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Estimation of EMG-Based Force Using a Neural-Network-Based Approach

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ABSTRACT The dynamics of human arms has a high impact on the humans' activities in daily life, especially when a human operates a tool such as interactions with a robot with the need for high dexterity. The dexterity of human arms depends largely on motor functionality of muscle. In this sense, the dynamics of human arms should be well analyzed. In this paper, in order to analyse the characteristic of human arms, a neural-network-based algorithm is proposed for exploring the potential model between electromyography (EMG) signal and human arm's force. Based on the analysis of force for humans, the mean absolute value of the electromyographic signal is selected as the input for the potential model. In this paper, in order to accurately estimate the potential model, three domains fuzzy wavelet neural network (TDFWNN) algorithm without prior knowledge of the biomechanical model is utilized. The performance of the proposed algorithm has been demonstrated by the experimental results in comparison with the conventional radial basis function neural network (RBFNN) method. By comparison, the proposed TDFWNN algorithm provides an effective solution to evaluate the influence of human factors based on biological signals.

INDEX TERMS Neural-network-based algorithm, force estimation, electromyography (EMG) signal, human factor, biomechanical model of surface EMG (sEMG)-force.

I. INTRODUCTION

Humans are particularly adept at performing the tasks which need high dexterity. For a cooperative task between a human and a robot, the human needs to be more dexterous and skillful to perform the task in order to achieve the security and smooth interaction, especially for the tasks involving interactive force or torque [1], [2]. In such tasks or activities, the robot should be developed to match the skillful and dexterous operation of the humans' arm. In general, the dexterity of human arm highly depends on its biomechanics and muscle activity [3], [4]. In this sense, the force generated by muscle plays a key role in the interaction. The human usually modulates one's force to achieve a good operation performance when he/she interacts with the external environments [5], [6]. Therefore, in order to achieve smooth interaction between the human and the robot instead of simple rigid interaction, it is essential to analyze the biomechanical model of human's muscle force and transfer it to the robot control.

As reported in [7], the human arm force is closely linked to muscle activations (MA). In biomechanics, electromyography (EMG) signals directly reflect the influence of MA and it is often used as an indicator for MA. EMG signals provide the information of force contribution for muscle groups and individual muscles. It is demonstrated that the force is produced by the MA [8], [9]. In general, surface EMG (sEMG) signals are easily collected in comparison with EMG signals [10]. The force generated by the MA contains the information of muscle activity and muscle contraction [11]. It is noted that the generated force depends on the level of MA despite of muscle fatigue. It is concluded that the arm force can be estimated by the sEMG signals. Therefore, it is possible to explore the potential relationship of sEMG signals and the generated force (sEMG-force) [12].

In order to accurately estimate the biomechanical model of sEMG-force of the arm, parametric model-based algorithms

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are proposed in the past decades. In [13], a force estimation model based on multi-scale physiology was proposed and this model could take place of Hill muscle model.[1] A forward dynamic model was presented to predict the muscle force and joint moments simultaneously involving EMG signals for healthy and impaired human subjects [15]. A muscle model based on physiological signals was discussed to estimate the relationship between EMG signals and force in voluntary contraction for human machine interaction and it proved that this proposed model was not the phenomenological model [16]. A biomechanical model of muscle was presented to estimate the force with sEMG peaks and it was evaluated by using mean absolute value (MAV) and coefficients of determination (R^2) [17]. Different Hill-type muscle dynamics models were presented for the purposes of force estimation and the authors analyzed their shortcomings, and it was suggested that the selection of Hill-type muscle model relied on the analysis of specific problem [18]. As mentioned above, the model of sEMG-force could be estimated fairly accurately. However, the approaches need to know the accurate parameters of muscle or muscle-based model and the convergence of the described parameters is sensitive to the computing time and computational complexity. Since the above approaches highly depend on the parameters of model and their applications in some important fields are restricted, nonparametric algorithms have been proposed to estimate the relationship model of sEMG-force.

