding window method is an effective way to extract features of an EMG signal. In this technique, the signals are subdivided with overlaps from each segment and are analyzed.

$$X_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{1}$$

$$X_{wl} = \sum_{i=1}^{N} |x_{i+1} - x_i| \tag{2}$$

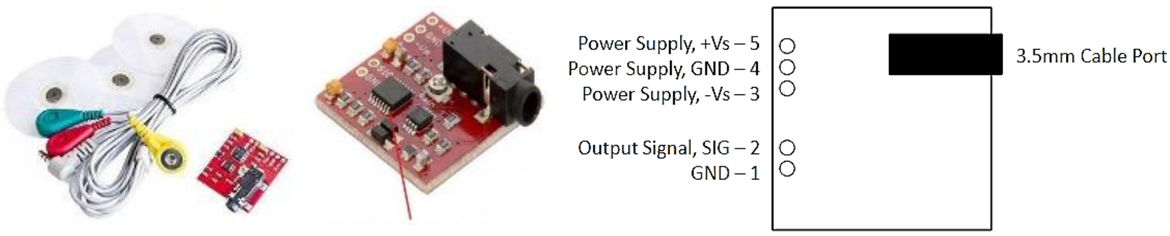
$$X_{emav} = \frac{1}{N}\sum_{i=1}^{N}|x_i| \quad (3)$$

Using the sliding window technique, the parameters are set according to Table 2. The number of segments can be varied depending on the duration of the signal's acquisitions. For a duration of 35 seconds of data acquisition, there were 12,669 data points in which three 5-second gripping (full fist) is done. The sampling frequency is set at 1000 Hz. The number of data points per segment is set to 120 with a half-segment overlap of 60.

Table 2. Sliding window parameters

Parameter	Value
No. of Segments	210
No. of points per segment	120
Overlap (half-segment)	60
No. of trials	3
No of data points	12669
Type of hand motion (formation)	Full fist
Sampling frequency	1000 Hz.

The SEMG device used in this work is composed of filters and amplifiers as presented in Figure 3. Figure 3(a) shows the SEMG device with electrodes of different colors and the electrode patches. An AD8226 instrumentation amplifier Figure 3(b) is built to the module with 0-1000 gain shown. The signal varies from 50 µV to 30 mV and is rectified, amplified, and smoothed to be compatible with the Arduino microcontroller with 0-1053 digital signal. See Figure 3(c) for the pin configuration. The full setup is presented in Figure 4, where two 9-Vdc batteries are wired, and the signal and ground are connected to the microcontroller.



(a) (b) (c)

Figure 3. SEMG module (a) with electrodes and patches, (b) with instrumentation amplifier, and (c) pin configuration

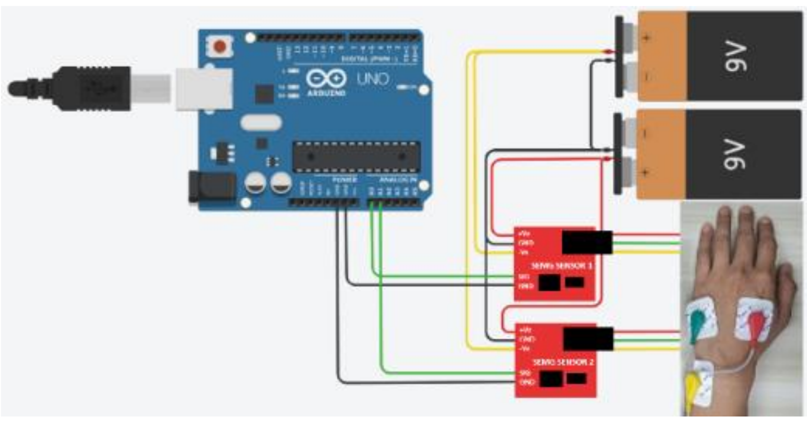


Figure 4. SEMG setup diagram consisting of microcontroller unit, the EMG module, electrodes, and two 9 V battery, which can have options for dual channel SEMG when there are multiple muscles of interest

3. RESULTS AND DISCUSSION

3.1. SEMG module development

The SEMG module was built and developed with a 3D printed PLA casing with two channels of electrodes as presented in Figure 5. An inside look is presented in Figure 5(a) and the whole package in Figure 5(b). Sample placement of the SEMG in the hand is shown in Figure 5(c), where the red and green electrodes are placed in the muscle of interest, and the reference electrode in yellow is placed in the bony part of the wrist.

