An Interpretative Fuzzy Rule-Based EEG Classification System for Discrimination of Hand Motor Attempts in Stroke Patients

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Abstract—Stroke patients have symptoms of cerebral functional disturbance that could aggressively impair patient’s physical mobility, such as freezing of hand movements. Although rehabilitation training from external devices is beneficial for hand movement recovery, for initiating motor function restoration purposes, there are still valuable research merits for identifying the side of hands in motion. In this preliminary study, we used electroencephalogram (EEG) datasets from 8 stroke patients, with each subject involving 40 EEG trials of left motor attempts and 40 EEG trials of right motor attempts. Then, we proposed an interpretative fuzzy rule-based EEG classification system for identifying the side in motion for stroke patients. In specific, we extracted 1-50 Hz power spectral features as input features of a series of well-known classification models. The predicted labels from these classification models were measured by four types of fuzzy rules, which determined the finalised predicted label. Our experiment results showed that our proposed fuzzy rule-based EEG classification system achieved 99.83 ± 0.42% accuracy, 99.98 ± 0.13% precision, 99.66 ± 0.84% recall, and 99.83 ± 0.43% f-score, which outperformed the performance of single well-known classification models. Our findings suggest that the superior performance of our proposed fuzzy rule-based EEG classification system has the potential for hand rehabilitation in stroke patients.

Index Terms—Stroke, Hand Motor Attempts, Rehabilitation, EEG, Fuzzy, Classification

I. INTRODUCTION

Stroke is the second most common cause of death worldwide and the third most common cause of disability [1]. The clinical symptoms may be caused by acute signs that originate from global or focal brain dysfunction, possibly leading to severe impairment for a patient’s ability to move [2]. During the first year after a stroke occurs, a third of stroke patients have deficient or nonexistent remaining hand function, such as freezing of hand movement, and rare cases showed significant functional movement recovery in the following years [3].

Even if conventional therapies have proven to be successful in acute and sub-acute stages of stroke recovery [4], clinical effectiveness for hand function restoration is still limited, due to the passive nature of conventional therapies [5]. Applying new rehabilitation therapeutic approaches to assist stroke patients for hand function restoration in home environment effectively is becoming more feasible and essential for post-clinical stroke rehabilitation [6]. For example, the neuro-feedback mechanism, teaching self-control of brain functions to subjects by measuring brain waves and providing a feedback signal, can achieve a significant training performance for therapy and rehabilitation purposes. Here, we consider the electroencephalogram (EEG)-based brain-computer interface (BCI) [7], one of the non-invasive neuro-feedback mechanisms, to assist stroke patients during rehabilitation stage [8]. Currently, the EEG-based BCI studies have become a key approach for devising modern neuro-rehabilitation techniques [9]–[12], and demonstrated promising feasibility for assisting in multiple healthcare domains [13]–[15]. Thus, we believe that the EEG-based BCI could be broadly used for stroke rehabilitation clinically and in home environment [16].

The related work investigated applying motor imagery (MI)-based BCI, the mental procedure of imagining body movements without physical actions [17], to help stroke patients in hand rehabilitation with the assistance of robotic and exoskeleton equipment on the paretic hand [18]–[20]. Another prior work focused on exploring using power spectra, a well-established method for the analysis of EEG signals, from the unaffected hemisphere for exoskeleton control [21], indicating a statistically significant behavioural improvement of the paretic limb.

Excepting the concentrated power spectra analysis, abnormal EEG complexity of the brain, measured by entropy [22]–[24], found in patients with acute stroke, showed an increased mean entropy value [25]. Current investigations focus on developing EEG-based BCI devices for hand function rehabilitation in stroke patients, and improving the performance of BCI classifiers to be applied for hand exoskeleton of stroke rehabilitation [25]. For instance, the eConHand showed 79.38% classification accuracy for controlling the light hand exoskeleton in outpatient environments [27].