For nonparametric algorithms, neural network and fuzzy models have been employed to analyses the relationship of sEMG-force [19]–[21]. In [22], a multilayer artificial neural network method was used to evaluate the force of elbow-induce wrist based on EMG signal with fast orthogonal search. A neural-network-based method was proposed for the upper limb prosthesis to validate the association of EMG signals and force [23]. Hou *et al.* developed a recurrent fuzzy neural network to explore the relationship among kinematics, EMG signals and force [24]. A deep learning method based on neural network with fuzzy theory was presented to estimate the interaction force in a unsupervised learning way for robot-assisted surgery [25]. In [26] [27], generalized regression neural network approach was proposed to accurately estimate force of the end-of-arm and grip by using the EMG signal as the input. In order to find the suitable neural network algorithms to predict the force involving EMG signals, long short-term memory (LSTM), convolutional neural network (CNN) and CNN-LSTM were applied. The results indicated that LSTM and CNN-LSTM could achieve relatively better performance [28]. Cao *et al.* developed extreme learning machine to predict handgrip force for myoelectric prostheses control [29]. For hand gesture recognition, gene expression programming method was developed to estimate the relationship between handgrip force and its corresponding EMG signals [30]. Compared with the parametric model-based algorithms, the nonparametric algorithms do no need to know the parameters of arm muscle model. They just need properly defined input and output of the neural-network-based approaches. Those model have the advantages of universality and non-limitation of model dynamics.

[1] Hill muscle model was first proposed by A. V. Hill to describe the linear model parameters of muscle [14].

In this paper, a novel neural-network-based approach is presented to accurately estimate the model of sEMG-force. The proposed approach estimates the model does not need prior information of the muscle model. It provides an effective way to construct the mapping relation between EMG signals and interactive force. The experimental results validated the effectiveness of the proposed method.

This paper is organized as follows. Section II describes problem statement of sEMG-force model and the preliminary knowledge on neural network. The proposed algorithm of three domains fuzzy wavelet neural network (TDFWNN) for estimating the force based on sEMG signals is given in Section III. The experiment setup, results and evaluation of the proposed method are presented in Section IV. Section V provides some discussion on the TDFWNN and the experiments. Conclusion is given in the Section VI.

II. PROBLEM STATEMENT AND PRELIMINARIES

A. PROBLEM STATEMENT

In this paper, we explore the potential relationship of sEMG-force by using a neural-network-based method. Because the relationship of sEMG-force is intrinsically nonlinear, it is difficult to utilize a linear algorithm to describe their relationship.

We assume that for a short time duration there exists a nonlinear time-invariant mapping φ between the EMG signals and force to describe their relationship. As presented in Figure 1, the potential model is defined as

$$\tilde{F} = \varphi(\tilde{X}) \tag{1}$$

where φ denotes the nonlinear mapping. $\tilde{X}$ is the representation of EMG signals. $\tilde{F}$ is the output of this model.

B. PRELIMINARY

In this section, we present the preliminary knowledge about RBFNN that will be used in the rest of this work. RBFNN was proposed by J. Moody and C. Darken in 1988. In general, this neural network has three layers with a single hidden layer [31], [32]. RBFNN belongs to local-approaching network, it is often used to deal with the nonlinear control [33], [34] and classification issues [35], [36]. As showed in Figure 2, RBFNN is represented as

$$y = \sum_{j=1}^{m} w_j h_j \tag{2}$$

where y is the output of RBFNN. w_j denotes the connection weights for the node j from the hidden layer to the output layer. h_j is the activation function for hidden layer, it is

