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Lightweight deep neural network models for electromyography signal recognition for prosthetic control

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Abstract: In this paper, lightweight deep learning methods are proposed to recognize multichannel electromyography (EMG) signals against varying contraction levels. The classical machine learning, and signal processing methods namely, linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), root mean square (RMS), and waveform length (WL) are adopted to convolutional neural network (CNN), and long short-term memory neural network (LSTM). Eight-channel recordings of nine amputees from a publicly available dataset are used for training and testing the proposed models considering prosthetic control strategies. Six class hand movements with three contraction levels are applied to WL and RMS-based feature extraction. After that, they are formed into appropriate input dimensions, and classified using the LDA, QDA, LDA-CNN, QDA-CNN, LSTM, and CNN. Depending on three prosthetic EMG validation approaches (Scheme 1-3), the accuracy rates of 41.68%, and 47.27% are yielded by LDA, and QDA with 32-dimensional RMS, and WL features while CNN with 2×16 input has 82.87% (up to 88.10%). The effect of the learnable filters of the DL approaches, and signal windowing on the success rate and delay time are discussed in the paper. The simulations show that 2D-CNN (accuracy of 82.87% with 1.7 ms delay) can be successfully adapted to prosthetic control devices.

Key words: Human-machine interaction, deep learning, prosthetic hand control, convolutional neural network, electromyography

1. Introduction

Multichannel surface electromyography (sEMG) processing is the first step of myoelectric control for prosthetic applications. The decision of the pattern recognition(PR) algorithm on sEMG signals can help disabled people recover their capabilities of residual limbs [1, 5]. It is reported that amputations caused by trauma occur at the rates of 3.8, 2.8, and 0.02 individuals per 100,000 for upper limb, finger, and hand amputations, respectively [7]. For this reason, research in the field of prosthetics has continued intensively to reduce the limitations of the disabled [8]. Sensor technologies, controller and mechanical design, signal processing, and machine learning algorithms are combined to produce comfortable prosthetics with correctly recognized movement using the signals from the residual limb [40].

EMG signal processing and control are effective approaches for an assistive tool for disabled people [1, 13, 18] or human-machine interactions (HMI) [2, 12, 14, 25, 32]. It is based on conveying the subject's intention by processing the acquired signal from electrodes [4, 9] to recover lost limb functions [11, 15]. The objective of the EMG PR task is to extract the related features at a given muscle location and to classify them

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into limb position, movement, or gesture. These applications are generally called HMI to repeat limb motion [16]. However, it is a challenging task to generate informative features from the electrodes on the residual limb [18, 19]. Thus, the classification errors of sEMG signal processing in prosthesis applications are lower when compared to HMI studies on healthy subjects [17].

Myoelectric control techniques deployed in commercially available prostheses are based on on/off, proportional, and direct activation with limited movement capabilities [20]. The electrode placement scheme, number of electrodes from healthy or residual limb, and movement types with varying force levels affect the performance of the EMG PR task [22, 34, 35]. Time-domain (TD) signal processing [14, 23, 26] (root mean square (RMS), waveform length (WL), mean absolute value (MAV), zero crossing rate (ZCR), sample entropy (SE), slope sign change (SSC)) are generally preferred due to higher accuracy compared to the frequency, and time-frequency methods such as Fourier transform (FT) [34], and wavelet transform (WT) [25]. Linear or quadratic discriminant analysis (LDA or QDA) are generally preferred machine learning algorithms with TD features due to fast response (low delay) depending on prosthetic control schemes [17, 24, 28]. On the other hand, *k*-nearest neighbor (*k*-NN), support vector machine (SVM), artificial neural network (ANN), and convolutional neural network (CNN) [21] have been studied to reach higher accuracy rates for both EMG classification and prosthetic control, but they have computational burden [27, 29].

The accuracy rates of PR methods using healthy subjects' sEMG have reached over 90% depending on the number of movement classes. MAV, ZCR, SSC, and WL-based features with *k*-NN classifier were deployed to Arduino microcontroller for 4-class hand gesture recognition [30]. It has an accuracy level of 94% while another has rates of 98.64%, and 96.27% applying RMS, SE, and WL-based features to the SVM, and general regression neural network for 9-hand movements [31]. In 2014, time-dependent power spectrum descriptors (TD-PSD) were proposed and performed on a publicly available healthy sEMG database [23]. LDA, *k*-NN, and SVM results indicated that error rates can be reduced up to 8% for 8-class hand gestures. In another study [21] using the same signals, and TD-PSD as feature vector to deep neural network (DNN), the accuracy level of 98.88% was yielded when compared to decision tree (88.36%), *k*-NN (90.64%), random forest (91.78%), and SVM (98.66%). EMG signals of seven able-bodied subjects were recorded using the MYO armband for 15 consecutive days for seven hand gesture classifications. The proposed CNN basically consists of a convolution ($32@3 \times 3$), max-pooling ($3@ \times 1$), and fully connected layer outperformed (error rate = 9.79%) sparse auto-encoders with raw samples (SSAE-r, error rate=10.98%), and LDA (error rate=14.73%) with aforementioned TD features [33]. In [37], particle swarm optimization and recurrent neural network (RNN) based 12-class EMG classification was performed on healthy subjects, yielding up to accuracy of 94.167%. Transfer learning (TL) approaches were adopted for AlexNet and VGG16 for healthy classification. Short-time Fourier Transform images of sEMG signals were used as input images, and AlexNet yields 98.65% while deep feature concatenation (AlexNet FC6 + AlexNet FC7 + VGG16 FC6 + VGG16 FC7) with SVM classifier had an accuracy rate of 99.04% [39]. sEMG PR approaches using conventional ML and DL techniques were also reviewed in [40].