(a) (b) (c)

Figure 5. The developed SEMG module: (a) inside look consisting of the components, (b) 3D printed casing of SEMG module with two channels of electrodes, and (c) sample placement of electrodes

3.2. Feature extraction

The SEMG data collection is done by doing 3 successive trials. The position was held for 5 seconds. The observed characteristic plot is plotted and presented in Figure 6. The raw SEMG data is plotted as full fist in the first graph. The whole duration of the data collection is around 36 seconds. The features plotted are the MAV, MF, EMAV, WL, SSC, and RMS.

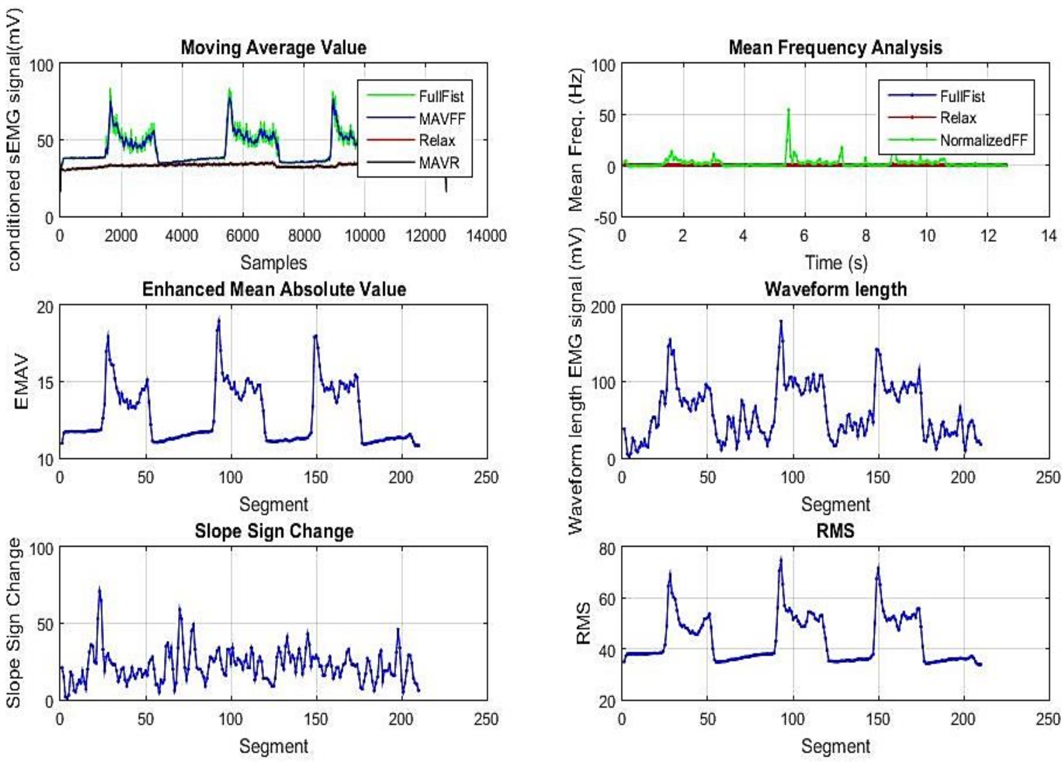


Figure 6. SEMG features plot for full fist hand movement in the of left column-down to the right column-down; MAV, EMAV, SSC, MFA, WL, and RMS

The collected data has to be trimmed where the region of interest is identified as shown in Figure 7. These data are compared to the data for the relaxed position from a healthy subject, assumed to be of no movement (or injury). These data are normalized accordingly using (4), (5), and (6): RMS_{norm} for the normalized RMS, WL_{norm} for the normalized WL, and $EMAV_{norm}$ for the normalized EMAV so that it can be comparable to other subjects useful for the classification of the state of the hand.