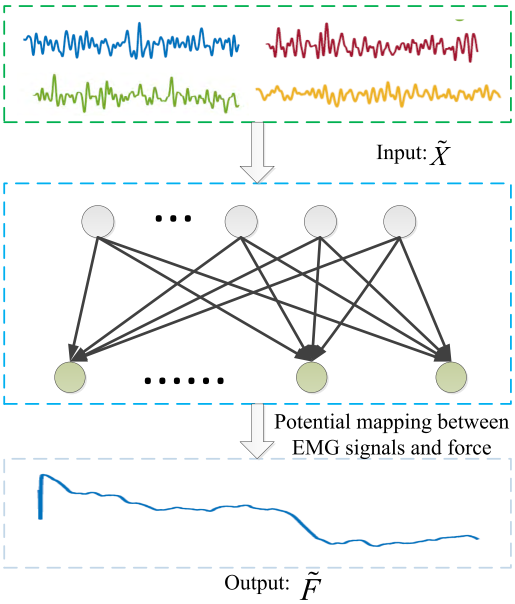

FIGURE 1. The proposed model of sEMG-force.

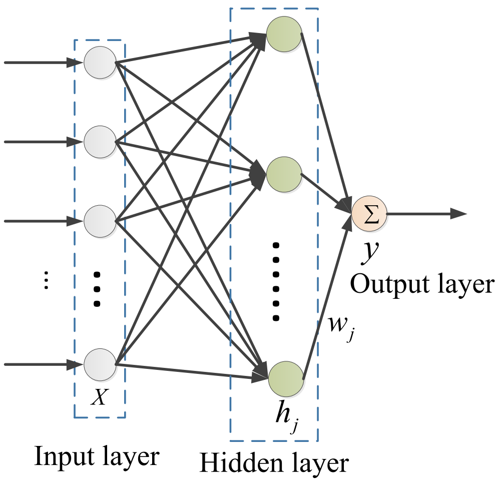

FIGURE 2. Framework of RBFNN.

represented as

$$h_j = \exp\{-\frac{\|X - C_j\|^2}{2b_j^2}\} \tag{3}$$

where X denotes the input of the RBFNN. $j = 1, 2, \ldots, m$. C_j and b_j are the parameters of basis function and basis function width for jth node in the hidden layer, respectively.

III. METHODOLOGY

Figure 3 shows the scheme of the proposed algorithm. This scheme aims to clarify the relationship of sEMG-force. A human subject interacts with a force sensor to collect the interactive force. Measured interaction force and sEMG signals feature are used as the input to the neural network. Generally, features of sEMG signals contain mean absolute value (MAV), wave length (WL), v-order, Willison amplitude (WA), and so on. It has demonstrated that MAV was superior to other features such as WL and WA for sEMG-force estimation applications [37], [38]. Therefore, in this work, we choose MAV as the sEMG signal feature. And mean square error (MSE) is used to evaluate the regression performance of the estimation model.

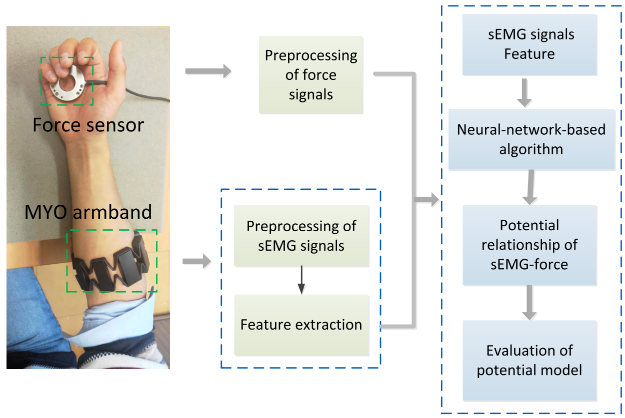

FIGURE 3. Framework of the system.

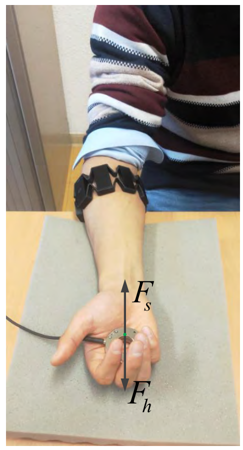

FIGURE 4. Interactive force analysis.