As stated before, it is a challenging task to recognize the hand movement using the signal acquired from the residual limb. That is why accuracy levels are dramatically lessened when compared to PR studies on healthy subjects [6, 18, 19]. In [17], the aforementioned method called TD-PSD on healthy subjects was applied to eight channel sEMG signals of nine transradial amputees. Three force levels (low, moderate, and high) of six hand movements were classified using LDA, Naive Bayes (NB), *k*-NN, and random forest algorithms depending tree schemes including inter-level (trained and tested with the same level), unseen level (tested without untrained force), and all levels (testing a force level on trained classifier with all levels). Scheme 3 is the scenario of an upper-limb prosthetic recognition called ”against varying contraction level” yielding a 17.42% error rate of LDA classifier with the help of spectral regression (SR) for dimensionality reduction. The bias effect of the unsupervised learning, SR was discussed in the study [28]. Phasor represented EMG feature extraction was introduced against varying contraction levels of prosthetic control, and the results were compared to TD-PSD with/without SR reduction. TD-PSD without SR-based features yielded 51.27%, 71.63%, and 79.85% for LDA, QDA, and k-NN, respectively while 60.45%, 71.17%, and 78.34% were obtained using phasor represented feature of the same dataset and validation. In another study [35], TD feature set with LDA classifier was performed on the recordings of the intact-limbed subjects, and error rates up to 30%-40% were reported within inter-level muscle contraction. In addition to these prosthetic PR approaches, wearable device [36] and the effect of the limb position (e.g, walking, sitting, an ascending a star) [11] during acquisition were analyzed. Accelerometer data combined with hybrid TD features can reduce the error rate by 5.81%.

Recently, deep learning (DL) algorithms have revolutionized several fields of PR methods [10]. Researchers spend their effort to improve the success rate of prosthetic applications adopting EMG to them. In [1], signals from 67 intact subjects and 11 hand amputees from 3 databases were analyzed using CNN, and the results were reported as 66.59%, 60.27%, and 38.09% for more than 50 hand movements. Zhai et al. [38] proposed a self-recalibrating algorithm using CNN to avoid user-dependent retraining. Thus, a stable EMG PR approach was introduced with reduced error rates of 10.18%, and 2.99% for intact, and amputee subjects.

The purpose of this paper is to improve EMG recognition performance against varying contraction levels by adopting RMS and WL features to a lightweight DL-based classifier. The RMS and WL based 2×16 dimensional features are extracted using 8-channel signals from transradial amputees with their differentiated versions for six class movements of three force levels (low, moderate, and high). The proposed DL-based models are performed on publicly available data set [17] considering the validation and prosthetic control approaches for benchmarking. With the help of low-dimensional feature space, and lightweight CNN, higher recognition rates can be achieved. The remainder is organized as follows: Section 2 the description of the amputee EMG database is given. The proposed feature extraction and the DL models are presented in Section 3. Consequently, simulation results of the DL-based recognition are examined in Section 4, and the conclusions are drawn in Section 5.

2. EMG dataset description

Al-Timemy et al. [17] recorded 8-channel EMG signals from 7 male traumatic, and 2 female congenital transradial amputees in 2016. The age of the participants is in the range of 19-57 summarized in Table 1.

This dataset consists of 9 folders (A1-A9) with 8 channels sampled at 2kHz. Eight to twelve s EMG signals for six hand movements were recorded from the residual limb shown in Figure 1

Five to eight trials were recorded for each movement (six classes as thumb flexion (TF), index flexion (IF), fine pinch (FP), tripod grip (TG), hook grip (HG), spherical grip (SG)), and each force level as low, moderate and high. Thus, there are 18 folders in each amputee's folder containing the EMG trials for the following 6 gestures with 3 force levels. To enhance reliability, 5-8 trials were recorded. Three of them were used for training, and the rest were testing of the machine learning algorithms (two to five trials). In the original study [17], the multichannel signals were divided into 150 ms length segments with 50 ms overlapping considering myoelectric control, and modified spectral moments based TF-PSD method was adopted as feature vector to increase recognition accuracy against varying force levels in three classification schemes; 1) Training and testing with the same single level 2) Testing with unseen level 3) Training with all levels, and testing with single level at a time. The proposed CNN method will be performed on this data using these 3 schemes for benchmarking.

Table 1. Information about the amputees.

Amputee	Age	Gender	Type
1	25	Male	Traumatic
2	33	Male	Traumatic
3	30	Male	Traumatic
4	27	Male	Traumatic
5	35	Male	Traumatic
6	29	Male	Traumatic
7	57	Male	Traumatic
8	19	Female	Congenital
9	31	Female	Congenital

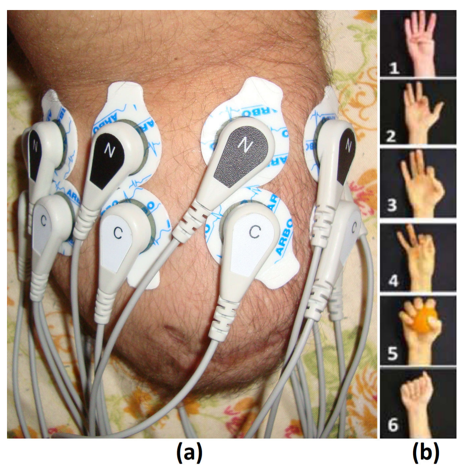

Figure 1. a) The electrode placement on a residual limb. b) Six hand gestures.

