An Efficient Deep Transfer Learning Network for Characterization of Stroke Patients' Motor Execution from Multi-Channel EEG-Recordings

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Abstract*— Recent advances in stroke rehabilitation technology have been focused on developing Intelligent Rehabilitation Robots (IRR) that can effectively engage post-stroke patients (PSP) in intuitive motor training for full function recovery. Most existing rehabilitation robots incorporate functionalities that are passive in nature, constraining PSP to predetermined trajectories that often deviate from patients' limb movement intentions, consequently hindering recovery. To resolve this issue, a robust deep-transfer learning driven network (DTLN) is developed to adequately characterize PSP's motion intention signatures from neural oscillations towards achieving intuitive and active training. Thus, we investigated and proposed the utilization of mu-frequency spectrum (muFS) based CWT approach for Scalograms construction, which serves as inputs to the DTLN model that characterizes multiple classes of PSP's motor execution signatures from multi-channel electroencephalography (EEG) recordings. Then, we evaluated the proposed method using EEG data from six PSP and compared the decoding results to those of related approaches under similar experimental settings. The proposed method resulted in a significant increment of 10.84 % - 13.19% decoding accuracy across stroke patients and better convergence in comparison to other methods. Additionally, the method exhibited distinct task separability for individual motor execution signature across patients. In conclusion, our method offers a consistently accurate decoding of motor tasks that could enable intuitively active robotic training in PSPs with impaired motor function.

***Keywords*—: Stroke rehabilitation, Deep transfer learning, Brain-computer Interface, Electroencephalography, Rehabilitation robots**

I. INTRODUCTION

The human arm play essential role in facilitating the performance of various tasks during activity of daily living. Unfortunately, Post-Stroke patients (PSP) often face challenges in fully utilizing their arms for daily tasks due to the loss of motor function [1-2]. This emphasizes the crucial need for advanced preventive and rehabilitation technology. Basically, conventional physiotherapy approaches have been used to try to restore lost limb functionality, and in recent years this has been augmented with Intelligent Rehabilitation Robot (IRR) strategies. In particular, IRR approaches have gained wide acceptance within research and clinical communities for their efficacy and ability to provide quality rehabilitation to large numbers of patients at a reduced cost [3-6].

In [7-9], techniques that facilitate intuitive robotic training capable of recognizing the intended limb movement of a PSP using non-invasive bio-signals such as electroencephalography (EEG) are proposed. EEG offers exceptional temporal resolution, facilitating direct recording of electrical potentials from the underlying neural brain tissues via non-invasive electrodes on the scalp [10]. Emerging evidence revealed that PSP's frequencies of EEG oscillations offers insights into cortical reorganization and alterations in inter-hemispheric balance related to the lesioned areas [14]. Therefore, these frequencies are considered as potential biomarkers that could be leveraged to characterize PSP's motor intentions.

Recent advances in IRR have incorporated EEG oscillations and traditional machine learning (TML) approaches for decoding PSP's motor intention which could serve as control input to the rehabilitation robot. However, the TML methods mostly incorporate signal processing and feature extraction techniques for decoding PSP's motor intention toward developing IRR for adequate restoration of limb functions [11-12]. However, the TML models often employ hand-crafted features and require experts' involvement to construct and characterize PSP's motor intention [12-13]. To overcome the constraints of TML approaches, deep learning networks that can automatically learn and construct rich feature set from biological signals have been proposed [17-18]. Moreover, the training of these networks from the scratch requires a lot of computational resources and a substantial volume of training data that could hardly be obtained in the case of PSPs

Thus, leveraging benchmark Deep Transfer Learning Network (DTLN) trained previously on large data in similar domain would be a viable option. To construct the input to DTLN, two common techniques based on time-frequency representation including Short-Time Fourier Transforms and Continuous Wavelet Transform (CWT) have been proposed [19]. Moreover, Scalograms derived from CWT offer variable resolution and incorporate multiple scales, offering appropriate time and frequency information in accordance with the uncertainty concept proposed by Heisenberg [20-21]. Furthermore, constructing Scalograms based on CWT from requisite EEG frequency oscillation characteristics can retain essential motor information for adequate decoding of ME tasks, particularly in severely impaired PSP. Thus, this is vital for initiating active robotic trainings required for adequate rehabilitation of PSP. Additionally, studies have shown that event-related desynchronization in the mu (10 Hz - 14 Hz) and beta (16 Hz – 26 Hz) frequency spectrums of EEG signals can evidence motor function recovery in stroke survivors [15-16]. However, investigating and extracting specific motor execution (ME) signatures from the motor cortex region of PSPs based on *mu frequency spectrum* (muFS) and *beta frequency spectrum* (*betaFS*), for constructing Scalograms that serve as input to DTLN has rarely been considered to date. In other words, investigating the use of Scalograms constructed from such frequency spectrums as input to DTLN for precise decoding of PSPs' motor intention in the context of IRR constitute a research gap that needs to be addressed.

