Deep Neural Network Approach in EMG-Based Force Estimation for Human-Robot Interaction

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***Abstract*—In the human-robot interaction, especially when hand contact appears directly on the robot arm, the dynamics of the human arm presents an essential component in human-robot interaction and object manipulation. Modeling and estimation of the human arm dynamics show great potential for achieving more natural and safer interaction. To enrich the dexterity and guarantee the accuracy of the manipulation, mapping the motor functionality of muscle using bio-signals becomes a popular topic. In this article, a novel algorithm was constructed using deep learning techniques to explore the potential model between surface electromyography (sEMG) signals of the human arm and interaction force for human-robot interaction. Its features were extracted by adopting the convolutional neural network (CNN) from the sEMG signals automatically without using prior knowledge of the biomechanical model. The experiments prove the lower error ($< 0.4N$) of the designed regression by comparing it with other approaches, such as artificial neural network (ANN) and long short-term memory (LSTM). It should be also mentioned that the anti-noise ability is an important index to apply this technique in practical applications. Hence, we also add different Gaussian noises into the dataset to demonstrate the robustness against measurement noises by using the proposed model. Finally, it demonstrates the performance of the proposed algorithm using the Myo controller and KUKA LWR4+ robot.**

***Impact Statement*—Predicting interaction force using surface electromyography (sEMG) is a popular technology in human-robot interaction. It increases the safety and the intelligence of human-robot collaboration. The novel deep learning algorithm we constructed in this article to explore the potential model between surface electromyography (sEMG) signals of the human arm and interaction force for human-robot interaction. The convolutional neural network (CNN) is implemented to extract features from the sEMG signals automatically without using prior knowledge of the biomechanical model. The experiments prove the lower error (¡ 0.4N) of the designed regression by comparing it with other approaches. It should also be mentioned that the anti-noise ability is also considered to apply this technique for practical applications. This technique could offer an alternative way for predicting the interaction force of the human-robot interaction.**

***Index Terms*—Force measurement, Human-robot interaction, Neural Networks, Surface electromyography**

I. Introduction

OVER the past few years, the booming development of robot technology has been witnessed. As a core part of robotics, the human-robot interaction (HRI) has attracted widespread attention and has been applied in many fields, including industrial programming [1], household service [2], [3], disaster rescue [4], educational guidance [5], medical surgery [6]–[8]. Especially in the medical domain, HRI is playing a significant role. For instance, Fujji et al. [9] utilized a robotic arm with a rigid endoscope instead of a camera assistant to help surgeons realize real-time observation in laparoscopic surgery. By using a seven-degree-of-freedom redundant robot, a teleoperated minimally invasive surgery was completed through the direct interaction between human hand and robot arm [10], [11]. To guarantee the safe and natural interaction between the human and robot, it is necessary to model and estimate the dynamics of human arm.

However, the high flexibility of the arm determines that it is difficult to establish the model accurately, especially involving interactive torque and force tasks [12]. Also, the time-consuming matter has become a challenge. These factors can directly affect the safety and practicability of HRI, and even threaten personal safety under poor performance [13]. Hence, it requires strict procedures to match the state-of-the-art robot with human's dexterous arm. Obviously, the force generated by muscle contraction affects the flexibility and efficiency of the arm [14], [15], which proves that the muscle force is an important indicator to control the robot arm smoothly. How to accurately and reproducibly estimate muscle force has become an important research target in biomechanics.

Nowadays, analyzing the motor functionality of muscle based on biological signals becomes an effective strategy. As one of the neurologic signals, the electromyography signal can directly reflect the level of muscle activity and movement intention, and it can be converted into motion commands to control myoelectric prostheses as well as robotic arms [16], [17]. Notably, the surface electromyography (sEMG) signals on human's skin can be collected easily. Therefore, sEMG signals are suitable for high-precision force estimation. In order to obtain a satisfactory interaction behaviour of the robot during HRI, the relationship between sEMG signals and the human's arm force (sEMG-force) is required to be explored.