3. Proposed deep learning based recognition

The proposed EMG recognition is based on the adaptation of the DL methods on multichannel EMG signals from residual limbs. Nine amputees' six hand movements (TF, IF, FP, TG, HG, and SG) with three contraction levels (low, moderate, and high) are classified. Considering the prosthetic control requirements, the proposed method should have robust recognition capability against varying contraction levels at low delay times.

The proposed method can be divided into two parts namely feature extraction, and classification using LDA and DL algorithms. The successfully applied methods in EMG recognition tasks, RMS and WL are extracted for eight-channel signals $(x_i[n])$ and their derivatives $(x_i{}'[n])$ where $i = 1, 2, 3\ldots, 8$, and $N = 50, 100, \ldots, 300$ denote channel number, and sample length of the windowing, respectively. Thus, RMS(R_i) and WL(W_i) features are

$$R_i = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_i^2 [n]} \tag{1}$$

$$W_i = \sum_{n=1}^{N} |x_i [n] - x_{i-1} [n]| \tag{2}$$

After computation of WL and RMS for each channel and their derivatives, the feature set $\mathbf{F}$ for the CNN, and CNN-LDA based classification is generated as 2×16 dimensional form by

$$\mathbf{F} = [\mathbf{R}_1 \ldots \mathbf{R}_8, \mathbf{R'}_1 \ldots \mathbf{R'}_8, \mathbf{W}_1 \ldots \mathbf{W}_8, \mathbf{W'}_1 \ldots \mathbf{W'}_8] \tag{3}$$

It is also reshaped as 4×8 sequences, 1×32 for LSTM, and LDA-based recognitions depending on the validation schemes (schemes 1-3) in Figure 2 for performance evaluation against force variation. Finally, the aforementioned machine learning methods in Figure 3 are performed.

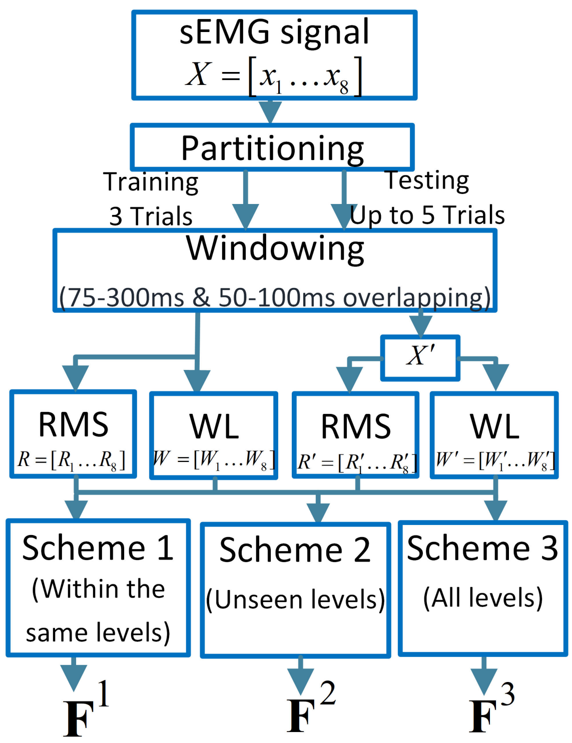

Figure 2. The feature extraction and validation scheme for performance evaluation against force variation.

The proposed classification of amputees' EMG signal to 6 hand movements with 3 force levels consists of four different combinations of techniques based on classic and DL algorithms. These are recognition using a (i) lightweight CNN, (ii) LSTM, (iii) LDA/QDA QDA, and (iv) CNN-LDA/QDA with $\mathbf{F}$ input (2×16, 4×8, 1×32, and 2×16, respectively). For (i), a convolutional (Conv) block having 64 filters with 2×3 kernels, ReLU activation, batch normalization (BN), and max pooling (1×2) are integrated to a fully connected (FC) layer with 256 neurons, and an output layer with a dropout layer (0.5). Without stride and padding, the feature vector to the FC is dropped to 13, and assigned to a class. In (ii), each feature is converted to a sequence (R, $\dot{R}$, W, and $\dot{W}$), and classified using the LSTM with 64 hidden layers and the FC layers. Their properties are summarized in Table 2.