However, there are few studies on the identification of the hands in the motion of stroke patients by assessing brain wave signals. If we can extract dynamic brain features and classify cerebral hemispheres related to the hand in motion, an EEG-
based BCI driven rehabilitation system may be applied to aid stroke patients in moving the paretic hand by controlling an exoskeleton or other devices.

Thus, in this study, we investigated the discrimination of hand motor attempts in stroke patients, by processing EEG signals collected from 8 stroke patients with impaired hand and finger functions, and extracting EEG features to train classifiers. In specific, the EEG data were firstly collected when the subjects were requested to conduct unilateral motor attempts, and then the EEG signals were labelled as "left" or "right" indicating the side of subjects’ motor attempts. Furthermore, the raw EEG data were transferred into power spectra, which were used for examining if exists significant differences of EEG power spectra between the left and right motor attempts and inputting EEG power features for training classifiers. The classifiers included in this study involved five well-known two-class classifiers and one interpretative fuzzy rule-based classifier, possibly to improve the performance results and decrease the possibility of false predicted labels. We expect that the proposed system in this preliminary study can be used to automatically generate stimulation for physical devices with the potential for stroke patients’ rehabilitation of hand movements.

II. MATERIALS AND METHODS

A. Participant and EEG Data Recording

The EEG dataset is provided from the Clinical Brain Computer Interfaces Challenge for the IEEE World Congress on Computational Intelligence conference 2020 1. Of note, Fig. 1 illustrates the procedure of the experiment, the analytical process of EEG data, and the applied classification models.

In this study, we only involved 8 hemiparetic stroke patients who have impaired functionality with either by left or right hand finger mobility. For the motor attempts, each subject conducted an equal number of left motor attempts as right motor attempts in the 80 trials with a sampling rate of 512 Hz. Each motor trial lasts 8 seconds, so the total numbers of each subject are 320 (8 seconds * 40 trials) for the left side and 320 (8 seconds * 40 trials) for the right side. Furthermore, their EEG signals were recorded simultaneously from 12 channels (F3, FC3, C3, CP3, P3, FCz, CPz, F4, FC4, C4, CP4, and P4) according to the 10-20 international system as shown in Fig. 1a.

B. EEG Data Analysis

All EEG data files were processed and analysed with EEGLAB in MATLAB software (The Mathworks, Inc.). EEGLAB is an extensible MATLAB toolbox for processing EEG and other electrophysiological signal data 2 that offers interactive plotting functions, time/frequency transforms, artifact removal, and other extensions for EEG processing.

1https://github.com/5anirban9/Clinical-Brain-Computer-Interfaces-Challenge-WCCI-2020-Glasgow
2https://sccn.ucsd.edu/eeeglab/index.php

1) EEG data pre-processing: The raw EEG data files we processed are firstly labelled for each trial as number "1" representing "right motor attempt" or number "2" representing "left motor attempt" as shown in Fig. 1b. Then, as shown in Fig. 1c, the raw EEG data were separated as left or right motion data based on the labels and filtered through 1Hz high-pass and 50 Hz low-pass finite impulse response filters as the recording sample rate is 512 Hz. The filtered data were then checked for any artifacts that need to be removed before being processed. Since no artifacts of visible muscle, eye-blink or other visible electromyography activity were detected, we proceeded processing on the filtered data. EEG signals have weak time-frequency-spatial characteristics, non-stationary, non-linear, and weak intensity, so to extract adaptive features reflecting frequency and spatial characteristics, it is critical to adopt feature extraction methods 28. For this study, we converted the time-domain EEG data into the frequency domain and extracted power spectral features for left and right side motor attempts, as shown in Fig. 1d. We used the 256-point Fast Fourier Transforms (FFTs) window, which was set at 256-point data length, and in each window, the segment was converted into frequency domain respectively.

2) Statistical Analysis: Before designing and applying classification models, since the EEG power spectra of each individual and cross-subjects are sufficient to conduct statistical analysis to determine if there is a significant difference between left and right motor attempts, we applied paired t-test to each frequency and channel of single-subject EEG power to determine the mean difference between the two sides. The p-value of the paired t-test sets under 0.05, indicating the significant difference level of the left and right motor attempts of the stroke subjects.