There are many existing parametric algorithms used to establish force estimation models. In [18], Hashemi et al. combined angle-based sEMG amplitude calibration with par-

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allel cascade identification to achieve force estimation, and the experimental results showed that the proposed approach had lower estimation error rate in dynamic muscle contraction. The authors in [19] collected sEMG signals based on a high-density electrode grid, and used the nonnegative matrix factorization algorithm to process the raw signals. Although this proposal greatly improved the quality of predictive force and reduced the number of electrode, it was limited to estimate force under isometric contraction. By using statistical methods to extract and visualize sEMG recordings, it can estimate human force and motion well, and improve the sEMG-based robotic arm control system [20]. Linear parameter varying approach was used to explore the muscle-force relationship of human neuromusculoskeletal system, and it provided new possibilities for robot control [21]. The above methods can complete accurate modeling between arm muscle and force, but they are highly dependent on algorithm parameters. Also, the convergence time and structure complexity of algorithms need to be optimized. Furthermore, since sEMG is weak and nonstationary, noise interference affects the performance of the estimator adversely.

Considering that parametric algorithms have many limitations, it is important to propose more nonparametric methods to build muscle-force models. Due to the expansion of data, the improvement of algorithms and the enhancement of computing power, machine learning (ML) and deep learning (DL) have gradually been used to solve robot-related problems. To solve the randomness and volatility of raw sEMG signals, the authors in [22] incrementally construct knowledge library based on decision tree by hierarchical projection regression algorithm. This proposal can project the original data to a lower dimensional feature space to match the real-time relationship between sEMG signals and motion state. A sEMG-based support vector machine approach [23] was presented to predict joint compression force, and the result of comparative experiments showed that it was a favourable estimator with low bias and high efficiency. Artificial neural network (ANN) was also used to extract the features of raw EMG signals in the time and frequency domains [24]. On the other hand, an increasing number of DL algorithms were developed to build force estimators, such as long short-term memory (LSTM), convolutional neural network (CNN), CNN-LSTM [25]. Ameri et al. [26] employed the regression CNN algorithm for independent and simultaneous motion control, but the robustness of the model needed to be further strengthened. Similarly, the author [27] proposed a recurrent deep neural network to estimate muscle forces, and then the accuracy of force model was improved based on transfer learning strategy. These nonparametric models, such as ANN and DL, do not need to capture prior information from arm muscles, and they have stronger anti-interference ability than parametric algorithms. When defining the input and output of the model, the best adaptive parameters can be trained.

A novel deep convolutional neural network (DCNN) is proposed in this paper based on a nonlinear regression model to map the interaction force and the sEMG signals. By combining several convolutional network layers, the ReLU activation function, and the dropout layer, the designed DCNN-based model aims to enhance the accuracy, save predictive time, and reduce the impact of noises. The model is an adaptive method which does not need any prior information and can extract valuable features automatically. Comparison experiments of the practical robot application are performed to demonstrate the efficiency of the proposed approach. Three major novel contributions of this work are concluded as follows:

1) A model-free approach using neural network is proposed to model the sEMG-force.
2) A novel nonliner regression algorithm using DCNN is implemented with capacity of fast computation, high accuracy and noise robustness.
3) The effectiveness and accuracy of the proposed method are depicted with a real-time demonstration.

II. Problem Statement

The potential relationship between sEMG and force can be denoted with a nonlinear mapping relation, which can be modeled using the mentioned DCNN model. We assume the input eight dimensions sEMG signals S^8 and the output one dimension force magnitude F^1. It should be noticed that, to ease the model complexity, we are using the force magnitude $F^1 = \sqrt{f_x^2 + f_y^2 + f_z^2}$ instead of the force vector which features with direction, where f_x, f_y and f_z are the 3-axis forces around three axes in the workspace. Because there are many noises in the raw sEMG signals, which affect the accuracy of the model, we propose a series of signal processing algorithms to solve these problems. The processed sEMG signals S^* can be adopted to build the DCNN model Φ, namely $\hat{F}_t = \Phi(S_t^*, \theta)$. Furthermore, θ is the parameter set of DCNN algorithm and the predicted force is defined as $\hat{F}_t$ at time t. In particular, S_t^* represents the feature vector which is extracted from the uncertain probability $p_t(S_t^*)$ at time t. The force F_t will change over time according to the input sEMG signals.