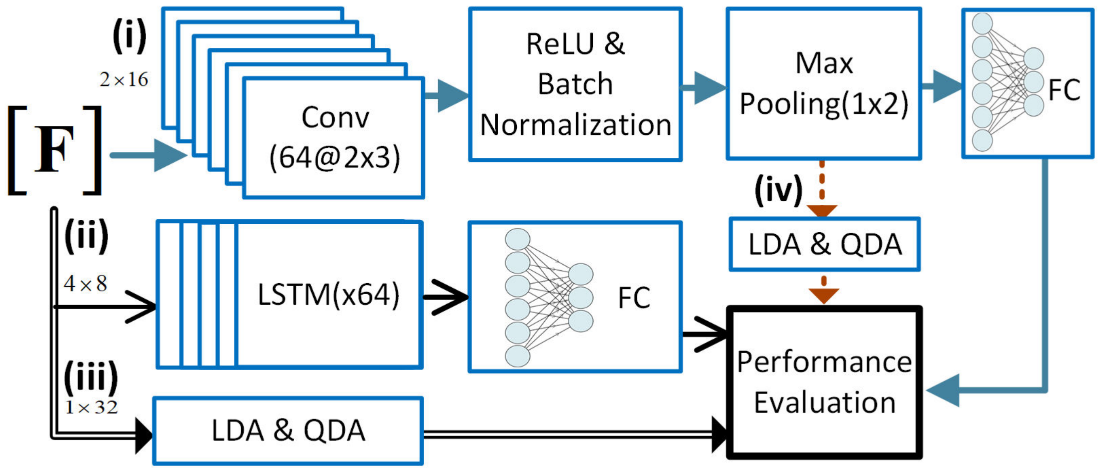

Figure 3. The proposed EMG recognition approaches classify 6 hand movements with 3 force levels.

Table 2. The CNN and LSTM Properties.

CNN	
Input	2×16, no normalization
Conv	64@2×3, no stride & padding
ReLU	———
BN	———
FC	256 neurons
Dropout	50%
Output	6 classes
Learning	Adam with 0.001 LR
LSTM	
Input	4×8, no normalization
Hidden units	64
FC	256 neurons
Dropout	50%
Output	6 classes
Learning	Adam with 0.001 LR

The LDA-based EMG recognition is the well-known approach due to low delay and was added to this study to compare with the proposed DL-based methods. In (iii), LDA is directly performed on the feature vector (1×32) while CNN features (1×13) generated from the last max-pooling layer are applied to LDA in the combination of the CNN-LDA/QDA (iv) in order to investigate the effects on recognition against varying contraction levels.

The prosthetic recognition strategies and the EMG signal database were described in [17]. Classification of six hand movements against tree force levels is the main objective of the proposed method. Three schemes were performed on the 8-channel amputee recordings.

- Scheme 1 is to evaluate the classifier using the same force level. In each step, it is trained, and tested with one force level.
- Scheme 2 is based on testing with untrained class (i.e. train using low-level recordings, and then testing using others)
- Scheme 3 is to test one force level using the classifier trained with all levels.

There are 5-8 trials belonging to each movement in a force level, and three of them are used for training. The aforementioned feature extraction is processed on the 150 ms windowed 8-channel EMG signals with 50 ms overlapping, and then the CNN, LSTM, LDA/QDA, and CNN-LDA/QDA are evaluated on the feature set depending on the schemes. The recognition results are given, and compared with the previous studies in the next section.

4. Results and discussion

The proposed DL-based recognition is performed on publicly available 8-channel EMG signals [1] of nine amputees according to the validation schemes 1-3. The main objective is to evaluate the classification of the six-hand gesture using the aforementioned machine learning methods against three force levels. In short, TF, IF, FP, TG, HG, and SG gestures with three force levels (low, moderate, and high) from nine transradial amputees are classified. For benchmarking, DL and feature extraction in this paper are adopted from the original study (6-classes, 3 forces, 9 amputees 8-channels, 8-12 s duration, 150 ms windowing with 50 ms overlapping, 5-8 trials, 2 trials for training, and the rest for testing, and evaluating using scheme 1-3).

Scheme 1 is the first simulation in this study. The machine learning algorithms are trained, and tested with the same force. A 32-dimensional feature vector is extracted for 18,350, 17,414, and 16,910 training samples (total of 52683) for low, moderate, and high, respectively. 23,800, 24,417, and 18,732 testing samples are used for low, moderate, and high-class evaluations (noting that deploying depending schemes). After reshaping input features compatible with the ML methods (2×16, 1×32, 4×8), the yielded performance graphs are given in Figure 4.

The accuracy rates of scheme 1 are the performance indicators disregarding the force effect. The worst case is the LDA with 49.22%, 39.94%, and 41.52% rates while the best CNN results are 79.89%, 79.34%, 78.83% within low, moderate, and high, respectively. QDA (61.50%, , 52.85%, and 48.22%) outperforms LDA, but CNN-LDA (71.63%, 73.17%, and 77.22%) is more successful than CNN-QDA (71.24%, 59.43%, and 66.14%). On the other hand, LSTM (63.33%, 65.84%, and 62.90%) cannot reach CNN, CNN-LDA, and CNN-QDA-based recognitions. The next experiments are conducted according to scheme 2 testing with unseen force levels. The recognition results of scheme 2 are shown in Figure 5.

