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Electromyography Signal Analysis and Classification using Time-Frequency Representations and Deep Learning

Ahmed M. Elbeshbeshy, Muhammad A. Rushdi, and Shereen M. El-Metwally

Abstract— **Analysis and classification of electromyography (EMG) signals are crucial for rehabilitation and motor control. This study investigates electromyogram (EMG) time-frequency representations and then creates conventional and deep learning models for EMG signal classification. Firstly, a dataset of single-channel surface EMG signals has been recorded for four subjects to differentiate between forearm flexion and extension. Then, different time-frequency EMG representations have been used to build conventional and deep learning models for EMG classification. We compared the performance of pre-trained convolutional neural network models, namely GoogLeNet, SqueezeNet and AlexNet, and achieved accuracies of 92.71%, 90.63% and 87.5%, respectively. Also, data augmentation techniques on the levels of raw EMG signals and their time-frequency representations helped improve the accuracy of GoogLeNet to 96.88%. Furthermore, our approach demonstrated superior performance on another publicly available 10-class EMG dataset, and also using traditional classifiers trained on hand-crafted features.**

I. Introduction

Limb loss is considered one of the most significant challenges that mandate the use of proper prosthetic implants in order to perform daily life tasks. In the United States, more than 1.7 million persons are living with limb loss [1]. Also, according to the World Health Organization (WHO), about 30 million people are estimated to be in need of prosthetic and orthotic devices [2]. This need motivated dramatic growth in the development of automatic prosthesis control techniques via the peripheral and central nervous systems. A review of these methods is given by Cloutier [3] and Williams [4]. Recently, myoelectric prostheses have emerged as key tools in this field. The control of these devices is completely dependent on electromyography (EMG) signals recorded at nearby residual muscles. This EMG-based control is achievable because the neuro-muscular system of the residual limb parts remains functional even after limb loss [5]. Also, the activity needed by an amputee to control a prosthesis is reasonably small based on the recorded EMG signals [6]. Numerous EMG-based systems have been recently used in different applications for action classification [7], emotion detection [8], and automated disease diagnosis [9]. Analysis of features and selection of the best feature set for a specific type of signals is a time-consuming multifaceted task. Therefore, many approaches have been proposed to overcome the limitations of traditional feature extraction methods. In particular, end-to-end deep learning models have been used in many applications to fully automate the feature extraction and classification operations [10]. As the deep learning systems became more mature, these systems demonstrated high degrees of effectiveness and capability for many applications.

II. Related Work

Numerous biomedical signal processing methods have been proposed for biomedical classification and detection tasks. In particular, we review here those methods involving time-frequency representations of biomedical signals. We also focus our attention on methods employing deep learning schemes, which generally demonstrate superior performance on signal processing tasks.

Xiong *et al.* [11] used time-frequency representations of ECG signals in order to train a 16-layer CNN classifier for automatic arterial fibrillation detection. The trained classifier achieved an accuracy of 85%. In the area of EEG signal analysis, CNNs have been trained on time-frequency EEG representations to diagnose sleep disorders such as sleep apnea, narcolepsy or insomnia. For example, Vilamala *et al.* [12] created time-frequency representations of sleep EEG signals using the short-time Fourier transform (STFT) for sleep stage categorization. Furthermore, Xia *et al.* addressed the problem of limb movement estimation using a hybrid architecture that combines a CNN with a recurrent neural network (RNN) [13]. The proposed system employed kinematic information derived from EMG signal channels for myoelectric prosthesis control. The experimental results showed higher performance of the hybrid CNN-RNN system in comparison to the CNN one.

Although surface EMG signals show high variations across different subjects (even with precise electrode placement) [14], trained CNN classifiers show high robustness against these variations [15]. So far, many classification problems employed manual feature engineering. However, deep learning has shifted the focus in classification problems towards using learned features instead of engineered ones. Also, pre-trained CNN models have been widely employed to alleviate the problem of biomedical data scarcity. In addition, spectrogram and scalogram time-frequency representations obtained using STFT and CWT offer better tools for advanced biomedical signal analysis. Consequently, there has been a surge in the use of time-frequency representations for training deep learning models. For example, STFT has been applied to transform surface EMG signals into spectrograms [16]. As well, CWT has been used to transform ECG signals into scalograms which are used for CNN training [17].