Therefore, this study first conducted investigation into mu and beta frequency oscillations of EEG, and then proposed the use of *muFS* based CWT approach for Scalograms construction, which serves as inputs to DTLNs to characterize multiple classes of PSP's ME signatures from multi-channel EEG recordings. The proposed method's (*muFS-CWT_Scalogram*) efficacy and robustness was examined in comparison to the other related methods under different experimental scenarios using multi-class EEG signals of stroke patients.

II. METHODOLOGY

A. Participants information

The study recruited ten ischemic stroke patients to participate in the data collection experiment. Preliminary examination revealed that the patients have no neurological condition they may hinder them from participating in the motor execution (ME) tasks deigned for the study. The patients agreed to participate in the study and provided permission for the publication of the study's results. The study's experimental protocol was approved by the Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences' Institutional Review Board and the Shenzhen Longhua District Central Hospital.

B. Data acquisition and pre-processing

Utilizing the international 10–20 standard, EEG signals of predefined upper limb ME tasks were recorded. This was accomplished using a 64-channel waveguard EEG Cap that incorporates an eegoTM amplifier from ANT Neuro, Netherlands. The ground electrode was situated at AFz and connected to CPz for referencing. Additionally, electrodes for the electrooculogram were situated on both sides of the supraorbital ridge and outer canthi to capture horizontal and vertical eye motions. The sampling frequency used is 1000Hz while the impedance was maintained around 5-8kΩ, depending on each stroke patient's tolerance level. The experimental procedure was well communicated to the patients, and they were directed to sit in a comfortable chair and engage in the ME tasks using their paretic limb. The tasks were guided by a video presented on a computer before them. As illustrated in Fig. 1, this study focused on four pivotal ME tasks, including two grasping movements (KG: key-grip and PG: power-grip) as well as two wrist movements (WE: wrist-extension and WF: wrist-flexion) which are commonly used in a wide range of daily activities.

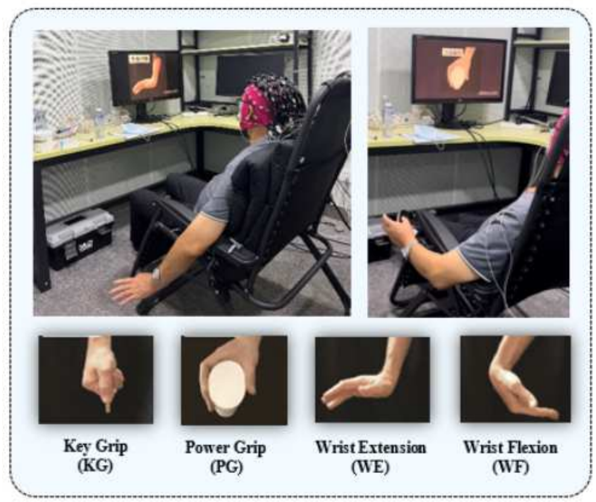

Figure 1. Representation of the experimental setting for EEG signal acquision for four classes of ME tasks performed by the stroke patients.

The patients were presented with a video sequence of ten images of a given active ME task and ten images of non-active task (rest), resulting in a total of 20 for each ME. Moreover, each active-task in the video was shown for a duration of 5s, followed by a 5s rest-period to prevent mental fatigue. All participants underwent two experimental sessions for each of the specified ME task. Due to the patients' level of motor impairment, only six out of the ten stroke patients completed the four ME tasks, and we proceeded with the analysis using their data. The data preprocessing and analysis was done using MATLAB and EEGLAB. The signal was decomposed using Independent Component Analysis and Artifact Subspace Reconstruction (ASR) technique [22] was used for artifacts elimination. Afterward, the active segment of the signals was epoched from -1s to 5s. The *muFS* and *betaFS* were extracted from eighteen channels located at the motor cortex region (denoted as ROI: region of interest) of the brain were explored for characterizing ME tasks performed by stroke patients.