Unseen force classification in scheme 2 has lower rates than in scheme 1, as expected. The CNN yields 74.39%, 70.07, and 44.68% while LDA are 36.74%, 41.12%, 31.74%, respectively. Generally, DL-based approaches have higher accuracy levels than 50% for scheme 2. Scheme 3 can be considered as a real prosthetic recognition. In this validation, the classifiers are trained using all force levels and then tested using a single

[1] https://www.rami-khushaba.com/electromyogram-emg-repository.html

force to analyze the performance of the algorithm against varying contraction levels. The accuracy levels are given in the graph in Figure 6

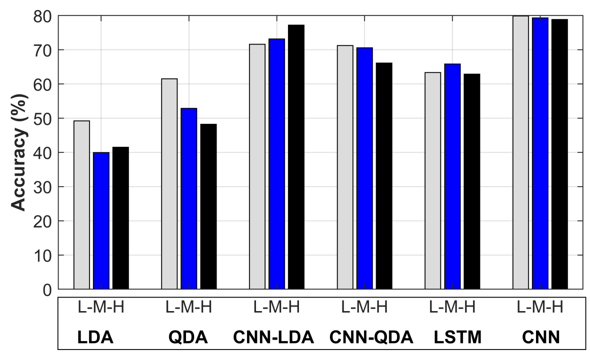

Figure 4. The accuracy rates of the LDA, QDA, CNN-LDA, CNN-QDA, LSTM, and CNN for scheme 1 (L: low. M: moderate. H: high).

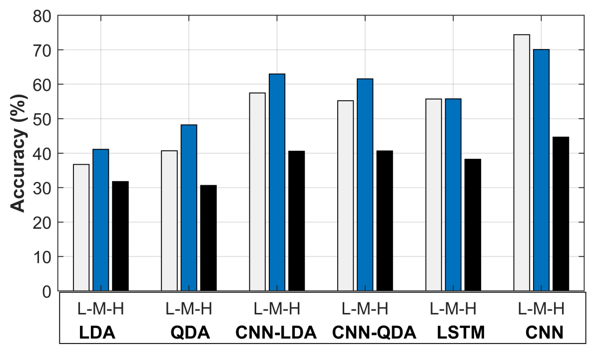

Figure 5. The performance results for scheme 2 (L: low. M: moderate. H: high).

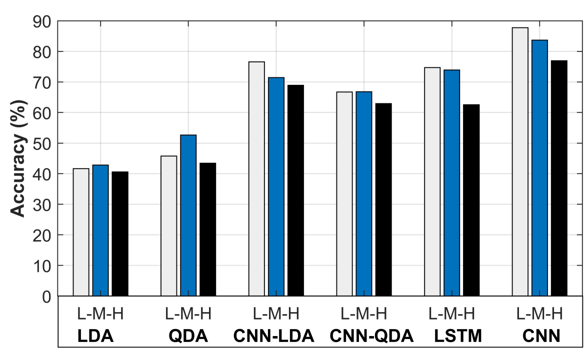

Figure 6. The accuracy results of the LDA, QDA, CNN-LDA, CNN-QDA, LSTM, and CNN for scheme 3 (L: low M: moderate H: high).

LDA (41.65%, 42.83%, and 40.58%) and QDA (45.76%, 52.64%, and 43.43%) for scheme 3 has average drop rate of 1.9%, and 6.92% compared to scheme 1. The CNN-LDA outperforms CNN-QDA and LSTM, but the highest accuracy results up to 88.10% are yielded by the CNN. The rates of the CNN-LDA are 76.59%, 71.43%, and 68.92% while LSTM have 74.72%, 73.92%, and 62.55%, respectively. The CNN yields 88.10%, 83.50%, and 77.00% for low, moderate, and high contraction level classifications, respectively. To make general comments on the classifier performances, the average accuracy rates of scheme 1 are 43.56%, 54.19%, 74.00%, 69.32%, 64.02%, and 79.36% for the LDA, QDA, CNN-LDA, CNN-QDA, LSTM, and CNN, respectively. These are changed to 36.53%, 39.82%, 53.66%, 52.47%, 49.89%, and 63.04% for scheme 2. Finally, the success rates for scheme 3 yield as 41.68%, 47.27%, 72.31%, 65.46%, 70.39%, and 82.87% for six-class hand movements with three force levels. All results are given in Table 3.

Table 3. The accuracy (%) and time (ms) of the proposed EMG recognition methods (Av: average accuracy).

Sch	Method	Low	Mod.	High	Av.	Time
1	LDA	49.22	39.95	41.53	43.67	1.0
	QDA	51.50	52.85	48.22	54.19	2.0
	CNN-LDA	71.63	73.17	77.22	74.01	**6.2**
	CNN-QDA	71.24	70.60	66.14	69.33	4.6
	LSTM	63.33	65.84	62.90	64.02	2.6
	CNN	**79.89**	**79.34**	**78.83**	**79.35**	4.4
2	LDA	36.74	41.11	31.75	36.53	1.1
	QDA	40.67	48.20	30.61	39.82	2.0
	CNN-LDA	57.46	62.98	40.55	53.66	4.2
	CNN-QDA	55.21	61.55	40.64	52.47	**5.7**
	LSTM	55.71	55.75	38.22	49.89	4.3
	CNN	**74.38**	**70.08**	**44.67**	**63.04**	2.6
3	LDA	41.65	42.83	40.58	41.68	1.0
	QDA	45.75	52.64	43.43	47.27	1.8
	CNN-LDA	76.58	71.42	68.92	72.31	4.0
	CNN-QDA	66.68	66.79	62.92	65.46	**5.5**
	LSTM	74.71	73.92	62.55	70.39	3.7
	CNN	**88.10**	**83.50**	**77.00**	**82.87**	2.7