A. Elbeshbeshy (email: elbeshbishy@gmail.com), M. Rushdi (email: mrushdi@eng1.cu.edu.eg) and S. El-Metwally (email: sh.elmetwally@eng1.cu.edu.eg) are with the Department of Biomedical Engineering and Systems, Cairo University, Giza, Egypt (The corresponding author, A. Elbeshbeshy, can be reached at +966-551-938007; fax: +966-209-9399).

In addition, the CWT was used for building EEG representations for seizure detection [18], and also EMG analysis in lower limbs [14]. The STFT was preferred over CWT due to the expensive computational requirements for the last one [19]. In particular, with non-stationary signals like EMG, the CWT proved its ability to visualize the blobs and edges in the scalogram representation [20]. To deal with the EMG nonstationary behavior, the CWT was applied to multichannel EMG signals and the produced scalograms were concatenated to form a 3D input for CNNs. However, the 3D inputs required a lot of preprocessing steps and significantly increased the computational cost. In our work, we propose a low-complexity approach based on single-channel and two-channel EMG recordings. Our approach addresses EMG classification tasks by employing time-frequency representations of the EMG signals for fine-tuning the weights of pretrained CNN models.

III. Materials and Methods

A. Dataset

In this work, EMG data samples were collected at Al-Jazeera Hospital, Riyadh, Saudi Arabia. Four healthy subjects were involved in this study: two males and two females with an average age of 28 ± 4 years. No subject had any forearm-related medical condition or history of nervous system problems. Informed consent forms were obtained from the participants prior to data collection. In addition, this process has been approved by the hospital management and the Ethics Committee for research purposes. EMG signals were recorded using a Micromed Neurowerk EMG System [21].

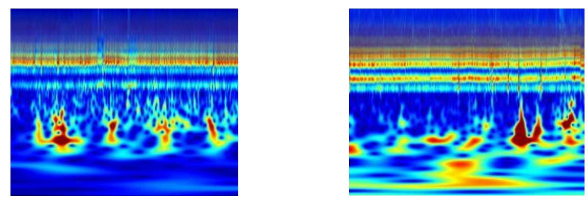
(a) (b)

Figure 1. Hand movement classes in our dataset: (a) Flexion, (b) Extension.

In accordance with the best practices for forearm EMG measurement, reference and active electrodes were placed circumferentially on the medial-flexor muscles in the superficial compartment of the forearm [19]. Instructions were presented to subjects using PowerPoint slides shown on a computer screen. Each subject was presented with timed slides, where each slide contained a single instruction to perform flexion or extension or have a break as shown in Fig. 1. If the subject made errors, or had delays in performing actions or following instructions, the trial was discarded. Timed breaks were allowed between performing gestures to prevent muscle fatigue or attention loss. After the subjects understood the instructions, they got themselves acquainted with the experimental protocol. Then, EMG data samples were collected from each participant while performing 30 repetitions of each of the flexion and extension movements with 6 seconds for each trial with a 2-second break between each two trials. Hence, a balanced dataset of 60 repetitions per subject was collected, with a sampling frequency of 10,000 *Hz*. The total number of trials for all participants is 240, where 60% of them were used for training while the rest were used for testing. Each trial is composed of 60,000 samples in length. The overall recorded data was collected in one matrix and labeled manually using MATLAB 2018a.

B. Data preprocessing

The acquired EMG data was pre-processed and transformed into three types of scalograms based on the CWT. The different scalogram types are based respectively on three mother wavelets: the generalized Morse wavelet, the analytic Morlet (Gabor) wavelet and the Bump mother wavelet [22]. As a result, the EMG data was transformed into three sets with 240 scalograms in each set. Each scalogram was scaled using cubic interpolation to a size of 224×224 pixels, and then used as input to the pretrained CNNs. Fig. 2 shows an example of the scaled scalograms for the cases of flexion and extension.



(a) (b)

Figure 2. Scalogram images obtained using the generalized Morse wavelet for (a) Flexion, and (b) Extension.