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C. Construction of CWT-Scalograms based on muFS and betaFS

To enhance the representation of the Scalogram inputs, we individually extracted ME information from the ROI based on *muFS* and *betaFS.* The information formed a feature vector (*fv*) that served as inputs to the CWT for constructing Scalograms to train and validate the DTLN. The *fv* is transformed through the application of CWT concept as follows.

$$Trans.(b,\tau) = \int \frac{1}{\sqrt{b}} \psi\left(\frac{t-\tau}{b}\right) fv(t)dt \quad (1)$$

In this context, $\boldsymbol{Trans}$ represents the transformation, τ denotes the translation time, and the scaling is denoted by b. Additionally, Ψ represents the selected mother-wavelet while $fv(t)$ corresponds to the input value at a given time (t). A decrease in the wavelet scale (b less than 1) leads to enhanced spectral resolution, whereas an increase in the wavelet scale (b greater than 1) yields improved temporal-resolution. The former case highlights transient-events, while the later emphasizes steady-state frequencies.

$$EngWav = \int_{-\infty}^{\infty} |\psi(t)|^2 dt \quad (2)$$

$$D = \int_{-\infty}^{\infty} \psi(t)dt = 0 \quad (3)$$

Where $\boldsymbol{EngWav}$ is the wavelet's energy while Ψ is the mother-wavelet. This yields the dual-properties associated to the wavelet as outlined in eqn. (1): finite energy as expressed in eqn. (2) and admissibility illustrated in eqn. (3).

$$S(b,\tau) = |Trans.(b,\tau)|^2 \quad (4)$$

A graph representing the correlation between transformed signals and scaled-wavelets/time is used to construct the Scalograms via eqn. (4). The Scalograms then serve as inputs to the DTLN for characterizing ME tasks of patients.

B. Evaluation of the experimental results

The effectiveness of the proposed method was assessed by comparing it with existing approaches using accuracy and robustness as metrics for characterizing ME tasks. In generating the input Scalogram images, we considered the raw EEG and those preprocessed through ASR technique. For the preprocessed and raw EEG signals, we applied the CWT technique on the *muFS* component to construct *muFS-CWTasr* and *muFS-CWTraw* based Scalograms, respectively. Similarly, we generated the requisite Scalograms based on *betaFS* for both the preprocessed and raw EEG signals, yielding *betaFS-CWTasr* and *betaFS-CWTraw*. The DTLNs decoded the ME tasks of PSPs based on the four variants of the CWT-Scalograms mentioned. The performance of these variants was evaluated using the classification accuracy (CA) metric as described in equation (5).

$$CA = \frac{No.\ of\ Correctly\ Classified\ Samples}{Total\ No.of\ Samples} * 100\% \quad (5)$$

The means of classification accuracy (CA) for our method were subjected to comparison with those of alternative approaches through a paired t-test for statistical analysis, where the level of significance is set at $p < 0.05$. Moreover, the GoogleNet pre-trained DTLN with 144 layers was utilized in this study. The RGB versions of the obtained Scalograms with dimensions 224 by 224 by 3 were used as input to the network. The initial layers focus on recognizing features deemed as low level and the subsequent layers delve deeper to construct high level features, to ensure accurate characterization of the ME tasks. We introduced a dropout-layer to randomly reset the input to 0 to handle overfitting/related issue. The DTLN built using 70% and 30% of the data was used to test the trained model. Employed training parameters are Batch Size:20; Epoch:80; Learning Rate:0.0001; and LossFunction: gradient descent.

III. Experimental Results and Discussion

A. The DTLN's decoding outcomes for ME tasks

This section presents the obtained results after training and validating the DTLN based on Scalograms inputs driven by the proposed method (muFS-CWTasr and muFS-CWTraw) and the benchmarked approach (betaFS-CWTasr and betaFS-CWTraw) Figure 2 presents the decoding results of the proposed method and compared approach across stroke patients and ME tasks.

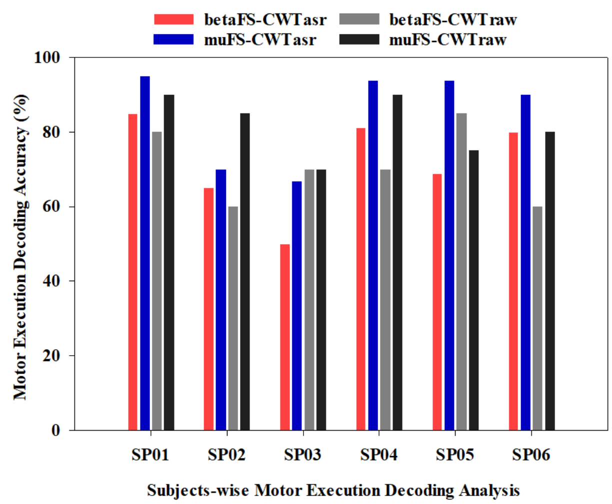

Figure 2: Performance of the DTLNs based on the proposed approach and other methods for decoding ME tasks of stroke patients (SP) across.

