A Hybrid Deep Learning Framework for Estimation of Elbow Flexion Force via Electromyography

Wei Lu1,2*, Lifu Gao3, Qianqian Zhang1,2, Zebin Li1,2

1 Institute of Intelligent Machines, Hefei Institutes of Physical Science, Chinese Academy of Sciences, Hefei, Anhui, 230031, China
2 Department of Science Island, University of Science and Technology of China, Hefei 230026, China
3Corresponding author’s e-mail: lw9296@mail.ustc.edu.cn

Abstract. Real-time and accurate estimation is beneficial for intention recognition, muscle rehabilitation evaluation and artificial limb control. However, it is difficult to estimate the elbow flexion force accurately. The aim of our model is to estimate elbow flexion muscle force, which can be used for elbow joint health assessment and prosthetic control studies. This paper proposed an end-to-end deep learning framework by fusing Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) neural network with attention mechanism, which is more suitable for time series EMG signal to improve the feature extraction ability and achieve a high flexion force estimation accuracy. Experimental results indicated that the proposed method can automatically extract the proper features of elbow motion behaviors without professional knowledge in feature extraction model. Moreover, the experimental result shows that the proposed framework performs well in the accuracy and generalization ability, outperforming the state-of-the-art methods.

1. Introduction
Elbow flexion force estimation is necessary to many biomedical engineering, such as hand gesture recognition and wearable power robot control. However, the biological signals signal is stochastic changing caused by electronic noise, background noise, and motion artifacts during acquisition process, which leads to the time-varying fluctuation of the EMG time series. These factors impose great challenges for the flexion force estimation tasks [1]. At present, there are mainly the following ways to realize force estimation [2]: Mechanomyography (MMG), electromyography (EMG), electroencephalogram (EEG) and electrocardiosignal (ECG). Electromyography (EMG) signal is a kind of biological electrical signal which produced by human muscle contraction. It has been extensively used to obtain human motion intention in wearable robot systems because of its effectiveness, portability, non-trauma and non-delay features [3]. Different motion modes would produce different frequency and amplitude of EMG signals. Therefore, a wealth of information can be drawn from EMG signals. Researchers have shown that the estimation of joint flexion force based on EMG is one of the most effective ways to realize motion intention recognition [4]. There are two widely used methods to define the relation between the EMG signal and force: parametric based and nonparametric based. Muye et al. [5] used the Hill-type musculoskeletal model to design a quantitative method for representation of the elbow joint force estimation. F.Romero et al. [6] proposed a flexion force estimate method by using the tendon length and contraction velocity which obtained from surface EMG and inverse dynamics analysis.
Thomas S et al. [7] presented a forward dynamic neuromusculoskeletal model which can be used to estimate and predict joint moments and muscle forces. Mitsuhiro et al. [8] presented a model which allows the estimation of muscle force from EMG signals associated with a physiology-based model of underlying microtubule dynamics. Youngjin Na et al. [9] proposed a force estimation method by combining biomechanical muscle model with surface EMG signal peaks.

As for nonparametric based methods, machine-learning-powered force estimation methods have become an effective tool in muscle force estimation and action recognition. Youn et al. [10] systematically study the feasibility of MMG for estimating the elbow flexion force at the wrist under an isometric contraction by using an artificial neural network in comparison with EMG. In [11], the author combined the angle-based amplitude of EMG signal with parallel cascade recognition for force estimation of dynamic contraction EMG signals. Allouch S et al. [12] combination PCA and laplacian arrangement to fitting relationship between sEMG and muscle force. Xia et al. [13] propose a model which based on deep learning to estimate kinematic information from multi-channel EMG signals. Xie et al. [14] applied a Long Short Term Memory (LSTM) neural network model for estimating the acceleration of the knee joint. Luo et al. [15] proposed a three domains fuzzy wavelet neural network (TDFWNN) algorithm without prior knowledge of the biomechanical model to estimate the force through EMG. In [16], Angelica I. Aviles et al. presented a method for estimating the applied forces that is based on using Fuzzy theory and Deep Learning. However, parameter optimization is a difficult and important task for machine learning methods. Furthermore, the crucial problem is that the gradient of the error function is easy to vanish after back propagation.