The aim of establishing model $\hat{F}_t = \Phi(S_t^*, \theta)$ is to find the best parameter space θ, which can be determined by computing the loss function:

$$\theta = L(\hat{F}_j - F_j) = \underset{\theta}{\operatorname{argmin}} \sum_{j=1}^{t} \left(\hat{F}_j - F_j\right)^2 \tag{1}$$

In this article, the regression accuracy of the proposed model is validated using the Mean Square Error (MSE), which is defined as

$$\varepsilon = \sum_{j=1}^{t} \left(\frac{\hat{F} - F}{j}\right)^2 \tag{2}$$

III. Methodology

1) Training Data Preparation: The 8D raw sEMG signal S^8 was collected from the Myo armband, which should be extended into a matrix. It has been well known that the convolutional network is more efficient using the Homogeneous matrix [28]. Hence, a new input map $S^{8\times 3}$ is constructed as:

$$S^* = [S; S - \bar{S}; \frac{S - \bar{S}}{\sigma(S)}]; \tag{3}$$

the average and variance of S are determined by the $\bar{S}$ and $\sigma(S)$, respectively.

2) DCNN Architecture: As it is discussed in Section I, many methods to build the relationship between sEMG signals and robot end force ignore to consider about the performance of noise robustness and fast computation. The DCNN method is the best approach to achieve the goals. Therefore, we design a novel regression architecture based on the CNN. Fig. 1 illustrates the basic structure of the proposed DCNN regression model.

The DCNN is composed of five deep convolutional segments which includes a regression layer and a full connection layer. The whole deep convolutional segments is composed of a batch normalization (BN) layer, a 2D convolution layer and rectified linear units (ReLU). The detailed feature of the developed neural network model framework can be concluded as:

- **Inputs:** the 8D sEMG matrix $\tilde{S}^{8\times 3}$. In Fig. 1, the 'inputs' shows the procedure of signal processing using Eq. 3.
- **Deep Convolutional Modules:** Five deep convolutional modules are implemented using the proposed DCNN algorithm. The first one, which can be defined as Conv.Module #1, consists of a 2D CNN layer, the second BN layer and a ReLU activation function. Although the last four convolution modules (Conv.Module #2 to Conv.Module #5) have the same layers, but they are filtered as a vector. The convolution operations were conducted basing on five window size, 4, 8, 12, 16 and 16. The sizes of yielded feature maps are 7×2, 6×1, 5×1, 4×1, and 3×1.
  The convolution operations were conducted basing on the window size 2×2. The BN layer is exploited to grant every layer of the CNN to be trained by itself unsupervised. The ReLU layer is designed to settle the vanishing gradient and exploding gradient problems.
- **Output:** The output layer is constructed with the regression layer of a fully-connected layer. Finally, the predicted forces will be output.

IV. Hardware System

Fig. 3 depicts an overview of the system description, which was implemented for the task of physical human-robot interaction. The corresponding involved device information are listed below:

- The EMG sensor used in this experiment is the Myo armband, which is able to transmit the raw EMG information over a Bluetooth Smart connection with 8 Channels (200 Hz).
- A KUKA robot is placed on the table to implement the task with physical human-robot interaction.
- The force sensor used in this paper is a 6-axis torque sensor. It is adopted to measure the online force of the physical human-robot interaction.

The gravity force of the tool tip has been eliminated in our previous works [29]–[31]. Hence the force sensor only measures the hand interaction force. The robot is working on Cartesian impedance control mode with a desired Cartesian pose to allow human-robot interaction.

In order to achieve high-efficient signal processing in real-time, the hand force estimation system was designed basing on two independent computers which communicated by the UDP protocol, so that the signals of force sensor and Myo armband can be mixed with timestamps. The force measurement developed in this work is similar to our previous work, which is conducted in real-time basing on the first computer with an i7-9750H CPU (2.60GHz) and 16 GB RAM [30]. The EMG signal collection node which is designed basing on ROS[1] Kinetic under Ubuntu is executed in the second computer with i7- 9700K (2.9GHz) and 16 GB RAM.