III. CLASSIFICATION MODELS

Since EEG power has been labelled for each trial, we used supervised machine learning-based classification approaches, where one training sample has one class label 29, to train the motor attempt classifiers. With the cross-validation measurement, we set the three folds to randomly select two portions from each side motion features as the training set and the third portion from each side motion features as the testing set for the classifiers. The two training sets from left motions and the
two training sets from right motions were combined as the training sets for each classifier, while the testing set from left motions and the testing set from right motions were combined as the testing set to be applied to each classifier. The training data labels were attached to the determined feature sets and then applied to the train classifiers, as shown in Fig. 1-e.

In this study, we used five well-known classification methods as classifiers which are Support Vector Machine (SVM), k-nearest neighbours (KNN), Naive Bayes, Ensembles for Boosting, and Discriminant Analysis Classifier [30]. Each side’s training sets of extracted power spectral features were provided to each classifier for training. The performance of each classifier was evaluated by applying the testing set to the trained classifiers to obtain the accuracy results. We also employed precision, recall, and F-score performance metrics to assess the performance of each classifier.

A. Classification Model Improvement

The fuzzy rule-based classifier is considered to be more interpretative and intuitive than other existing classification methods [31]. Because multiple classification models were involved in this study, to utilise fuzziness for mechanism and to acquire the maximum classification accuracy, we applied a fuzzy rule-based classification method to improve the classification model. As shown in Tab I, a single fuzzy If-Then rule that if \( x \) is \( A \) then \( y \) is \( B \) is applied as an assumption in the form. The top three accurate classifiers are ranked as 1st, 2nd, and 3rd. If the classifier with the highest accuracy rate states positive, then the rule-based label is positive, while in all other cases, the rule-based label is negative.

| Predicted Labels | Classifier 1 | Classifier 2 | Classifier 3 | Rule-based labels |
|------------------|--------------|--------------|--------------|------------------|
| Ranking-Accuracy | 1st          | 2nd          | 3rd          | THEN             |
| Rule 1           | Positive     | IF           |              |                  |
| Rule 2           | Positive     | Positive     | Positive     | Positive         |
| Rule 3           | Positive     | Negative     | Positive     | Negative         |
| Rule 4           | Positive     | Other Cases  | Positive     | Negative         |

IV. RESULTS

For this study, we present two groups of findings which are the feature-based results of the EEG power spectra and the label classification performances of the five classifiers plus a fuzzy rule-based classifier trained by the training sets and evaluated by the testing sets of 8 stroke patients. The results of this study are presented from two perspectives as power spectral feature-based and classifier-based.

We separated and plotted the power spectra of left and right motor attempts to inspect if there are significant differences of EEG signals for left and right-hand motions. As shown in Fig. 2 it demonstrated the power spectra of left (blue colour) and right (red colour) motor attempts with the significant differences presented as black “asterisk”. We also calculated the mean value of the significant difference of power spectra for each frequency and channel between left and right motor attempts in four frequency bands waves (delta, theta, alpha, and beta). For each of the 12 channels, the power spectra escalate rapidly and reach a peak at the frequency around 5 to 10 Hz, and maintained comparatively steady until surge to the highest power spectra level at 50 Hz. For 10 out of 12 channels (expect FC4 and P4), when the signal frequency is between approximately 10 to 40 Hz, the power spectra of left motor attempts and right motor attempts have the most significant differences (\( p < 0.05 \)). These feature results are aligned with the tendency of power spectra mean value for the four frequency bands waves (delta, theta, alpha, and beta) of the 12 channels, as shown in Fig. 3. For left and right motor attempts, on average, the most significant differences (\( p < 0.05 \)) of power spectra mean value appear close to channel C4 in delta frequency range (3 Hz or lower), channel P3 in theta range (3.5 to 7.5 Hz), channel CPz in alpha range (7.5 to 13 Hz), and channel F4 in beta range (14 Hz to greater). The significant differences of the four frequency bands waves are demonstrated on brain scale map plotted with the 12 channel locations in Fig. 3 and the calculation is as follow, where \( \Delta P \) representing the significant difference (\( p < 0.05 \)) of power spectra between left and right motion, movement of left and right hands, \( P_R \) stands for power spectra of right motion, and \( P_L \) stands for power spectra of left motion.