$$RMS_{norm} = \frac{RMS_x - RMS_{min}}{RMS_{max} - RMS_{min}} \tag{4}$$

$$WL_{norm} = \frac{WL_x - WL_{min}}{WL_{max} - WL_{min}} \tag{5}$$

$$EMAV_{norm} = \frac{EMAV_x - EMAV_{min}}{EMAV_{max} - EMAV_{min}} \tag{6}$$

WL_{min} : waveform length of relaxed hand
WL_{max} : maximum waveform length in full-fist position
WL_x : waveform length of the actuated hand
RMS_x : RMS of the actuated hand.
RMS_{min} : RMS for the relax position
RMS_{max} : RMS for the full-fist position of the hand
$EMAV_x$: EMAV for the actuated hand
$EMAV_{min}$: EMAV for the relax position
$EMAV_{max}$: EMAV of the full fist position of the hand

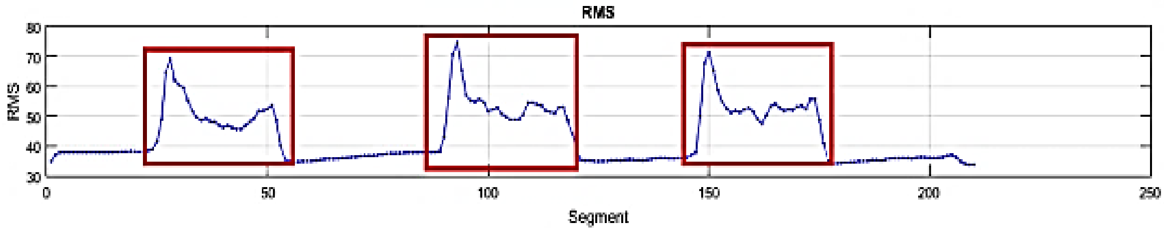


Figure 7. Regions of interest boxed in red. These signals are taken with approximately 5 minutes interval

3.3. Feature selection

The candidate features that can be used for the classification of SEMG signals are the following: MAD, SSC, EMAV, RMS, and WL. However, not all these features can be useful for classification. In this work, three features were selected that have high distinction in classifying the SEMG signals. The feature selection is based on the classification of signals from a healthy participant with a 5-second interval of muscle action. Figure 8 shows the 5 features with normalized segmented SEMG data. In these features, three were selected, the RMS, EMAV, and WL as these features are less likely to have ambiguities in classification.

3.4. Injury level classification – FIS system

The injury level is classified based on the 3 features: RMS, WL, and EMAV. An FIS classifier system was created using the Mamdani model as presented in Figure 9. The output is the health status or the injury level of the hand. The FIS developed is modeled in MATLAB Simulink to facilitate visual simulation when the input is varied. It is built with a multiplexer and classifier as shown in Figure 10.

The membership functions for the inputs are assigned according to the expert's opinion which can go from levels 1-5. These levels of input are uniformly defined, where level 1 and level 5 are trapezoids, and levels 1-3 are triangular: Figure 11(a) RMS, Figure 11(b) WL, and Figure 11(c) EMAV. The output has member functions the same as that of the inputs as shown in Figure 11(d). The surface plot is presented in Figure 12, where two inputs are shown, the RMS and WL, to see their relationship to the out based on the rules defined which contribute to this shape.

The rules are based on the "majority" principle with one step change increment. The set of rules are presented in Figure 13(a). When two out of the three rules are both in one membership function, the output will be the dominant membership function. For example, the RMS and WL are level 2, and the EMAV is level 1, then the hand injury level is level 2. The rule view is also presented in Figure 13(b), where a centroid is used to identify the hand injury level at the output. This setup is also simulated in MATLAB Simulink and has a good performance result based on the expert's opinion.

