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DFNN-based Gesture Recognition with the Shift and Damage of the HD-sEMG Electrodes

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Abstract— **The surface electromyography (sEMG) signals can be used to identify the activity intention. Recently, High-density (HD) electrodes have been widely used to record sEMG signals for myoelectric control. However, the problem of the electrodes shift or damage in dons and doff often happens, it will have a greatly bad influence on the accuracy and stability of gesture recognition. In this paper, we propose a deep fast neural network (DFNN) to attenuate these issues by utilizing the spatial-temporal features of sEMG signals. The performance of the proposed model is compared with the locality sensitivity analysis (LSDA) and long short-term memory (LSTM), and they are all tested to classify nine gestures in these situations including the electrodes shift (10mm), shift (10mm) and damage (6). Without pre-training, the proposed DFNN model can high average 93.35%, and the error between individuals is less than 0.045 when the electrodes shift and damage.**

I. Introduction

The electromyography (EMG) signal is a bridge to establish the relationship between external machine equipment and human motion intention [1]. And the EMG based method has been used in amputation or congenital limb impairment so that people with disabilities can regain their physical function [2]. As a quantitative measurement method of muscle activity, high-density surface electromyography (HD-sEMG) signals are often collected by non-invasive electrodes, which provides a simple and intuitive method for human-computer interaction [3]. At present, this new type of human-computer interaction has been applied to prosthetic limb control, robot exoskeleton, VR games, industrial robots and other fields [4].

Generally, surface electromyography (sEMG) acquisition devices are divided into high-density (HD) electrodes and sparse multi-channel (SMC). Among them, the SMC method has higher requirements for the placement of electrodes on muscle [5], which limits its application in muscle connector interface applications (MCIs). On the contrary, HD electrodes can accurately record the temporal and spatial changes of surface muscle potential through several closely connected electrodes, which is more robust to the location of electrodes [6]. In the field of sEMG control, researchers have proposed a variety of algorithms for prosthetic limb control. The traditional pattern recognition algorithm required to carry out data segmentation, feature extraction and classifier design [7]. For amplitude information, the features include root mean square (RMS), autoregression (AR), standard derivate (SD) and so on. The commonly used classifier models are support vector machine (SVM), locality sensitivity discriminant analysis (LSDA), decision tree (DT), random forest (RF), and so on [8]. With the development of the integrated circuit industry, deep learning is gradually applied in the field of sEMG signal processing. Because of its good expansibility and accuracy, and the end-to-end capability. The deep learning methods-based recognition has more advantages compared with the traditional methods. As for time-series signal, the sEMG signal has been used in gesture recognition combined with long short-term memory (LSTM) model [9], but when using HD electrodes, the LSTM model will lead to the lack of spatial information. To solve the problem, Gen et al. proposed to use the instantaneous sEMG to compensate for the lost spatial information of sEMG signals and achieve a better recognition effect [10]. In practical applications, the gesture recognition based on HD-sEMG electromyography often occurs the phenomenon of dislocation and damage of the electrodes, for example in dons and doff. The new deep learning approach should be developed to solve this problem.

Hargrove et al. (2006) found that in the 10-class myoelectric recognition, the shift of 10mm of electrodes would reduce the classification accuracy from 90% to 60% [11]. To reduce the effects, they proposed that the classifier should be trained with signals from all expected displacement locations. This will consume much time and cannot cover all the situations [12]. Aaron J. Young et al. (2011) also investigated how the size or the placement of the electrodes affected robustness with electrodes shift. They found that the shifts perpendicular to the muscle fibers affected accuracy more than shifts parallel to the muscle fibers in the recognition [13]. Antonietta Stango et al. (2015) compared variogram (Variog) features with RMS features, time-domain (TD) features, time-domain autoregressive (TDAR) features and found that the Variog features are superior to the others. They also investigated the effect of the noise in signals or the number reduced of electrodes in gesture recognition. In recent years, many people tried to use the deep learning method to realize gesture recognition. For example, Md. Rabiul Islam et al. (2019) creatively proposed to use a shallow convolutional neural network architecture with the instantaneous HD-sEMG images to recognize the neuromuscular activity [15].

In this paper, we propose a novel deep fast neural network (DFNN) model, which utilizes the temporal and spatial

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characteristics of the sEMG signal, to lessen the effect of electrodes shift and damage.