The results in Fig. 2 show that the Scalograms generated based on the proposed approach (muFS-CWTasr and muFS-CWTraw) led the DTLN model to achieve higher decoding accuracy for all patients and ME tasks compared to other approaches (betaFS-CWTasr and betaFS-CWTraw), except for the fifth patient who could not perform all the tasks well due to their level of impairment. Overall, the muFS approach achieved the best decoding performance when Scalograms based on muFS-CWTasr was used. This reveals that *muFS* may aid adequate learning of essential patters of EEG signals, especially when processed with ASR than using the raw signals. Moreover, we computed and analyzed the average decoding accuracy and standard deviation across stroke patients and ME tasks based on the proposed approach and related approaches as presented in Table 1. From Table 1, it can be observed that the proposed method achieved significant increment (at $p < 0.05$) in accuracy in the range of 10.84 % - 13.19% with a lower standard deviation across stroke patient. Thus, such lower standard deviation values indicate the reliability of the muFS approach since there is no wide difference in the results obtained across subjects.

Table 1: Average DTLN's ME decoding performance across patients for the proposed approach and other approaches.

Compared Methods	Average Decoding Accuracy (ADA) and Standard Deviation (STD)	
	ADA (%)	**STD (%)**
betaFS-CWTasr	71.67	13.13
muFS-CWTasr	**84.86**	**12.95**
betaFS-CWTraw	70.83	10.21
muFS-CWTraw	**81.67**	**8.165**

C. Performance of the DTLN motor execution task decoding

Considering the difference in characteristics of individual ME task in the experiments, it is essential to examine how well the proposed method can effectively decode them in comparison to other methods. Thus, confusion matrices were plotted using data from a representative patient on the proposed and conventional method to decode the four distinct ME tasks as shown in Figure 3.

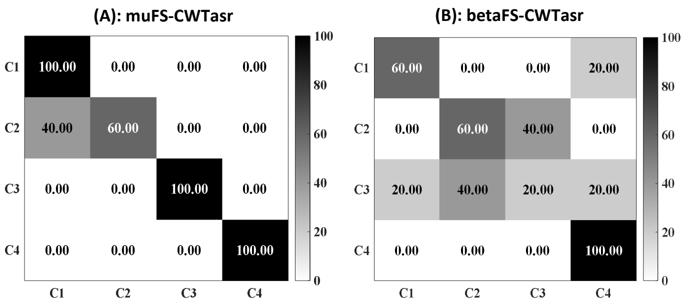

Figure 3. Decoding of Stroke patient's individual ME task with our approach (A) and the compared approach (B), across the ME tasks. Note that: C1 is Key grip, C2 is Power grip, C3 is Wrist extension, and C4 is Wrist flexion.

By examining the entries along the confusion matrices diagonal (Figure 3), it is observed that our approach (A: ***muFS-CWTasr***) overall recorded significantly higher decoding accuracy for the individual ME tasks (90%) compared to the other method (B: ***betaFS-CWTasr***) that achieved lower (60%), though same accuracy value was recorded for C4 task (Wrist flexion). This result further evidence the efficacy of the proposed method in facilitating accurate and robust decoding of ME tasks of patients.

IV. CONCLUSION AND FUTURE WORK

The need to develop intelligently intuitive and adaptive rehabilitation robotic system capable of restoring the lost limb functions in PSPs is on the rise. Decoding of ME signatures of PSPs from bio-signals can serve as input to reinforce active and accurate robotic training towards adequate restoration of their limb function via IRR. In spite of the promising benefits, existing IRR have only recorded marginal success. This is partly because of their inability to efficiently decipher multiple classes of motor executions due to individual differences in the physiology of patients, especially in chronically impaired persons [19-20]. Therefore, this study proposed and examined the use of mu frequency (***muFS)*** based CWT approach for Scalograms construction, which serves as inputs to DTLNs to characterize multiple classes of PSP's ME signatures from EEG recordings. Moreover, the performance of the proposed (*muFS-CWT_Scalogram*) was examined and compared with other related methods under standard experimental settings. The experimental results evidenced the efficacy of the proposed approach in attaining consistently high decoding accuracy for ME tasks from non-invasive brain signals of PSPs. Besides, our approach can potentially aid precise and robust decoding of stroke patients' motor intentions, particularly in severely impaired persons. This can effectively support intuitively active motor training in IRR, potentially facilitating full function recovery in stroke patient.

Despite the promising results in this study, there is a need to further investigate the performance of the proposed method in real-time using additional dataset from stroke patients with various characteristics.

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