A. DATA ACQUISITION AND FEATURE EXTRACTION

In order to accurately estimate the model of sEMG-force, force and sEMG signals are sampled from a variety of hand grip strength. We sampled 10 times (cases 1-10) for the sEMG signals and force signal with two healthy human subjects (2 males, age from 20-30 years old). The force average values of 10 cases is presented in Table 1.

The applied force of the human subject is F_h and the feedback force of sensor is F_s, respectively. The force analysis is showed in Figure 4, it has[2]

$$F_s = F_h \tag{4}$$

[2]The force signal is preprocessing by using a third-order median filter, the parameter of this filter is 30.

TABLE 1. Average values of force for 10 cases.

Case	1	2	3	4	5	6	7	8	9	10
Value	8.7422	7.8749	14.1819	16.0288	17.3807	-14.6338	20.3994	17.5363	14.6971	15.7803

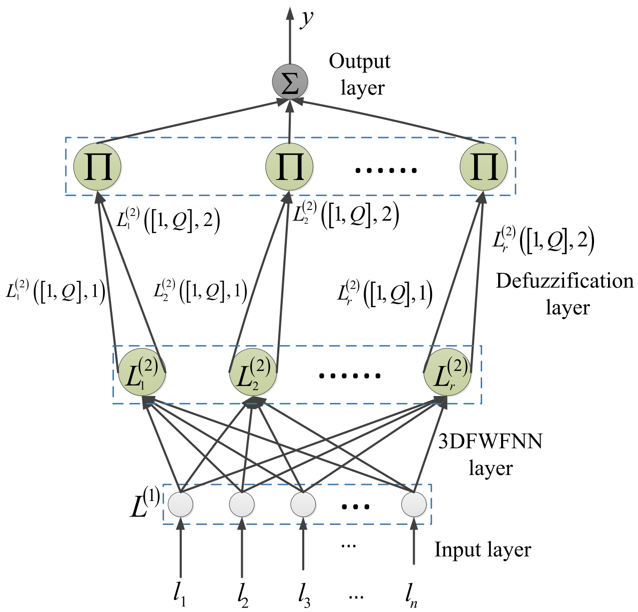

FIGURE 5. Structure of three domains fuzzy wavelet neural network.

The interactive force F_s[3] is represented as

$$F_s = [f_x,\ f_y,\ f_z]^T \tag{5}$$

where f_i, $i = x,\ y,\ z$. represents the interactive force in X-Y-Z coordinate axis.

B. FORCE ESTIMATION BASED ON THREE DOMAINS FUZZY WAVELET NEURAL NETWORK

As mentioned above, nonparametric algorithms such as the neural-network-based approach are effective to estimate the model of sEMG-force. Inspired by [39], [40], a neural-network-based algorithm is utilized to explore the potential mapping relationship of sEMG-force in this work.

Structure of three domains fuzzy wavelet neural network (TDFWNN) is shown in Figure 5. The neural network has four layers: input layer, TDFWNN layer, defuzzification layer and output layer.

1) LAYER 1

This is a input layer. It directly transmits the input signals $X^{(1)}$ to the next layer. $L^{(1)}$ is the output of the first input layer. The relationship of $X^{(1)}$ and $L^{(1)}$ is defined as

$$L^{(1)} = X^{(1)}$$

$$= [l_1^1,\ l_2^1,\ \ldots,\ l_i^1,\ \ldots,\ l_n^1], \quad i = 1,\ 2,\ \ldots,\ n. \tag{6}$$

where $l_1^1 = (\bar{u}_1, f_1),\ \ldots,\ l_n^1 = (\bar{u}_n, f_n)$. $\bar{u}_i$ and f_i are the features of EMG signals and interactive force, respectively. n is the amount of the input layer.