V. Experiments and Discussion

To demonstrate

In this paper, the efficiency of the novel proposed approach is demonstrated in a lab setup condition. We design three experiments to estimate the performance of the DCNN-based regression model for mapping the 8D sEMG signals to the force. The first one aims to prove the high accuracy of the proposed DCNN algorithm by comparing it with LSTM, multiple layers neural network (MNN) and single-layer neural network (SNN). Meanwhile, the online predictive time is the primary index to evaluate time efficiency. Lastly, we add two types of Gaussian noise into the sEMG signals to judge the noise robustness ability.

A. Data Collection

As it is described in Fig. 2, one participant wears the Myo armband and moves the end of the robot from top to down (up-down), also from the left side to right side (left-right), and from front to back (front-back). Fig. 4 show the three-hand movements in detail.

The subject was commanded to perform these three movements with a repetition of twenty times. The sampling frequency of the two devices is 200Hz. Finally, the 'up-down' dataset has 11828 samples, 'left-right' dataset has 10868 samples, and the 'front-back' dataset has 13932 samples, respectively. The collected 8D sEMG signals and force signals will be analyzed by MATLAB 2019a with a computer server (16.0 GB RAM, 2.80 GHz CPU and Intel(R) i7 Core).

B. Force Estimation

In this paper, the dataset was divided into two parts: the first 80% samples and the other 20% samples. The first were chosen for training the model, and the other for testing. By comparing the MSE values among DCNN, LSTM, SNN and MNN models (see Table I), the proposed DCNN model gets the lowest MSE to predict all of the three-hand movements. The SNN model has 30 nodes in the hidden layer, while MNN is set 20 nodes and 30 nodes in its two layers. The SNN gets the highest errors than the other approaches. The reason might be the chosen number of nodes is too less to regress the force. Hence, adopting two layers to build the MNN model can solve the under-fitting problem.

[1]Robot Operating System, http://www.ros.org/

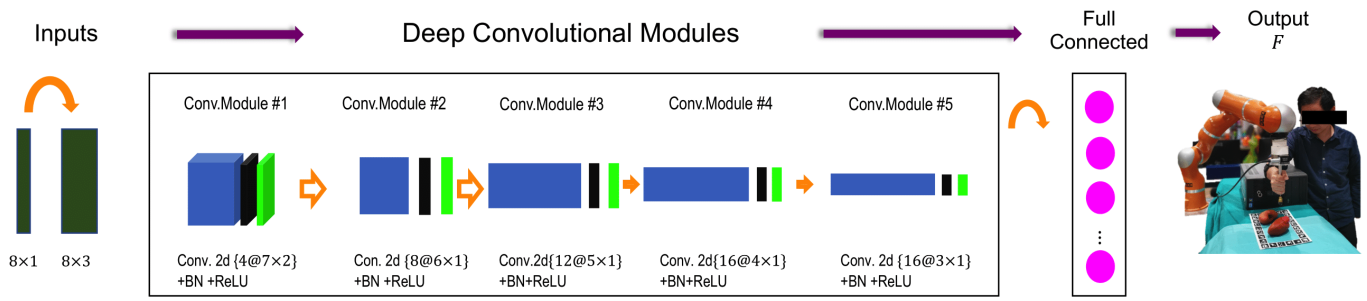

Fig. 1: The schematic diagram of proposed deep convolutional neural network (DCNN) structure.