II. METHODS

A. Dataset and Preprocessing

1) Dataset

The data used in the experiments are provided by the University Medical Center Göttingen. There are seven able-bodied subjects (3 males and 4 females), whose average age is about 29 years and one 78-year-old unilateral trans-radial traumatic amputee with 53 years old post-amputation.

The sEMG signals are collected by an adhesive grid using OT Bioelettronica with 192 electrodes that comprised 8 rows and 24 columns, and the distance between rows or columns is 10 mm. The sampling rate is 2048 Hz, and the signals are amplified with a gain of 500.

The adhesive grid is placed on the circumference of the forearm, while a reference electrode is placed on the wrist. In the experiments, nine gestures (see Figure 1.) are classified including wrist flexion, wrist extension, radial deviation, ulnar deviation, forearm pronation, forearm supination, hand open, hand closing, and the rest position. Four repetitions of each movement are recorded, for a total of four trials for each subject. For more details about the data acquisition process, please refer to the article of Antonietta Stango (2015) [14].

Figure 1. Nine classes of gestures

2) Preprocessing

The window of 2.2s (4500 samples) centered at such sample was taken as the static of the task. Then the RMS of the sEMG was calculated with a window of 150 samples.

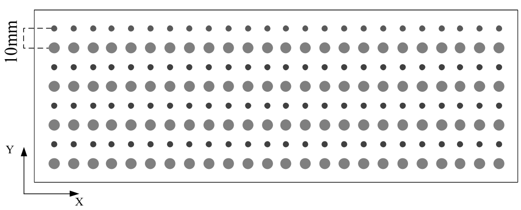

Figure 2. Upwards/Downwards shift 10mm (4*24 electrodes)

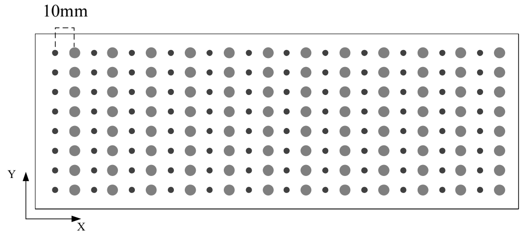

Figure 3. Inwards/Onwards shift 10mm (8*12 electrodes)

a) Shift 10mm

Upwards/Downwards: As shown in Figure 2. , the spacing between rows is 10 mm. In the shift upwards, the bigger points represent the electrodes used to train, while the smaller ones are used to test. And the shift downwards is contrary to above.

Inwards/Onwards: As shown in Figure 3. , the spacing of each column is also 10mm. In the shift inwards, the bigger points are the electrodes used for training, while the smaller ones are for testing. And the shift onwards is contrary to the shift inwards.

b) Shift 10mm & 6 Electrodes Noised

In this task, 6 channels signals are selected randomly to be replaced by white Gaussian noise in train set as well as test set. The form of shift was same to task a).

3) Featured sEMG Image

In the experiment, we transform the sEMG signals based on its location into image called featured sEMG image (see Figure 4.) [16]. The image integrates the spatial and temporal characteristics of the HD-sEMG. When the electrodes shift 10mm or shift 10mm with damage 6, the matrix-type is (12*8).

Figure 4. The Featured sEMG Image (12*8) based on sEMG signals

B. Deep Fast Convolutional Neural Network (DFNN)

1) DFNN Structure

In this paper, we propose a model based on convolutional neural network (CNN) to identify multi-class gesture recognition. The detailed architecture of the DFNN model is described in Figure 5. , which has ten layers, the structure is motivated from the work of Md. Rabiul Islam *et al* [15], and we attempt to update the structure for our problem. The idea to design this model is based on the following principles: (i) the HD-sEMG signals have the spatial-temporal features; (ii) the convolutional neural network is capable to capture the local edge features and can effectively avoid the uneven distribution caused by the electrodes shift and damage.