2) LAYER 2

In this layer, the activation function is three domain fuzzy wavelet transformation (TDFWT) for each neuron node of layer 2. It can be represented as

$$F_p^2(L^{(1)}) = \frac{1}{\sqrt{a_p}}\hat{\phi}(\frac{L^1 - b_p}{a_p}) \tag{7}$$

where $F_p^2(L^{(1)})$ denotes the activation function for the pth neuron node. $b_p = (b_{1,p}, b_{2,p}, \ldots, b_{n,p}), p\epsilon[1, 2, \ldots, P]$ represents the translation vector. a_p is the scaling parameter for layer 2. P is the total amount of TDFWT layer. $\hat{\phi}$ represents the three domain fuzzy wavelet function (TDFWF) and it is given as

$$\hat{\phi} = \int_{l\epsilon R}\int_{\phi\epsilon\phi^i} \frac{\mu(l,\phi)}{(l,\phi)} \tag{8}$$

where $\mu(l,\phi)\epsilon[0,\ 1]$ is the fuzzy membership function, $\hat{\phi} \equiv \{(l,\phi),\ \mu(l,\phi)|\forall l\epsilon R, \forall\phi\epsilon\{\phi^i\}, i = 1,\ 2,\ \ldots,\ n\}$. ϕ^i is the wavelet function for ith element.[4]

TDFWF contains primary wavelet function and secondary membership function. The primary wavelet function $P_{\hat{\phi}}(l)$ (for all $l \in R$) is defined as

$$P_{\hat{\phi}}(l) = \bigcup \phi^i(l), \quad i = 1,\ 2,\ \ldots,\ n. \tag{9}$$

The output of TDFWT layer is defined as a form of matrix as below

$$L_p^{(2)} = \begin{bmatrix} \frac{1}{\sqrt{a_p}}\phi^1(\frac{L^{(1)} - b_p}{a_p}) & \bar{\mu}(\phi^1) \\ \frac{1}{\sqrt{a_p}}\phi^2(\frac{L^{(1)} - b_p}{a_p}) & \bar{\mu}(\phi^2) \\ \cdots & \\ \frac{1}{\sqrt{a_p}}\phi^Q(\frac{L^{(1)} - b_p}{a_p}) & \bar{\mu}(\phi^Q) \end{bmatrix}_{Q\times 2} \tag{10}$$

where Q represents the amount of possible wavelet functions.[5] $\bar{\mu}(\phi)$ denotes the mean membership function for this layer and it can be represented as below

$$\bar{\mu}(\phi^{(i)}) = \frac{\sum_{l\epsilon X}\mu(l,\phi^{(i)})}{\sum_{l\epsilon X}\sum_{\phi\epsilon\{\phi^{(i)}\}}\mu(l,\phi)} \tag{11}$$

[3]Since the force sensor was gravity compensated before experiment, the sensor's gravity can be neglected.

[4]ϕ^i is the sum of basic wavelet functions for ith element.

[5]In general, the value of Q is greater, the cost of calculation of the network is higher and the performance of network is better. It is noted that the bigger is not the better for the value of Q.

3) LAYER 3

This layer is used to compute the centroid of fuzzy output of $L_p^{(2)}$ via defuzzification. The output of defuzzification layer is given as

$$L_p^{(3)} = [L_p^{(2)}(1,\ 1)\cdot L_p^{(2)}(1,\ 2),\ \ldots,\ L_p^{(2)}(Q,\ 1)\cdot L_p^{(2)}(Q,\ 2)] \tag{12}$$

where Q is the total amount of nodes for layer 3.

4) LAYER 4

This layer computes the output of the total network. The approximated model (nonlinear relationship) of sEMG-force can be represented as

$$L_p^{(4)} = \sum_{p=1}^{P}\sum_{q=1}^{Q} \bar{w_p} L_p^{(3)}(q) \tag{13}$$

where $L_p^{(4)}$ is the output of the TDFWNN. $\bar{w_p}$ indicates the wavelet coefficient[6] and it can be defined as

$$\bar{w_p} = \int_{-\infty}^{+\infty} f(l)\frac{1}{\sqrt{a_p}}\hat{\phi}(\frac{l-b_p}{a_p})dl \tag{14}$$

where $f(l)$ is an input signal.

$$\tilde{F} = L_p^{(4)} \tag{15}$$

where $\tilde{F}$ is the potential model based on TDFWNN.