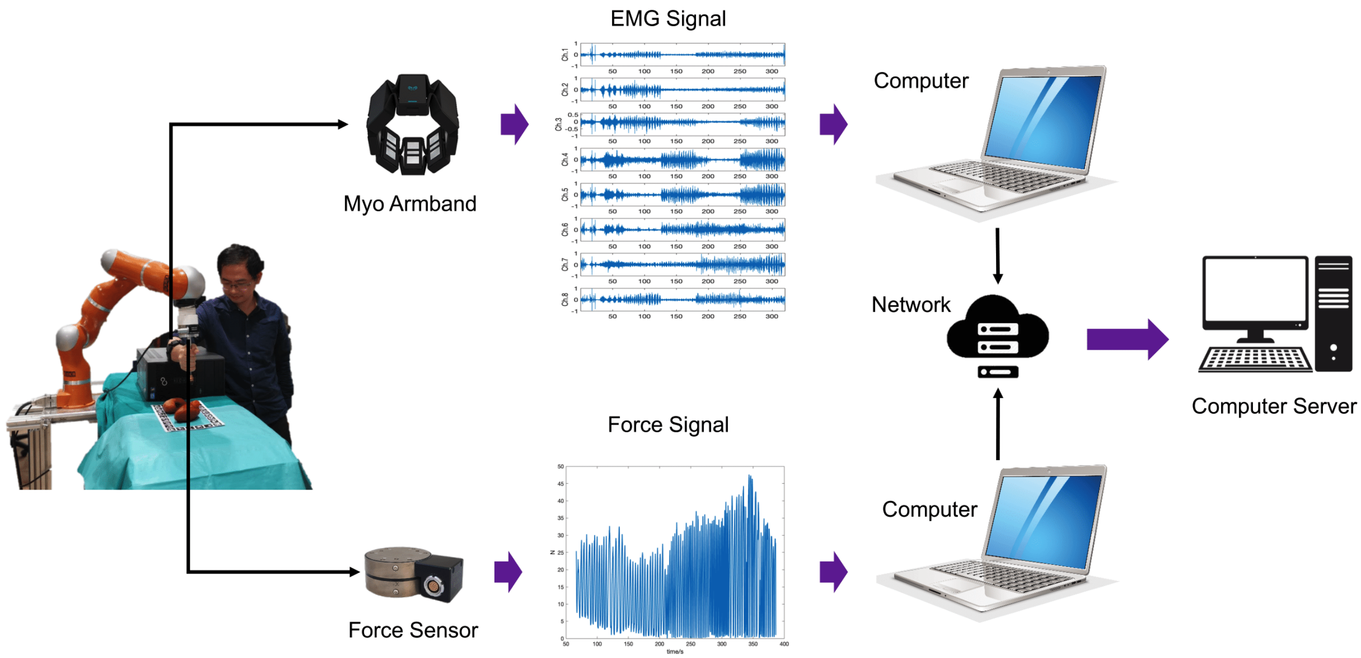

Fig. 2: The schematic diagram of EMG-based force estimation using force sensor and Myo armband.

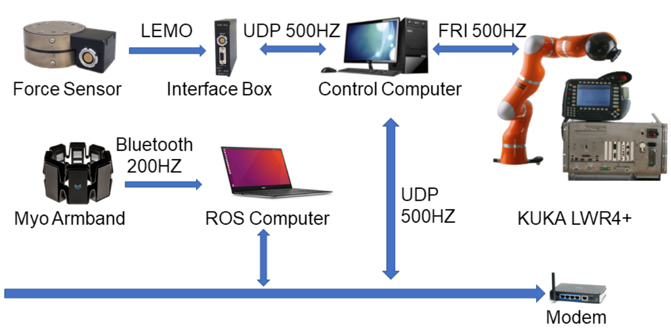

Fig. 3: Overview of the hardware system.

TABLE I: The comparison of MSE among DCNN, LSTM, SNN and MNN models.

Hand Activity	Method			
	DCNN	LSTM	SNN	MNN
Up-Down	0.03	0.21	66.89	0.62
Left-Right	0.01	0.11	66.42	0.81
Front-Back	0.04	0.34	80.58	0.35

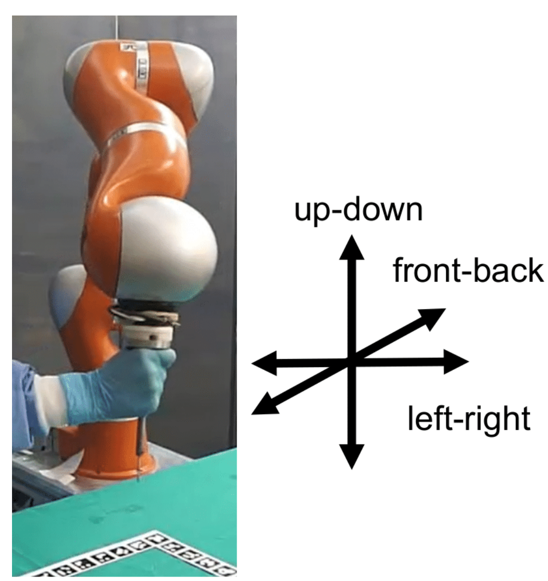

Fig. 4: The schematic diagram of the three hand movements.