Referring to scheme 3 results in Table 3, LDA has the lowest performance of 42.83%, but it has the fastest response of 1ms. Others (QDA, LSTM, CNN, CNN-LDA, and CNN-QDA) have 1.8, 2.7, 3.7, 4.0, and 5.5 ms delay for a single sample using a laptop computer with Intel core i5 9300H processor, 16 GB DDR4 RAM, and NVDIA GeForce GTX 1660 Ti Max-Q with 6GB memory. Moreover, the execution environment is selected as GPU for all simulations. The CNN with a 2.7 ms delay and an accuracy rate up to 88.10% has a promising result considering EMG recognition and prosthetic control. The CNN-based features with QDA and LDA yield up to 76.58%, but not practical solutions due to computational cost. Next, the effects of the window length and overlapping on the recognition schemes are also investigated in this paper. 300 ms and 75 ms windowing with 50 ms overlapping, and 150 ms windowing with 100 ms overlapping are applied to the mentioned WL and RMS-based feature extraction. These features are given to the input of the machine learning algorithms depending on the validation scheme 1-3 for comparison. Firstly, scheme 1 using 300 ms with 50 ms overlapping is performed on the dataset, and the results are given in Figure 7.

In scheme 1 for 300 ms with 50 ms overlapping, again the CNN is the highest accuracy level of 79.00%, 80.54%, and 79.90% with -0.90%, +1.20%, and +1.07% changes. For scheme 2, the accuracy graph is shown in Figure 8.

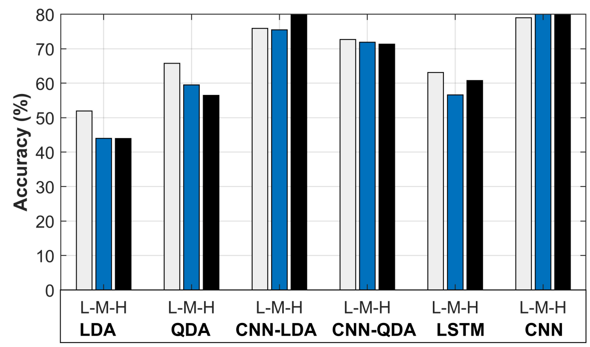

Figure 7. The classification accuracy rates for scheme 1(300 ms windowing with 50 ms overlapping).

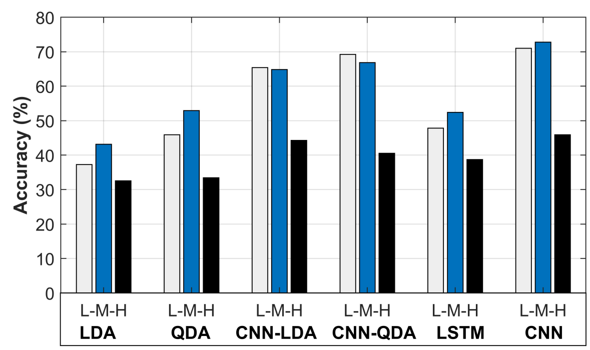

Figure 8. The accuracy rates for scheme 2 (300 ms windowing with 50 ms overlapping).

Changes of -3.36%, +2.72%, and +1.24% for CNN classification of the EMG signal depending on scheme 2 validation are yielded. Scheme 3 validation is also applied to 300 ms windowing with 50 ms overlapping, and the results are given in Figure 9.

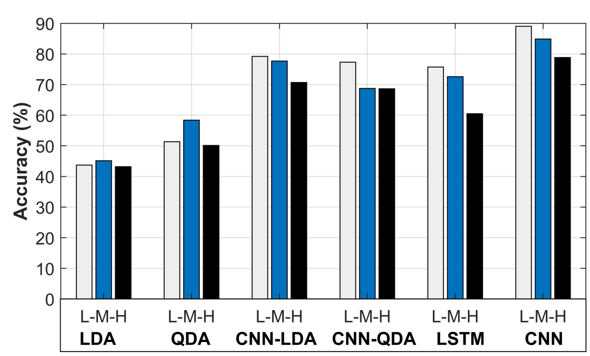

Figure 9. The accuracy rates for scheme 3 (300 ms windowing with 50 ms overlapping).

The performance increases of the CNN for scheme 3 with 300 ms with 50 ms overlapping are +1.32%, +1.18%, and +1.89% for low, moderate, and high force levels, respectively. CNN has the highest accuracy level of 89.04%, while LDA has 45.11% with an increase rate of 2.28%. In addition, increased windowing length has an increasing effect on the classifiers, LDA, QDA, CNN-LDA, CNN-QDA, and CNN. These ratios are 0.1% for CNN-QDA and 9.2% for LSTM. To be sure about the effect of windowing on the prosthetic recognition of the

EMG signals, 75 ms windowing with 50 ms overlapping is also simulated, and negative accuracy changes are obtained for all classifiers. Reduction rates of -1.78%, -2.21%, and -2.35% for scheme 1, -2.93%, -3.28%, and -4.76% for scheme 3 have existed for 75 ms length signal. The performance of the machine learning algorithms on 300 ms, and 75 ms windowing with 50ms overlapping are summarized in Table 4 and Table 5.

Table 4. The accuracy (%) of the proposed deep learning-based EMG recognition methods on 300 ms windowing.