\[
P_{\Delta}(p < 0.05) = P_R - P_L
\]

The classifier results are demonstrated in Tab II with the five
Our proposed fuzzy rule-based EEG classification system can achieve \(99.83 \pm 0.42\)% accuracy, \(99.98 \pm 0.13\)% precision, \(99.66 \pm 0.84\)% recall, and \(99.83 \pm 0.43\)% F-score, and outperform the performance of single existing classification model. The diagnostic ability of this proposed fuzzy-rule classifier system is also illustrated by a receiver operating characteristic (ROC) curve in Fig. 4 to verify its discrimination threshold.

**TABLE II**

| Classifier                  | Accuracy (%) | Precision (%) | Recall (%) | F-score (%) |
|-----------------------------|--------------|---------------|------------|-------------|
| SVM                         | 99.80 ± 0.40 | 99.80 ± 0.46  | 99.80 ± 0.46 | 99.80 ± 0.46 |
| KNN                         | 98.33 ± 0.95 | 98.41 ± 1.37  | 98.28 ± 1.44 | 98.33 ± 0.95 |
| Naive Bayes                 | 79.52 ± 2.95 | 78.55 ± 4.50  | 80.23 ± 3.53 | 79.30 ± 2.67 |
| Ensemble for Boosting       | 98.40 ± 1.06 | 98.75 ± 1.28  | 98.07 ± 1.51 | 98.40 ± 1.05 |
| Linear Discriminant Analysis | 99.73 ± 0.48 | 99.75 ± 0.53  | 99.72 ± 0.79 | 99.73 ± 0.48 |
| Fuzzy-rule Classifier       | 99.83 ± 0.42 | 99.98 ± 0.13  | 99.66 ± 0.84 | 99.83 ± 0.43 |

**V. DISCUSSION AND CONCLUSION**

Stroke is one of the most common causes for disability, and stroke survivors commonly suffer impaired mobility. Since hand function is not the top priority of stroke rehabilitation compared to hemiplegic gait, it is difficult for stroke patients to gain adequate hand and finger functions \[32\]. In recent years, an increasing number of researches applied EEG and MI-based BCI systems to stroke patients’ hand rehabilitation, especially with robotic or exoskeleton. There is also a difference between the affected and unaffected cerebral hemispheres correlated with the restoration of impaired hand’s motor function. Therefore the significance of classifying which side of hands is in motion via EEG signal processing can not be neglected for stroke rehabilitation.

In this study, we proposed an interpretative fuzzy rule-based EEG classification system for hand motor attempts in stroke patients. The predicted labels from these classification models were measured by four types of fuzzy rules with a series of state-of-art classification models. The experiment results show that our proposed fuzzy rule-based EEG classification system exceeds the performance of many single classification models for left and right motor attempts classification, with an accuracy rate of 99.83%, precision rate of 99.98%, recall rate at 99.66%, and F-score rate at 99.83%. Our findings suggest that the superior performance of the fuzzy rule-based EEG classification system is effective in accurately classifying the hand in the motion of stroke patients. The results of this proposed system also indicate its feasibility in facilitating further EEG-based BCI systems for stroke rehabilitation.

**Fig. 3.** Brain Scale Map Plot of Significant Difference of Power Spectra between Left and Right Motor Attempts

**Fig. 4.** ROC Curve for the Fuzzy-Rule Classifier
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REFERENCES

[1] V. L. Feigin, B. Norrving, and G. A. Mensah, “Global burden of stroke,” Circulation research, vol. 120, no. 3, pp. 439–448, 2017.

[2] I. S. W. Parry et al., National clinical guideline for stroke. Citeeseer, 2012, vol. 20083.