The multiple convolutional layers not only can extract feature automatically but also save time to predict a result.

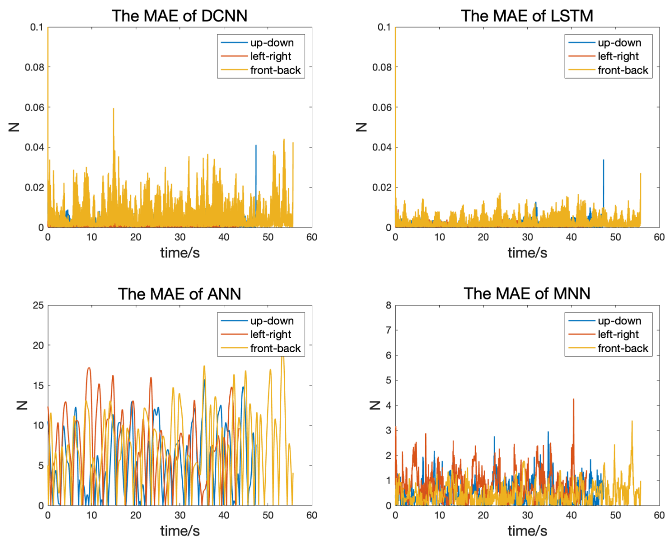

Fig. 5: The comparison mean absolute error (MAE) predicting on the training dataset among DCNN, LSTM, ANN and MNN models with the three different hand activities.

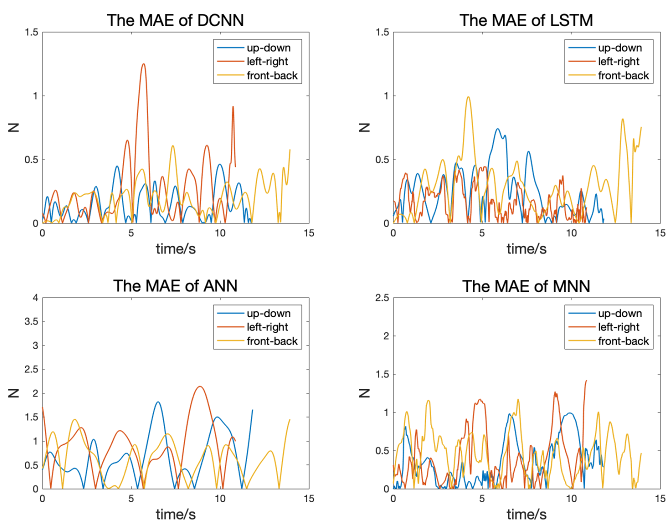

Fig. 6: The comparison mean absolute error (MAE) predicting on the testing dataset among DCNN, LSTM, ANN and MNN models with the three different hand activities.

TABLE II: The comparison of online predicting time (s) among different neural networks models, among DCNN, LSTM, SNN and MNN models.

Hand Activity	Method			
	DCNN	LSTM	SNN	MNN
Up-Down	0.0007	0.0021	0.0063	0.0066
Left-Right	0.0008	0.0023	0.0060	0.0065
Front-Back	0.0008	0.0020	0.0062	0.0068

Table II shows the online time by comparing these four models. It can be conclude that DCNN is an optimal method for predicting results in real-time. Specially, all of the ANN-based models requires plenty of time to predict a result, while the DCNN model only needs about 0.0008s.

We add Gaussian noises into the sEMG signals with two types of signal noise rate (SNR) (i.e., 1db and 5db) to assess the accuracy of the trained DCNN model for its ability in noise robustness. Table III shows the comparison MSE among these methods, which proves that the DCNN is the best approach to remove the influence of noise.

TABLE III: The comparison of MSE with noise among the DCNN, LSTM, SNN and MNN models.