Sch	Method	Low	Mod.	High	Av.
1	LDA	51.96	43.97	43.97	46.63
	QDA	65.78	59.51	56.46	60.58
	CNN-LDA	75.90	75.49	80.34	77.24
	CNN-QDA	72.68	71.90	71.31	71.96
	LSTM	63.11	56.61	60.78	60.17
	CNN	79.00	80.53	79.90	79.81
2	LDA	37.26	43.16	32.57	37.66
	QDA	45.90	52.90	33.44	44.08
	CNN-LDA	65.41	64.84	44.29	58.18
	CNN-QDA	69.25	66.84	40.53	58.87
	LSTM	47.81	52.40	38.70	46.30
	CNN	71.03	72.80	45.92	63.25
3	LDA	43.72	45.11	43.19	44.01
	QDA	51.34	58.39	50.14	53.29
	CNN-LDA	79.22	77.65	70.71	75.86
	CNN-QDA	77.28	68.73	68.63	71.55
	LSTM	75.73	72.58	60.47	69.60
	CNN	89.04	84.85	78.83	84.24

Table 5. The accuracy (%) of the proposed deep learning-based EMG recognition methods on 75 ms windowing.

Sch	Method	Low	Mod.	High	Av.
1	LDA	45.95	36.22	38.55	40.24
	QDA	56.29	46.23	41.62	48.05
	CNN-LDA	70.32	69.62	71.33	70.42
	CNN-QDA	66.30	63.59	62.23	64.04
	LSTM	62.31	63.54	61.19	62.35
	CNN	78.11	77.13	76.48	77.24
2	LDA	36.07	39.15	30.80	35.34
	QDA	35.91	42.90	27.87	35.56
	CNN-LDA	53.83	57.63	38.31	49.93
	CNN-QDA	53.57	52.40	34.04	46.67
	LSTM	57.89	55.70	37.29	50.29
	CNN	73.48	66.93	43.59	61.33
3	LDA	39.70	40.05	38.24	39.33
	QDA	40.29	45.89	37.43	41.20
	CNN-LDA	68.18	65.95	59.98	64.70
	CNN-QDA	53.40	57.00	50.50	53.63
	LSTM	72.85	71.50	60.52	68.29
	CNN	84.79	80.39	72.18	79.12

The last analysis is based on investigating the overlapping length. The levels are increased by +0.08%, +0.93%, and +0.02% for the CNN, +4.91%, +4.03%, and +4.46% for the LSTM, but negative changes are yielded by -1.48%, -9.45% for CNN-LDA and CNN-QDA. The detailed accuracy graphs of the classifiers for scheme 3 with 100 ms overlapping are given in Figure 10 (similar results are valid for scheme 1 & 2 with 100 ms overlapping based feature extraction given in Table 6.

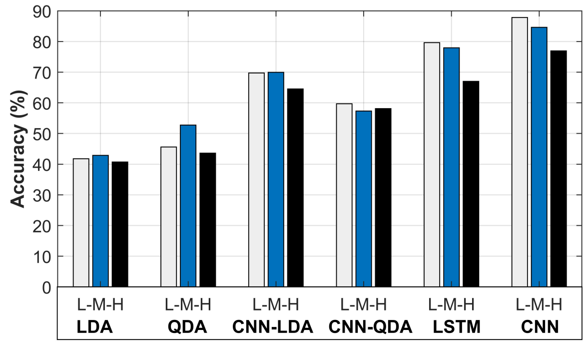

Figure 10. The accuracy rates of the LDA, QDA, CNN-LDA, CNN-QDA, LSTM, and CNN for scheme 3 (150 ms windowing with 100 ms overlapping).

Table 6. The accuracy (%) of the proposed deep learning-based EMG recognition methods on 100 ms overlapping.

Sch	Method	Low	Mod.	High	Av.
1	LDA	49.25	40.07	41.45	43.59
	QDA	61.55	52.86	48.40	54.27
	CNN-LDA	72.91	74.23	74.47	73.87
	CNN-QDA	71.94	72.34	67.77	70.68
	LSTM	66.13	70.71	66.90	67.91
	CNN	81.07	79.91	78.70	79.89
2	LDA	36.90	41.36	31.99	36.75
	QDA	40.69	48.22	30.70	39.87
	CNN-LDA	56.68	60.14	43.59	53.47
	CNN-QDA	58.78	46.01	40.13	48.31
	LSTM	63.23	58.05	39.37	53.55
	CNN	76.14	69.76	46.39	64.10
3	LDA	41.78	42.89	40.73	41.80
	QDA	45.60	52.75	43.59	47.31
	CNN-LDA	69.74	69.94	64.55	68.08
	CNN-QDA	59.69	57.34	58.12	58.38
	LSTM	79.62	77.95	67.00	74.86
	CNN	87.79	84.60	76.96	83.12

Referring to Table 6, overlapping is not a serious effect on the CNN classification. As a result, the given figures and tables indicate that WL and RMS features of 8- channel EMG signals can be successfully combined with the CNN to categorize into 6-class hand movements with three force levels. The learnable filters in the convolutional layer are capable of increasing the class separability against contraction levels. Signal windowing also affects the accuracy of the classifiers. The wider signal length (300 ms) yields a higher rate of nearly 1.5%, and the shorter (75 ms) causes a nearly drop rate of 4%. In addition to these experiments, a similar CNN topology with 1×32-dimensional input feature is adopted for EMG classification. Instead of 64@2×3 filter blocks, 64@1×3 filters is used with a 1-dimensional vector. This 1D-CNN yields accuracy rates of 86.60%, 82.70%, and 75.61% for low, moderate, and high contraction levels under scheme 3 validation. It has an average accuracy rate of 81.64% with a drop rate of 1.15% compared to the aforementioned 2D-CNN. For detailed recognition analysis class by class, the confusion matrices of low, moderate, and high using the CNN are shown in Figure 11