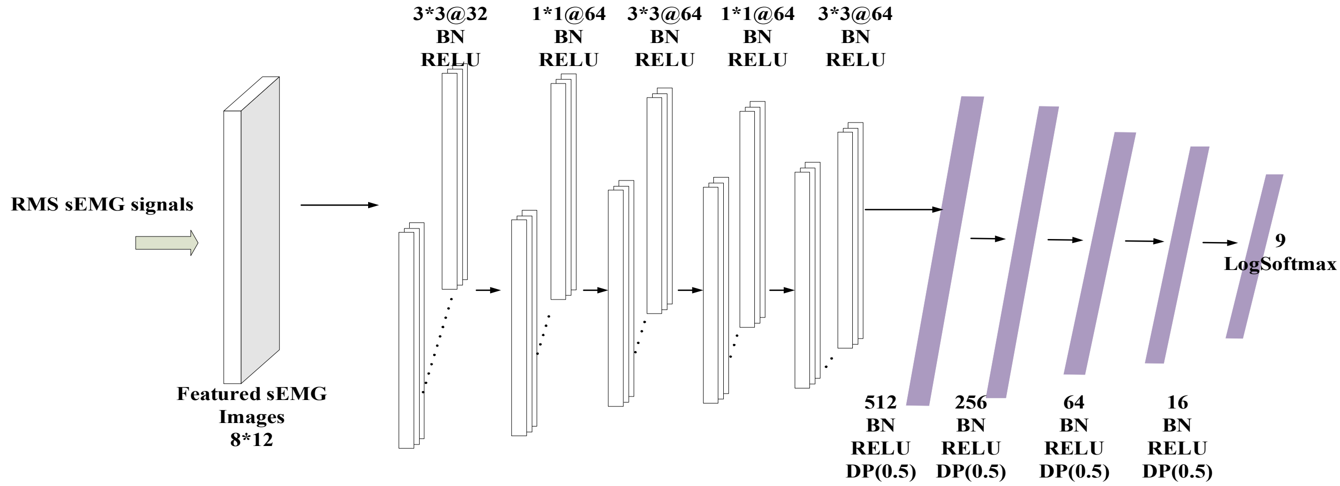

Figure 5. The diagram of DFNN structure

The input to the DFNN model consist of the size 12*8 images. The first five hidden layers consist of convolutional layers and locally connected layers. The convolutional layers consist of 64 filters with the kernel 3*3 and stride 1. After each convolution (3*3), two locally connected layers of 64 filters with 1*1 are applied as to be the local nonlinear transformer, which can make the model learn more complex feature representations [17]. The output of each hidden convolutional featured image a_{ij} produced by a convolutional operation can be computed as follows:

$$a_{ij} = \sigma\left[f\left(\sum_{n=1}^{N} \sum_{k=1}^{K} W_{n,k} X_{i+n,j+k} + \omega_b \right) \right],$$

where $W_{n,k}$ represents the weight of the matrix in row n, column k. $X_{i+n,j+k}$ is the value in the position of row $i+n, j+k$. ω_b is the weight bias, and σ represents a nonlinear activation function.

The last four hidden layers are composed of 512, 256, 64, and 16 fully connected layers, respectively. The model ends with a K-way fully connected layer and a LogSoftmax function, where K represents the number of gestures to be classified. The fully connected layer can combine the local feature information, and generate the probability distribution of the gestures.

The batch normalization (BN) and ReLu nonlinear activation functions are added after each convolution layer, which can improve the learning ability and effectively prevents over-fitting [18].

2) Training

The sEMG signals are recorded with the sampling 2048HZ. The training sets are 3240, and the testing sets are 1080. To reduce the computational complexity and optimize the parameters effectively, Adam is used to optimizing our model parameters, which has better performance than SGD [19].

The batch size is 40, and the training sets are randomly chosen from samples. We use separately 200 and 500 epochs for training. The learning rate is initialized to 0.001 for all methods. To prevent the over-fitting, dropout with probabilities 50% is used to perform well. After each epoch, the testing set is used to analyze the model performance. It's worth to mention that the proposed model does not require pre-training and can converge fast around 25 epochs.

III. EXPERIMENT

The experimental schematic illustration is shown in Figure 6. . We mainly classify nine gestures under the electrodes shift and damage, and compare three methods including: LSDA, LSTM and DFNN, to state that the proposed model has better performance. 96 channels are used when the electrodes shift 10 mm or 10 mm with damage 6. As for using the LSDA and LSTM, the RMS sEMG signals are inputted to the model directly, but for the DFNN, we use the featured sEMG images as inputs. The epoch of the LSTM is 500, and the DFNN is 200 and 500.