Method	SNR	Hand Activity		
		Up-Down	Left-Right	Front-Back
DCNN	1db	2.16	2.01	1.80
	5db	12.27	13.38	12.94
LSTM	1db	4.97	5.94	5.55
	5db	27.96	30.00	29.44
SNN	1db	10.01	9.73	9.83
	5db	59.87	58.95	57.78
MNN	1db	15.86	16.77	14.39
	5db	66.38	68.86	69.05

The mean absolute error (MAE) of predicted forces on training and testing datasets are depicted in Fig. 5 and Fig. 6. The designed DCNN strategy obtains the lowest error than the other approaches. Fig. 7 shows the predictive curves of the three different training datasets. The SNN model cannot track the raw force curve, while the predicted curve of the DCNN model almost coincides with it.

VI. Conclusion

In this paper, a nonlinear regression model is exploited using the DCNN technique to navigate the relation between the sEMG signals with the interaction force. It adopts the CNN to extract features from the sEMG signals automatically without using prior knowledge of the biomechanical model. The experiments prove the lower error ($< 0.4N$) of the designed regression by comparing it with other approaches. Compared with traditional methodes such as SNN, MNN and LSTM, the proposed DCNN method improves the calculating performance and robustness to noise. Therefore, the DCNN method can improve the prediction accuracy of the dynamics force under noises. The feasibility of practical applications can also be ensured.

In the future, we will focus on more challenging problems in the sEMG-force control system, which can improve the accuracy of the DCNN regression method. Since this experiment is only performed on a fixed position, future works will involve position-free validation. Furthermore, the developed force estimation model could also be introduced to enhance the human-robot interaction.

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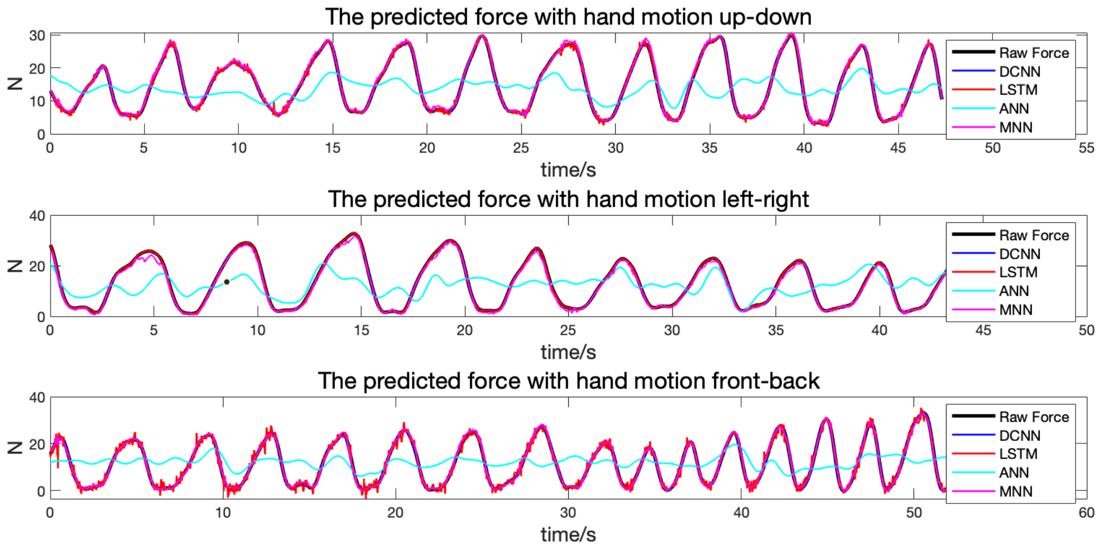

Fig. 7: The comparison force curves testing on training dataset among DCNN, LSTM, ANN and MNN models with the three different hand activities. The top graph is 'up-down', the middle one is 'left-right', and the bottom graph is 'front-back'.

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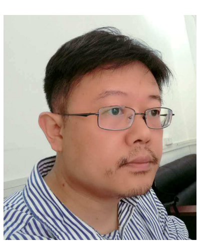

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