[3] E. Buch, C. Weber, L. G. Cohen, C. Braun, M. A. Dimyan, T. Ard, J. Mellinger, A. Caria, S. Soekadar, A. Fourkas et al., “Think to move: a neuromagnetic brain-computer interface (bci) system for chronic stroke,” Stroke, vol. 39, no. 3, pp. 910–917, 2008.

[4] J.-C. Chen and F.-Z. Shaw, “Progress in sensorimotor rehabilitative physical therapy programs for stroke patients,” World Journal of Clinical Cases: WJCC, vol. 2, no. 8, p. 316, 2014.

[5] Z. Yue, X. Zhang, and J. Wang, “Hand rehabilitation robotics on poststroke motor recovery,” Behavioural neurology, vol. 2017, 2017.

[6] P. Trujillo, A. Mastroproieto, A. Scano, A. Chiavena, S. Mrakic-Spota, M. Caimmi, F. Molteni, and G. Rizzo, “Quantitative eeg for predicting upper limb motor recovery in chronic stroke robot-assisted rehabilitation,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 25, no. 7, pp. 1058–1067, 2017.

[7] X. Gu, Z. Cao, A. Jolfaei, P. Xu, D. Wu, T.-P. Jung, and C.-T. Lin, “Eeg-based brain-computer interfaces (bcis): A survey of recent studies on signal sensing technologies and computational intelligence approaches and their applications,” arXiv preprint arXiv:2004.12522, 2020.

[8] R. Mohanty, A. M. Sinha, A. B. Remsik, K. C. Dodd, B. M. Young, T. Jacobson, M. McMillan, J. Thoma, H. Advani, V. A. Nair et al., “Machine learning classification to identify the stage of brain-computer interface therapy for stroke rehabilitation using functional connectivity,” Frontiers in neuroscience, vol. 12, p. 353, 2018.

[9] U. Chaudhary, N. Birbaumer, and A. Ramos-Murguialday, “Brain–computer interfaces for communication and rehabilitation,” Nature Reviews Neurobiology, vol. 12, no. 9, p. 513, 2016.

[10] A. Chowdhury, Y. K. Meena, H. Raza, B. Bhushan, A. K. Uttam, N. Pandey, A. A. Hashmi, A. Bajpai, A. Dutta, and G. Prasad, “Active physical practice followed by mental practice using bci-driven hand exoskeleton: a pilot trial for clinical effectiveness and usability,” IEEE journal of biomedical and health informatics, vol. 22, no. 6, pp. 1786–1795, 2018.

[11] Z. Cao, K.-L. Lai, C.-T. Lin, C.-H. Chuang, C.-C. Chou, and S.-J. Wang, “Exploring resting-state eeg complexity before migraine attacks,” Cephalalgia, vol. 38, no. 7, pp. 1296–1306, 2018.

[12] Z. Cao, C.-T. Lin, W. Ding, M.-H. Chen, C.-T. Li, and T.-P. Su, “Identifying ketamine responses in treatment-resistant depression using a wearable forehead eeg,” IEEE Transactions on Biomedical Engineering, vol. 66, no. 6, pp. 1668–1679, 2018.

[13] Z.-H. Zhou and M.-L. Zhang, “Multi-label learning,” 2017.

[14] Z.-H. Zhou and M.-L. Zhang, “Multi-label learning,” 2017.

[15] Z. Cao, C.-T. Lin, K.-L. Lai, L.-W. Ko, J.-T. King, K.-K. Liao, J.-L. Fuh, and S.-J. Wang, “Extraction of ssveps-based inherent fuzzy entropy using a wearable headband eeg in migraine patients,” IEEE Transactions on Fuzzy Systems, 2019.

[16] Z. Cao, C.-H. Chuang, J.-K. King, and C.-T. Lin, “Multi-channel eeg recordings during a sustained-attention driving task,” Scientific data, vol. 6, no. 1, pp. 1–8, 2019.

[17] P. Stroke, “Robotic devices and brain–machine interfaces for hand rehabilitation post-stroke,” J Rehabil Med, vol. 49, pp. 449–460, 2017.