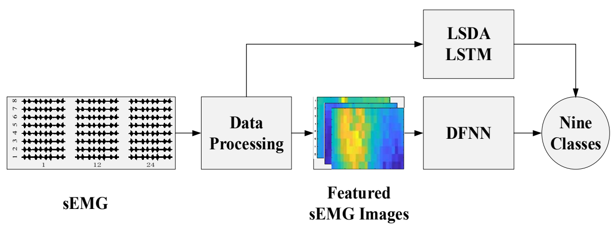

Figure 6. The overall experimental illustration

The proposed DFNN model is based on featured image for gesture recognition, which can retain the sEMG signals' spatial and temporary characteristics of the HD-sEMG.

IV. RESULT

By analyzing seven abled-bodied individuals, the DFNN can high 93.96% when the electrodes shift 10mm in the four directions (In, On, Upward, Down), and it has only less error (0.03) between different individuals. While the electrodes shift 10mm and damage 6, the DFNN can high 92.7% and has an error (0.05). As for LSDA, its average accuracy is 90.9%± 0.33, 89.3%±0.02 for two situations including the electrodes shift 10mm, shift 10mm and damage 6, and the average accuracy is 75.4%±0.08 and 78.1%±0.05 for the LSTM. Compared with LSDA and LSTM, the DFNN has better generalization ability and well stability among diverse individuals and gestures. When the electrodes shift 10mm, the accuracy of the LSDA is less than the proposed model because the internal and external movement may occur corresponding to the position of the muscle groups. However, the DFNN can utilize the spatial distribution characteristics of the sEMG signal to effectively reduce this impact by using the local feature invariance. Owing to the ability to learn spatio-temporal features, the proposed model has better stability and robustness to tackle the problem of the electrodes shift and damage.

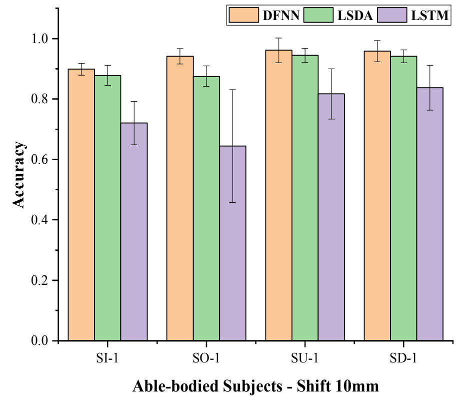

Figure 7. Results of Shift 10mm, including Shift Inwards (SI-1), Shift Onwards (SO-1), Shift Upwards (SU-1) and Shift Down (SD-1).

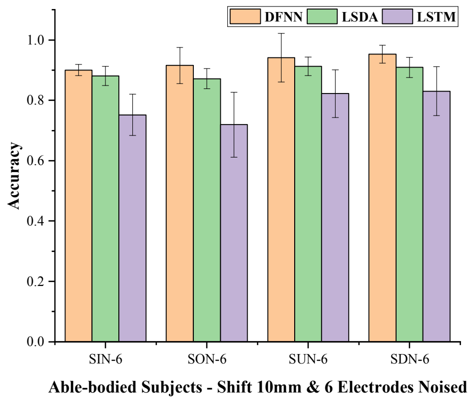

Figure 8. Results of Shift 10mm with 6 electrodes noised, including Shift Inwards with 6 electrodes noised (SIN-6), Shift Onwards with 6 electrodes noised (SON-6), Shift Upwards with 6 electrodes noised (SUN-6) and Shift Down with 6 electrodes noised (SDN-6).

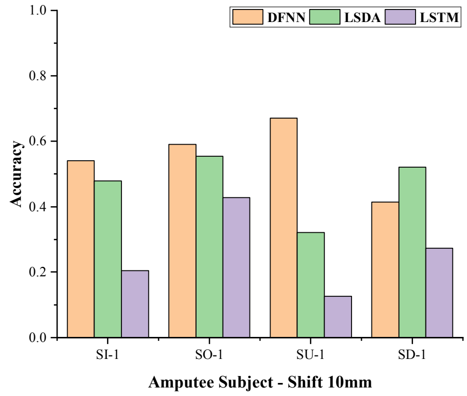

Figure 9. Results of amputee subject of Shift 10mm, including Shift Inwards (SI-1), Shift Onwards (SO-1), Shift Upwards (SU-1) and Shift Down (SD-1)