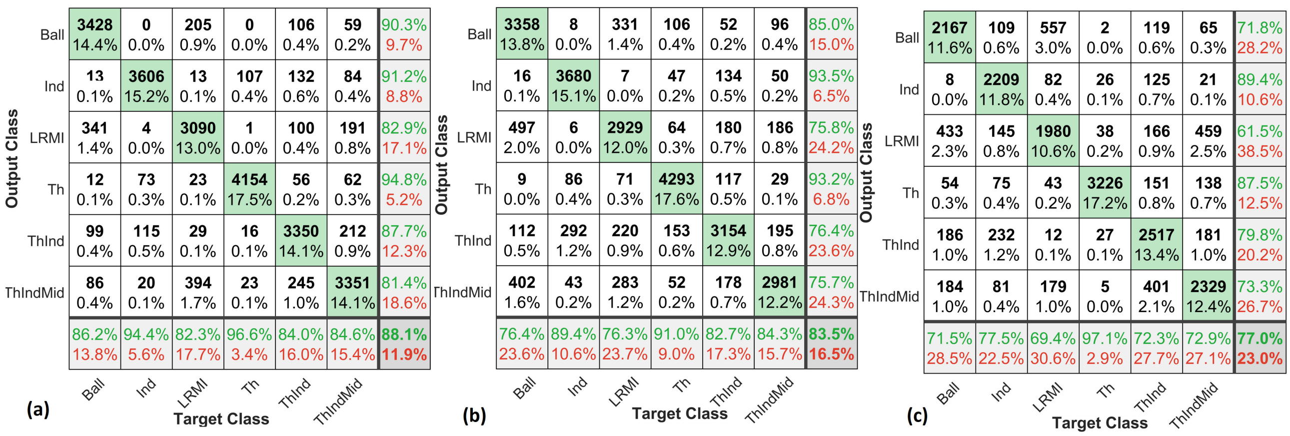

Figure 11. The confusion matrices of the CNN (Scheme 3: (a) low, (b) moderate, and (c) high).

The CNN has great performance in the classes Th, and Ind, yielding up to 94.80%. However, the worst case has occurred at Thindmid with a rate of 73.30%. Instead of using feature extraction, 8-channel sEMG time series have been directly applied to the LSTM. It yields a correct rate of 36.76% for six class movements with three contraction levels. Finally, the results of the proposed CNN-based EMG recognition for prosthetic control are compared to previous studies performed on the same amputee database validated depending on scheme 3 in Table 7.

Table 7. The accuracy (%) comparison with the previous studies.

Study	Accuracy	Methods
He et al. [34]	74.14	DFT-Norm-2
Al-Timemy et al. [17]	82.58	TD-PSD, SR, LDA
Onay and Mert [28]	78.34	PRE, k-NN
This study	82.87	RMS, WL, CNN

In the original study of the database [17], SR was applied to extracted TD-PSD features. The SR was a time-consuming semisupervised subspace learner to reduce dimensionality to 5. It was reported that it has a biasing effect on accuracy rate [28], and the TD-PSD & LDA, and TD-PSD & k-NN have 51.27% and 79.85% [28]. In PRE method [28], 78.34% was obtained with lower processing time. As a result, the proposed DL-based EMG recognition method is capable of achieving high accuracy rates (up to 88.10%, an average of 82.87%) consisting of only two signal processing techniques, and the lightweight CNN. Considering the prosthetic control for amputees, six hand movements with three force levels can be distinguished using the 2D-CNN. After offline training of the proposed model, it can be also deployed to GPU or microcontroller with CNN accelerator module-based embedded systems for real-time prosthetic control due to having lightweight architecture.

5. Conclusion

Deep learning (DL) based electromyography (EMG) recognition using root mean square (RMS) and waveform length (WL) features is performed on 8-channel amputee recordings. 6 Hand movements with 3 contraction levels (low, moderate, and high) are classified using a linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), lightweight convolutional neural network (CNN), long short-term memory neural network (LSTM), LDA-CNN, QDA-CNN, and 1-D version of the CNN (1D-CNN) considering the prosthetic control requirements. 1×32 (LDA, QDA, and 1D-CNN), 2×16 (CNN), or 4×8 (LSTM)-dimensional RMS and WL features are evaluated according to the validation schemes. The classical and the most preferred LDA and QDA classifiers are compared to DL methods against varying contraction levels. Depending on scheme 3 validation (training using all forces, and testing with a single force level at a time), LDA and QDA yield 41.68%, and 47.27% while DL-based results are 72.32%, 65.46% 70.39%, and 82.87% (up to 88.10%) for LDA-CNN, QDA-CNN, LSTM, and CNN, respectively. Learnable filters in CNN classifiers and CNN-based features in LDA-CNN and QDA-CNN have a high impact on amputee EMG recognition against force levels. The lightweight structure consists of a single convolutional block, ReLU, max pooling, drop-out, and fully connected layer for a low delay of 2.7 ms while LDA and QDA have 1.0, and 1.84 ms delays for a single sample with 8-channel EMG signals. The lightweight architecture of the proposed 2D-CNN can also be deployed to embedded hardware for real-time applications.

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