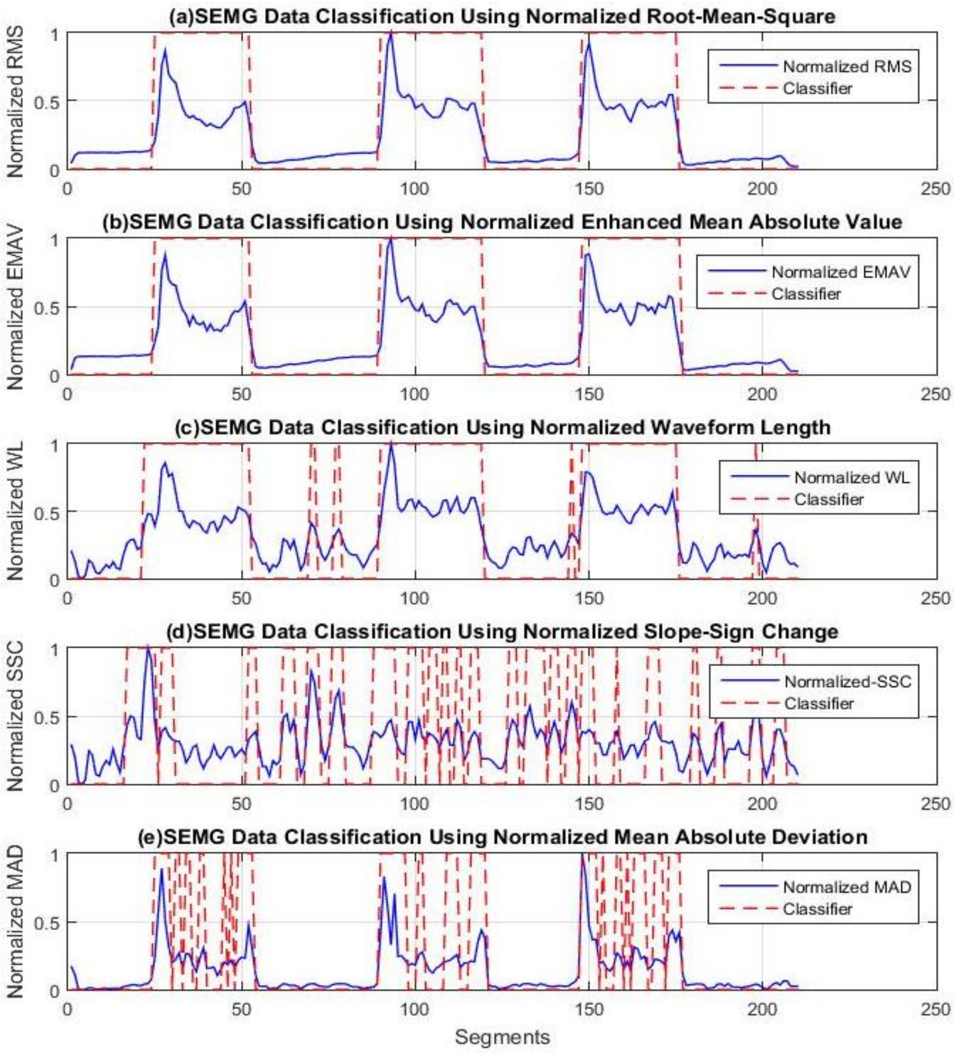


Figure 8. Feature selection using the normalized data: RMS, EMAV, WL, SSC, MAD (the value of 1 in red dashed-lines signifies muscle actuation for a healthy subject, the value 0 signifies unactuated muscle assumed to be an injured state)