We selected ResNet to automatically extract the valid feature of EMG instead of a manual way. Then the BiLSTM network with attention mechanism was selected to map the nonlinear relationship between EMG features and flexion force. To verify the estimation results, the experimental condition was selected as the elbow flexion in the horizontal plane during isometric contraction. The outline of our approach is illustrated in Figure 1. To highlight the advantages of muscle force estimation which we proposed, we compared our algorithm with other mainstream force estimation algorithms in the experiment.

![Image of the force estimator](image)

**Figure 1** The outline of our force estimator

2. Materials and Methods

2.1 Decoupling and Windowing

Suppose the EMG acquisition system collected the raw EMG time series which is noted by:

\[ S_t(l) = \{S_1^t, S_2^t, ..., S_k^t\}, \]

The non-linearity series part of raw EMG series can be obtained by the sliding average filter, noted by: \( MS_t(l) = \{MS_1^t, MS_2^t, ..., MS_k^t\}, \)
\[ MS_t^k = \begin{cases} 
\frac{s_1^k + s_2^k + \cdots + s_{w_1}^k}{w_1}, & k = 1, 2, \ldots, w_1 - 1 \\
\frac{s_{k-w_1+1}^k - s_{k-w_1+2}^k}{w_1}, & k = w_1, w_1 + 1, \ldots, L 
\end{cases} \]

(1)

Where \( w_1 (w_2 < L) \) is the sliding window size;

Muscle contraction is a continuous process, so we adopt a sliding window with overlapping window to divide the entire EMG series into multiple discrete time series by sliding window. Considering that the nonlinear sequence has strong characteristics of time series and historical data hide rich operating experience. We presuming \( W_x \) is window size, EMG time series signal are divided into several segments by the window. Let, \( x_i = S_t(l), \bar{x}_t = MS_t^l \),

\[ x_i = (\bar{x}_{t-\Delta t+1}, \bar{x}_{t-\Delta t+2}, \ldots, \bar{x}_t) \]

(2)

Where, \( \Delta t \) is the slide step, \( t \) is the window size, \( t = T_x, T_x + \Delta t, T_x + 2\Delta t, \ldots \)

2.2. ResNet for feature extraction

The traditional force estimation method used the statistics of the extracted features from the biological signal. However, all those methods require manual parameter tuning for feature extraction, which leads to poor accuracy and higher sensitivity to the noise. Studies have proved that the deep neural network is more effective in the feature extracting of one-dimension time-series [17]. In this study, we used ResNet to extract the different features of electromyography. It is a 1-dimensional operation on the 2-dimensional input data and it was used to extract the spatial features of the time-series from the input.

2.3. BiLSTM with attention for force estimation

There were two common problems with the model using LSTM: vanishing gradient problem and can't encode information back to front. Therefore, BiLSTM networks mitigate this problem by combining two normal LSTMs, information can flows both in the forward time direction and backward direction. Considering that EMG features series contains different temporal information, not all feature contributes equally to the estimate of force. By introducing an attention mechanism, encoding the full input sequences into a fixed-length vector is no longer needed. We employed an attention mechanism to improve the learning efficiency and ability to learn important features for regression tasks.

\[ P(y_t|y_1, y_2, \ldots, y_{t-1}, X) = g(y_{t-1}, s_t, C_t) \]  

(3)

\[ s_t = f(s_{t-1}, y_{t-1}, C_t) \]  

(4)

\[ C_t = \sum_{i=1}^{T} \alpha_{t,i} h_i \]  

(5)

\[ \alpha_{t,i} = \frac{\exp(e_{t,i})}{\sum_j \exp(e_{t,j})} \]  

(6)

\[ e_{t,i} = \text{score}(s_{t-1}, h_i) \]  

(7)

Where, \( y_1, y_2, y_{t-1}, y_t \) is output at time step 1,2, \( t - 1, t \), respectively, \( X \) is input of current moment, \( C_t \) is output, \( \alpha_{t,i} \) is the weight of attention layer, \( h_i \) is output of hidden layer, \( s_{t-1} \) is a summary of the previous period which from 0 to \( (t-1) \) time step.