C. Pretrained networks

We initially investigated the retraining of CNNs extensively trained on ImageNet [23]. This dataset has more than 1.2 million images classified into 1,000 categories. Pretrained CNNs can be further retrained to be tailored for problems with small datasets [24]. In this work, a transfer learning approach was followed where the last few layers of such pertained CNN architectures were fine-tuned using the EMG scalograms. In particular, transfer learning was applied to the final layers of the GoogLeNet, SqueezeNet, and AlexNet CNN pretrained models. Extensive experiments were carried out to evaluate and compare the EMG classification performance for the three CNN architectures. Also, the effect of the learning rate and the optimization technique was analyzed. The best performance was obtained using the stochastic gradient descent with momentum, an initial learning rate of 1×10^{-4}, and a mini-batch size of 30 observations for each iteration.

IV. Results

The CNN training and testing have been performed using the MATLAB 2018a Deep Learning Toolbox, on a laptop with an Intel Core i3 1.50-GHz processor and a 4-GB RAM.

TABLE I. EMG Classification Results with Three CNN Types

	GoogLeNet	**SqueezeNet**	**AlexNet**
Training time	45 min	25 min	20 min
Accuracy	92.71%	90.63	87.5%

As shown in Table I, the above-mentioned CNN architectures were compared according to the training time, and the classification test accuracy. These results were obtained using scalograms constructed from the generalized Morse mother wavelet transform of raw EMG signals. As shown, GoogLeNet clearly achieved the best performance. Furthermore, the performance of the GoogLeNet-based CNN was further evaluated using other mother wavelets for scalogram construction. A significant improvement in accuracy is obtained using the analytic Morlet (Gabor) wavelet as shown in Table II.

TABLE II. THE EMG CLASSIFICATION RESULTS WITH THREE MOTHER WAVELETS FOR THE GOOGLENET-BASED CNN MODEL

Analytic Morlet	Morse Wavelet	Bump Mother
95.83%	92.71%	86.46%

In addition, data augmentation was applied to increase the training data, and hence improve the generalization performance. Specifically, adding noise to training data tends to strengthen the learning performance [25]. In our experiments, white Gaussian noise equivalent to 30% of the original recorded sEMG signal power has been added [26]. Thus, the training data size was doubled from 144 to 288 using this augmentation technique. Scalograms were obtained for the augmented data and used to retrain the GoogLeNet-based CNN model with the analytic Morlet (Gabor) wavelet (See Fig. 3).

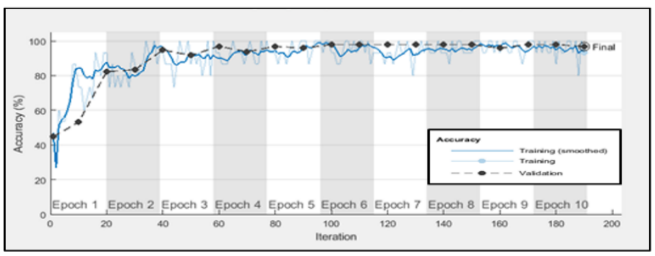


Figure 3. Training progress of GoogLeNet with data augmentation.

This process resulted in an improved accuracy of 96.88%. For further validation of the proposed system, we investigated its performance in the classification of publically-available two-channel EMG data associated with ten classes of finger movements [27] (See Fig. 4).

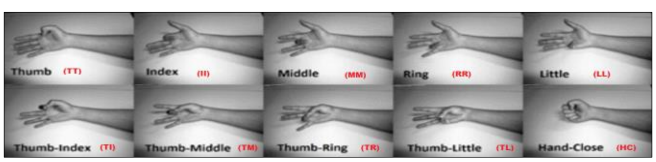


Figure 4. Ten classes of finger movements [47].

Khusbaba *et al*. [28] categorized the EMG signals associated with these finger movements using a manual feature engineering approach. For each of the two EMG channels, scalograms were obtained for all trials with 137 scales and 20,000-sample length representing 5 *sec* for each trial. Also, non-overlapping 500-millisecond sliding windows were used to yield ten scalograms for each channel with a size of 137×2,000. Each scalogram was rescaled with cubic interpolation to a size of 1,000×2,000. Each corresponding channel-specific scalograms were concatenated vertically to yield a combined scalogram of a size of 2,000×2,000. Finally, each combined scalogram was rescaled to a size of 224×224 to fit the input layer of the GoogLeNet-based CNN. Out of a total of 6,000 scalograms, we randomly selected 3,960 scalograms for training, and the remaining 2,040 ones for testing. The training data was augmented with data contaminated with white Gaussian noise with a mean equivalent to 30% of the original scalogram [26]. Hence, the training data size was doubled from 3,960 to 7,920. A GoogLeNet-based CNN architecture with the same above-mentioned settings was trained for 2 epochs with this augmented 10-class data using a batch size of 60. The trained model achieved an overall accuracy of 94.7% compared to 93.33% without data augmentation. The classification time for each scalogram was less than 350 milliseconds. The associated training parameters without and with data augmentation are listed in Table III.