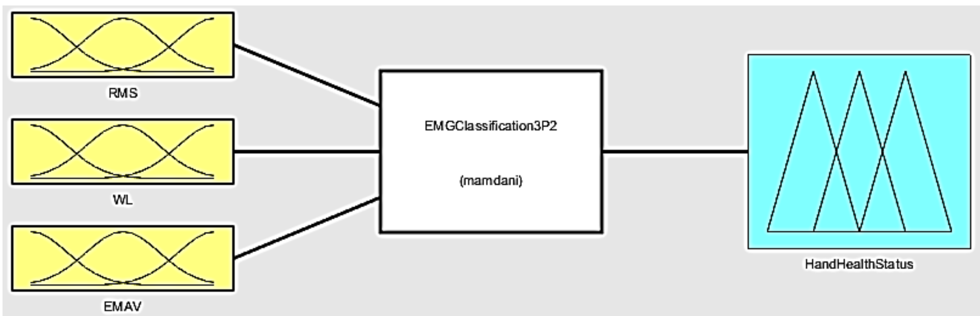


Figure 9. The 3-parameter fuzzy inference system classifier for the SEMG data

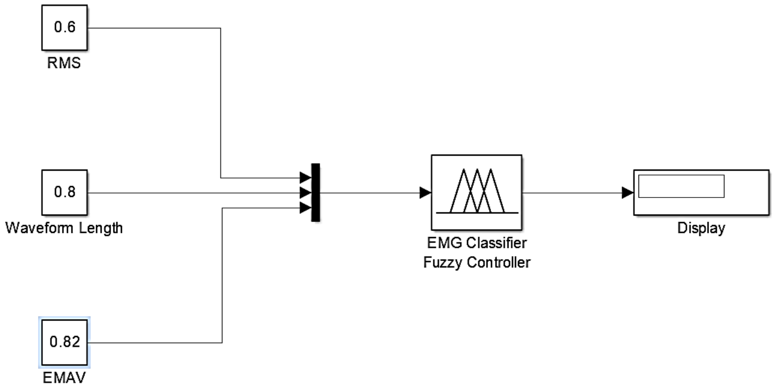


Figure 10. Simulink block representation and simulation of the FIS

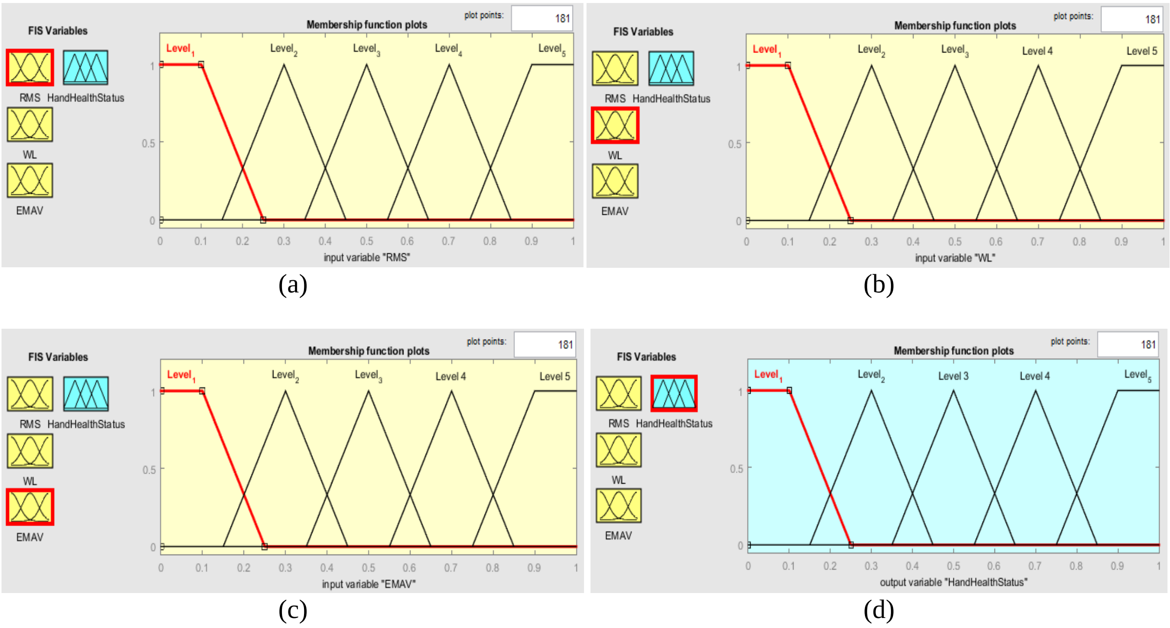


Figure 11. Inputs, outputs, and membership functions for the FIS system (a) RMS, (b) MAV, (c) WL, and (d) output-injury level