2.4. Training Process

We adopt the cross-entropy cost function as the cost function of ResNet:

\[ J_1 = -\frac{1}{m} \sum_{n=1}^{m} [y^{(n)} \log \hat{y}^{(n)} + (1 - y^{(n)}) \log (1 - \hat{y}^{(n)})] \]

(8)

Where, \( y^{(n)} \) represents the input value, \( \hat{y}^{(n)} \) represents the expected value.

We adopt the mean square error cost function as the cost function of BiLSTM:
$$J_2 = \frac{1}{N} \sum_{i=1}^{N} (y_i - y_p)^2$$

(9)

Where, $y_i$ represents the actual value, $y_p$ represents the estimated value.

2.5. Evaluation

In this paper, we choose the coefficient of determination ($R^2$) as the evaluation indexes of algorithm performance.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - F_e)^2}{\sum_{i=1}^{N}(y_i - F_t)^2}$$

(10)

Where, $F_t$ is actual force, $F_e$ is estimated force, $F_{max}$ is the maximum of the actual force, $F_{min}$ is the minimum of the actual force, $F_t$ is the mean value of actual force.

3. Experiments

3.1. Subjects and experimental setup

We choose four healthy adults with a mean age of 24±3 years who participated in our experiment. As shown in Figure 2, two EMG sensors were placed at each end of the belly of the biceps. The Sampling frequency is set to 1000Hz. They were asked to sit on the chair and the right elbow joint was fixed at a different angle ($30^\circ$, $60^\circ$, $90^\circ$, $120^\circ$) and positioned on the test desk for isometric contraction. A one-directional force sensor is mounted on the wrist to measure elbow flexion.

![Figure 2. Experimental setup](image)

3.2. Training Data

We split our dataset into training part and test part with the ratio of 7:3 for validating the performance. The hyper-parameters of models were fully tuned which are listed in Table 1.

| Hyper-Parameter          | ResNet | BiLSTM |
|--------------------------|--------|--------|
| Activation Function      | ReLU   | ReLU   |
| Optimizer                | Adam   | Adam   |
| Dropout                  | 0.5    | 0.5    |
| Initial Learning Rate    | 0.0001 | 0.0001 |
| Batch Size               | 128    | 128    |
| Epoch                    | 1000   | 1000   |
3.3. Effectiveness of decoupling method

We use moving-average filter method to separate the raw EMG time series into non-linearity part and non-stationary part. The sliding window size \( w_4 (w_4 < L) \) is 8 in this experiment. Figure 3 shows the decoupling effect on raw EMG signal. The blue line represents the raw EMG signal, the green line represents the non-linearity EMG signal.

![Decoupling effect on raw EMG signal](image)

Figure 3. Decoupling effect on the EMG raw data

3.4. Estimation result

The results are shown in Figure 4. The subgraph (a)-(c) are a raw signal of EMG; The subgraph (d)-(f) are filtered signals after decoupling algorithm. The subgraph (g)-(i) are actual measured force under three contraction condition; The subgraph (j)-(l) are the comparison of the actual force and the estimated force in test data.

![ESTIMATION RESULT](image)

Figure 4. Estimated force results for different contraction
4. Conclusion
This paper presents an elbow flexion force estimation algorithm to build the mapping relationships between the EMG signal and the elbow flexion forces. The experiment results show that the ResNet-BiLSTM method can get a good performance. The method improves the accuracy of the force required for the motion control of the wearable assisted robots and provides effective input information for human motion intention recognition.

Acknowledgments
This work was supported in part by the Strategic Priority Research Program of the Chinese Academy of Sciences under Grant No. XDA22040303.

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