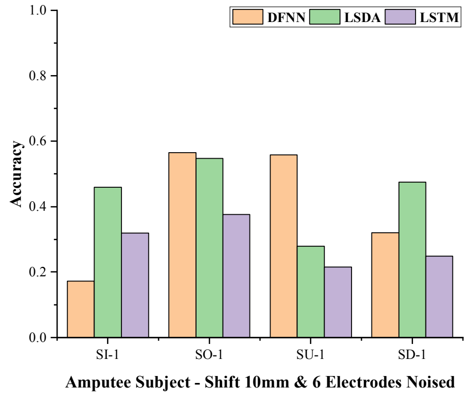

Figure 10. Results of amputee subject Shift 10mm with 6 electrodes noised, including Shift Inwards with 6 electrodes noised (SIN-6), Shift Onwards with 6 electrodes noised (SON-6), Shift Upwards with 6 electrodes noised (SUN-6) and Shift Down with 6 electrodes noised (SDN-6)

As for one amputee, when the electrodes occur in the following cases including: shift 10mm, shift 10mm and damage 6, the DFNN can achieve higher average (55.3%, 40.3%) than the LSDA (46.8%, 43.0%) and LSTM (25.8%, 28.9%). In Figure 10. , the DFNN performs not well, because the damage of the electrodes may cause the fluctuations of the data and this experiment limits in one amputee subject. As the shift and damage of the electrodes, the proposed model is not affected dramatically compared to the LSDA and LSTM, it can also achieve high accuracy and well stability.

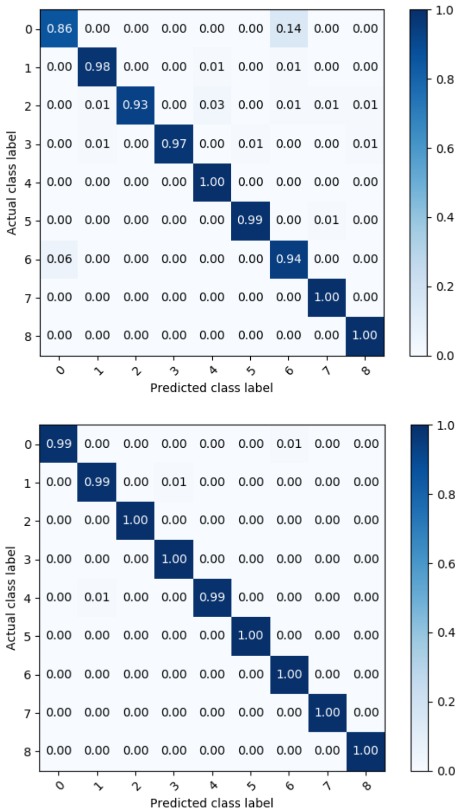

Figure 11. Confusion matrixs of the subject 7, including Shift 10mm (Onwards and Upwards)

V. DISCUSSION

In this paper, we design a novel DFNN model, a faster efficient framework, to solve the impact of electrode shift and damage in gesture recognition. We perform a series of experiments to verify that the DFNN can achieve state-of-the-art performance and robustness for gesture recognition. For all situations (shift 10mm, shift 10mm and damage 6), DFNN can reach average 93.35% in able-bodied subjects, and have 4%-8% improvement over the latest work [14]. For amputee subject, we also improve the recognition accuracy and can high 67.0%. Compared to the previous approaches mostly based on temporal features, the proposed model based on sEMG image promotes the new research for the electrodes shift and damage in human-computer controlled dynamic gesture recognition, and it may contribute to the real-time control of the MCIs.

VI. CONCLUSION

This work compares the performance of the proposed model with different methods. And the proposed model based on spatio-temporal featured image can improve the robustness and accuracy of gesture recognition in practical applications. Currently, we apply RMS to extract the time-feature of sEMG signals, hence, the performance of the recognition is largely depended on the length of the windows. In the future, we will adopt a self-adapting algorithm based on LSTM with an attention mechanism to extract the time-features, and we expect it will improve the performance among amputate subjects and greater moving distance.

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