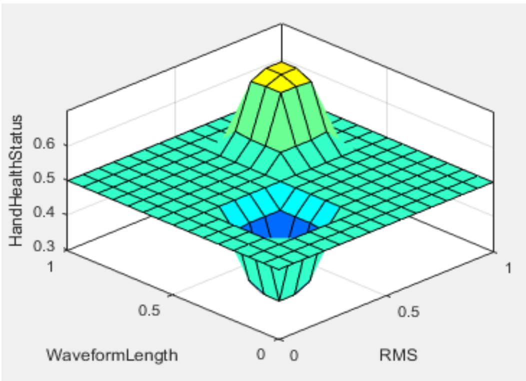
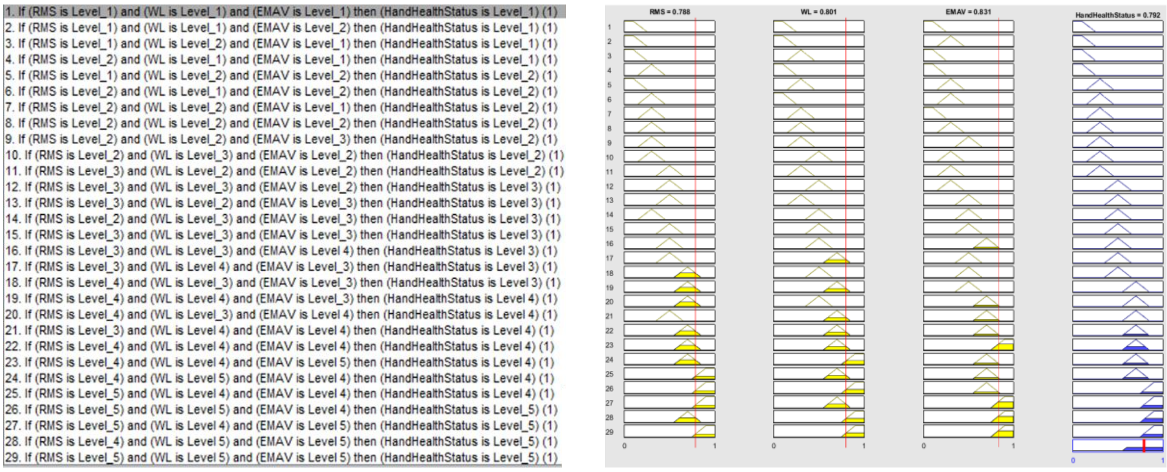


Figure 12. Surface Plot of the FIS



(a) (b)

Figure 13. FIS rules (a) FIS rules list (b) FIS rule viewer (the columns are in order as follows, RMS, WL, MAV, and the [output] hand injury level, and the decision weight is based on centroid)

4. CONCLUSION

The assessment of hand injury level is a subjective task that the experts are doing. The developed guides for assessment serve as standards for this task. However, this subjectivity can be translated into measurable data that can be standardized by normalizing the signals. SEMG with added intelligence can be automated using artificial technologies available today. In this work, a hand injury level classification through a FIS was successfully developed using the SEMG signals. An SEMG device module was set up to acquire signals from the muscles, in particular, the flexor pollicis and flexor digitorum, where most of the tendon gliding exercises can be used for both assessment and rehabilitation of the hand. The SEMG signals are processed by filtering and amplification. The three features selected for the classification of these signals are the RMS, WL, and EMAV because of their high distinctive range or level between an injured and a healthy hand musculoskeletal activation. These signals are normalized so that they can be comparable to other subjects for generality. The rules provided in the FIS are based on the expert's opinion with predefined rehabilitation programs. The classification was verified through simulation in MATLAB Simulink. This work paves the way for developing advanced systems in rehabilitation medicine. This is significant for distant consultation where the patient with this device can be assessed by the expert for the recommendation of rehabilitation programs or exercises. In the future, the setup will be tested on both healthy and injured subjects in the rehabilitation clinic for evaluation. The module will further be developed into a useful product once proven successful.