TABLE III. TRAINING PARAMETERS OF THE GOOGLENET-BASED CNN MODEL FOR THE 10-CLASS EMG CLASSIFICATION PROBLEM

Training parameters	Without Data Augmentation	With Data Augmentation
Training scalograms	3,960	7,920
Number of iterations	132	316
Iterations per epoch	66	158
Training time	119 min 27 sec	532 min 19 sec
Achieved accuracy	93.33%	94.66%

The corresponding confusion matrix of this ten-class problem is shown in Fig. 5.

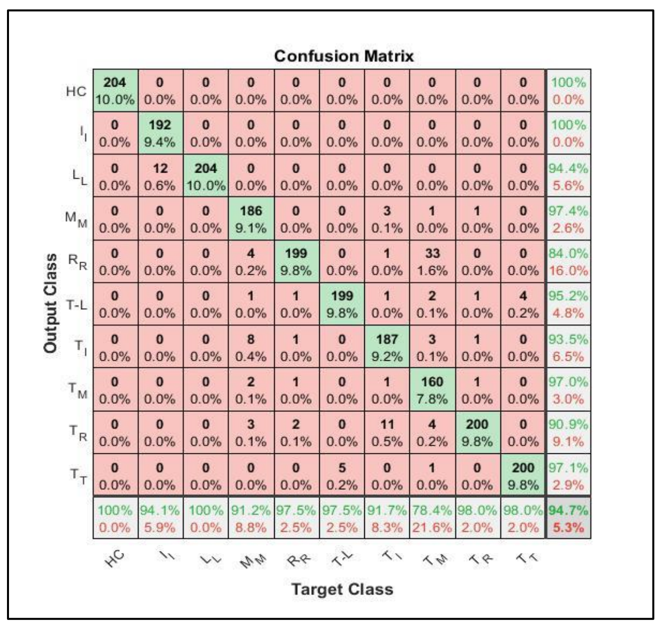


Figure 5. The confusion matrix for the 10-class EMG classification with data augmentation.

In addition, we compared the proposed deep learning system with traditional classifiers employing a manual feature engineering approach. These classifiers are based on temporal, spatial, and frequency-domain features which we extracted for the our collected two-class EMG dataset. The best classification results for a traditional classifier were achieved using the fine Gaussian support vector machine with an accuracy of 89.60%.

V. Conclusion and Future Work

We developed an end-to-end deep learning system employing transfer learning for EMG signal classification. The need for such systems which introduce fast and highly accurate classification increased dramatically. Relying only on one-channel EMG electrode, we were able to achieve good classification performance on a collected two-class EMG dataset. The proposed system could be fine-tuned for other binary classification applications. With technological advancements in the era of the Internet of things, there has been a growing need for the design of commercial wearables whose functions could be extended to include EMG sensors. Therefore, we investigated the fine-tuning of pretrained CNN architectures for EMG classification problems with different numbers of classes. We investigated CNN variants which can be generally integrated into systems for prosthetic control, robotic manipulations, or supporting daily tasks for able-bodied people. The GoogLeNet-based CNN model achieved the best performance with less than 350 milliseconds needed for the classification of each frame. In addition, our approach was validated with a ten-class finger movement dataset. Two EMG channels were recorded and helped obtain good spatial information for individual and combined finger movements. Concatenating the scalogram features from the two channels led to improved CNN performance. The classification performance was further improved through data augmentation [29], which improved the classification accuracy of the GoogLeNet-based model. We also compared the proposed deep learning models against traditional classifiers based on hand-crafted features. The best classification results for a traditional classifier were achieved using the fine Gaussian support vector machine with an accuracy of 89.60%. Clearly, our system gives superior results compared to traditional classifiers based on manual feature engineering.

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