[18] M. Scott, S. Taylor, P. Chesterton, S. Vogt, and D. L. Eaves, “Motor imagery during action observation increases eccentric hamstring force: an acute non-physical intervention,” Disability and rehabilitation, vol. 40, no. 12, pp. 1443–1451, 2018.

[19] K. Ang and C. Guan, “Eeg-based strategies to detect motor imagery for control and rehabilitation.” IEEE transactions on neural systems and rehabilitation engineering: a publication of the IEEE Engineering in Medicine and Biology Society, vol. 25, no. 4, pp. 392–401, 2017.

[20] A. Yurkewich, D. Hebert, R. H. Wang, and A. Mihailidis, “Hand extension robot orthosis (hero) glove: development and testing with stroke survivors with severe hand impairment,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 27, no. 5, pp. 916–926, 2019.

[21] D. T. Bundy, L. Sounders, K. Baranayi, L. Leonard, G. Schalk, R. Coker, D. W. Moran, T. Huskey, and E. C. Leuthardt, “Contralateral brain–computer interface control of a powered exoskeleton for motor recovery in chronic stroke survivors,” Stroke, vol. 48, no. 7, pp. 1908–1915, 2017.

[22] Z. Cao, M. Prasad, and C.-T. Lin, “Estimation of ssvep-based eeg complexity using inherent fuzzy entropy,” in 2017 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE). IEEE, 2017, pp. 1–5.

[23] Z. Cao and C.-T. Lin, “Inherent fuzzy entropy for the improvement of eeg complexity evaluation,” IEEE Transactions on Fuzzy Systems, vol. 26, no. 2, pp. 1032–1035, 2017.

[24] Z. Cao, W. Ding, Y.-K. Wang, F. K. Hussain, A. Al-Jumaily, and C.-T. Lin, “Effects of repetitive ssveps on eeg complexity using multiscale inherent fuzzy entropy,” Neurocomputing, 2019.

[25] S. Liu, J. Guo, J. Meng, Z. Wang, Y. Yao, J. Yang, H. Qi, and D. Ming, “Abnormal eeg complexity and functional connectivity of brain in patients with acute thalamic ischemic stroke,” Computational and mathematical methods in medicine, vol. 2016, 2016.

[26] A. Chowdhury, H. Raza, Y. K. Meena, A. Dutta, and G. Prasad, “On-line covariate shift detection-based adaptive brain–computer interface to trigger hand exoskeleton feedback for neuro-rehabilitation,” IEEE Transactions on Cognitive and Developmental Systems, vol. 10, no. 4, pp. 1070–1080, 2017.

[27] Z. Qin, Y. Xu, X. Shu, L. Hua, X. Sheng, and X. Zhu, “econhand: A wearable brain-computer interface system for stroke rehabilitation,” in 2019 9th International IEEE/EMBS Conference on Neural Engineering (NER). IEEE, 2019, pp. 734–737.

[28] C. Kim, J. Sun, D. Liu, Q. Wang, and S. Paek, “An effective feature extraction method by power spectral density of eeg signal for 2-class motor imagery-based bci,” Medical & biological engineering & computing, vol. 56, no. 9, pp. 1645–1658, 2018.

[29] Z.-H. Zhou and M.-L. Zhang, “Multi-label learning,” 2017.

[30] R. M. Mehmood, R. Du, and H. J. Lee, “Optimal feature selection and deep learning ensembles method for emotion recognition from human brain eeg sensors,” IEEE Access, vol. 5, pp. 14 797–14 806, 2017.

[31] A. Riid and J.-S. Preden, “Design of fuzzy rule-based classifiers through granulation and consolidation,” Journal of Artificial Intelligence and Soft Computing Research, vol. 7, no. 2, pp. 137–147, 2017.

[32] C.-Y. Chu and R. M. Patterson, “Soft robotic devices for hand rehabilitation and assistance: a narrative review,” Journal of neuroengineering and rehabilitation, vol. 15, no. 1, p. 9, 2018.