REFERENCES

[1] Z. Zhang, Y. Tang, S. Zhao, and X. Zhang, "Real-time surface EMG pattern recognition for hand gestures based on support vector machine," *IEEE International Conference on Robotics and Biomimetics, ROBIO 2019*, pp. 1258–1262, 2019, doi: 10.1109/ROBIO49542.2019.8961436.

[2] 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.

[3] I. M. Khairuddin, S. N. Sidek, A. P. P. A. Majeed, M. A. M. Razman, A. A. Puzi, and H. M. Yusof, "The classification of movement intention through machine learning models: the identification of significant time-domain EMG features," *PeerJ Computer Science*, vol. 7, pp. 1–15, 2021, doi: 10.7717/PEERJ-CS.379.

[4] H. Hamzeh, M. Madi, and A. A. Alghwiri, "The long-term effect of neurodynamics vs exercise therapy on pain and function in people with carpal tunnel syndrome: a randomized parallel-group clinical trial," *Journal of Hand Therapy*, vol. 34, no. 4, pp. 521–530, 2021, doi: 10.1016/j.jht.2020.07.005.

[5] J. D. Sault, D. J. Jayaseelan, J. J. Mischke, and A. A. Post, "The utilization of joint mobilization as part of a comprehensive program to manage carpal tunnel syndrome : a systematic review," *Journal of Manipulative and Physiological Therapeutics*, vol. 43, no. 4, pp. 356–370, doi: 10.1016/j.jmpt.2020.02.001.

[6] K. Shem, J. Wong, and B. Dirlikov, "Effective self-stretching of carpal ligament for the treatment of carpal tunnel syndrome: a double-blinded randomized controlled study," *Journal of Hand Therapy*, vol. 33, no. 3, pp. 272–280, 2020, doi: 10.1016/j.jht.2019.12.002.

[7] Z. Bartkowiak, M. Eliks, M. Zgorzalewicz- Stachowiak, and L. Romanowski, "Effects of nerve and tendon gliding exercises combined with low-level laser or ultrasound therapy in carpal tunnel syndrome," *Indian Journal of Orthopaedics*, vol. 53, no. 2, pp. 347–352, 2019, doi: 10.4103/ortho.IJOrtho.

[8] N. Friedman *et al.*, "Retraining and assessing hand movement after stroke using the MusicGlove : comparison with conventional

hand therapy and isometric grip training," *Journal of NeuroEngineering and Rehabilitation*, 2014.
[9] Y. Kwon, A. Dwivedi, A. J. McDaid, and M. Liarokapis, "On muscle selection for EMG based decoding of dexterous, in-hand manipulation motions," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2018, vol. 2018-July, pp. 1672–1675, doi: 10.1109/EMBC.2018.8512624.
[10] Y. Kwon, A. Dwivedi, A. J. McDaid, and M. Liarokapis, "Electromyography-based decoding of dexterous, in-hand manipulation of objects: comparing task execution in real world and virtual reality," *IEEE Access*, vol. 9, pp. 37297–37310, 2021, doi: 10.1109/ACCESS.2021.3062364.
[11] O. Pearce, M. T. Brown, K. Fraser, and L. Lancerotto, "Flexor tendon injuries: repair & rehabilitation," *Injury*, vol. 52, no. 8, pp. 2053–2067, 2021, doi: 10.1016/j.injury.2021.07.036.
[12] R. S. Susman, L. Nyati, and M. S. Jassal, "Observations on the pollical palmar interosseous muscle (of Henle)," *Anatomical Record*, vol. 254, no. 2, pp. 159–165, 1999, doi: 10.1002/(SICI)1097-0185(19990201)254:2<159::AID-AR1>3.0.CO;2-H.
[13] G. Bello-Hellegouarch, M. A. Aziz, E. M. Ferrero, M. Kern, N. Francis, and R. Diogo, "'Pollical palmar interosseous muscle' (musculus adductor pollicis accessorius): Attachments, innervation, variations, phylogeny, and implications for human evolution and medicine," *Journal of Morphology*, vol. 274, no. 3, pp. 275–293, 2013, doi: 10.1002/jmor.20090.
[14] I. A. Ozkan, "An ensemble classifier for finger movement recognition using EMG signals," *International Journal of Applied Mathematics Electronics and Computers (IJAMEC)*, vol. 2019, no. 4, pp. 96–99, 2019.
[15] C. Altın and O. Er, "Comparison of different time and frequency domain feature extraction methods on Elbow Gesture's EMG," *European Journal of Interdisciplinary Studies*, vol. 5, no. 1, p. 35, 2016, doi: 10.26417/ejis.v5i1.p35-44.
[16] C. Spiewak, "A comprehensive study on EMG feature extraction and classifiers," *Open Access Journal of Biomedical Engineering and Biosciences*, vol. 1, no. 1, pp. 17–26, 2018, doi: 10.32474/oajbeb.2018.01.000104.
[17] M. J. B. Enojas and M. C. Ramos, "Modeling Bi-directional Wedge-type Segmented Soft Pneumatic Bending Actuator for Hand Rehabilitation using Finite Element Method," in *2023 8th International Conference on Robotics and Automation Engineering, ICRAE 2023*, 2023, pp. 53–57, doi: 10.1109/ICRAE59816.2023.10458586.
[18] M. J. B. Enojas and M. J. C. Ramos, "Segmented soft pneumatic bending actuator with artificial neural network for parameter prediction," *International Journal of Machiene Learning and Computing*, vol. 12, no. 4, pp. 149–153, 2022, doi: 10.18178/ijmlc.2022.12.4.1094.
[19] A. Deboucha, "The surface electromyography noise filtering and unwanted recordings attenuation for lower limb robotic system," *IAES International Journal of Robotics and Automation (IJRA)*, vol. 11, no. 1, pp. 62–69, 2022, doi: 10.11591/ijra.v11i1.pp62-69.
[20] M. Farzad, J. MacDermid, L. Ferreira, M. Szekeres, S. Cuypers, and E. Shafiee, "Do current upper limb orthotic classification systems help clinicians choose and design effective orthoses? A scoping review with expert interviews," *Journal of Hand Therapy*, vol. 37, no. 1, pp. 60–69, 2024, doi: 10.1016/j.jht.2023.05.008.
[21] J. L. Sullivan, J. O. Coulthard, P. Davis, S. Flinn-Wagner, E. La Croix, and V. Mayer, "The American society of hand therapists," *Journal of Hand Therapy*, vol. 4, no. 1, pp. 23–29, 1991, doi: 10.1016/S0894-1130(12)80216-X.
[22] T. S. Pidgeon, "Flexor tendon injuries," *American Academy of Orthopaedic Surgeons*. Accessed: Jan 2022. [Online]. Available: https://orthoinfo.aaos.org/en/diseases--conditions/flexor-tendon-injuries/.
[23] J. B. Tang, "Flexor tendon injuries," *Clinics in Plastic Surgery*, vol. 46, no. 3, pp. 295–306, 2019, doi: 10.1016/j.cps.2019.02.003.
[24] E. Y. Lee and A. Y. T. Lim, "Nerve compression in the upper limb," *Clinics in Plastic Surgery*, vol. 46, no. 3, pp. 285–293, doi: 10.1016/j.cps.2019.03.001.
[25] D. M. K. Tan and J. X. Lim, "Treatment of carpal instability and distal radioulnar joint instability," *Clinics in Plastic Surgery*, vol. 46, no. 3, pp. 451–468, 2019, doi: 10.1016/j.cps.2019.03.006.
[26] J. B. Tang, "New developments are improving flexor tendon repair," *Plastic and Reconstructive Surgery*, vol. 141, no. 6, pp. 1427–1437, 2018, doi: 10.1097/PRS.0000000000004416.
[27] G. Rotter, K. Noeres, I. Fernholz, S. N. Willich, A. Schmidt, and A. Berghöfer, *Musculoskeletal disorders and complaints in professional musicians : a systematic review of prevalence , risk factors , and clinical treatment effects*, vol. 93, no. 2. Springer Berlin Heidelberg, 2020.

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