C. EVALUATION OF THE MODEL

In order to evaluate the regression performance of the potential model of the sEMG-force, MSE and coefficient of determination (R^2) is utilized in this paper.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(F_{si} - \tilde{F_i})^2 \tag{16}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(F_{si} - \tilde{F_i})^2}{\sum_{i=1}^{n}(F_{si} - \bar{F_{si}}))^2} \tag{17}$$

where F_{si} is the measured interactive force. $\tilde{F_i}$ is the output based on TDFWNN or RBFNN. $\bar{F_{si}}$ represent the mean value of the output.

IV. EXPERIMENTS AND RESULTS

A. EXPERIMENT SETUP

Figure 6 shows experimental setup of the overall system. We interacted with a force sensor (FT16498, ATI Industrial Automation, USA) to collect the interactive information. The interactive force is converted by a converter device (NI USB-6361, National Instruments, USA). sEMG signals are preprocessing by a EMG sensing device (MYO armband, Thalmic Labs, Canada) which communicates with the signal processing computer via Bluetooth. Visual Studio 2010 (VS 2010) and MATLAB process the sEMG signals and force signal are used to construct the software system for processing on the Microsoft Windows 10 operation system (OS).

[6] $\bar{w_p}$ reflects the energy distribution of TDFWNN both in time and frequency plane.

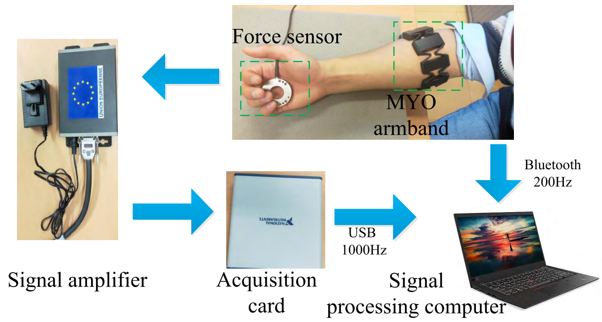

FIGURE 6. Description of the overall system.

In the experiment, the human subjects hold the force sensor and clench it in each case. The experiments are carried out 10 times and each subject operates 5 times in the experimental process. The human subjects have enough rest before every trial (case). The sampling data is divided into training data (50%) for regression and testing data (the other 50%) for validation.

B. FORCE ESTIMATION

In order to verify the feasibility and effectiveness of the proposed algorithm, experiments as introduced above have been performed in this study. As mentioned, two healthy human subjects participated in the experiments (cases 1-5 are performed by the first subject, cases 6-10 are carried out by the other subject). In the experiments, the sample frequency for force and sEMG signal are 1000 Hz and 200 Hz, respectively. The Morlet wavelet is used as the mother wavelet function.

For subject 1, Figures 7(a), 8(a), 9(a), 10(a) and 11(a) show the estimated force of the potential model based on RBFNN in cases 1-5. The estimated results based on TDFWNN are showed in Figures 7(c), 8(c), 9(c), 10(c) and 11(c). In the figures, the red curves represent the measured force signal. It can be seen that the TDFWNN algorithm achieves a better performance for estimating the potential relationship of sEMG-force in comparison with that of RBFNN. From the error curves (Figures 7(b) 7(d), 8(b) 8(d), 9(b) 9(d), 10(b) 10(d) and 11(b) 11(d)), it can be clearly seen that the estimation error of TDFWNN is much smaller than that of RBFNN.

For subject 2, we can draw a similar conclusion that the proposed algorithm can perform better for estimating the potential model of sEMG-force from Figures 12-16 in cases 6-10 with respect to the error of the potential model. The TDFWNN achieves smaller error by comparing with that of the RBFNN method. It is noted that the error of TDFWNN for estimating force are not all positive.

In the experimental results, we have magnified the figures in order to analyse the error of estimated force by using RBFNN method in 0-2s for cases 1-10. It can seen that the curves of error are converged to zero after 2s for RBFNN

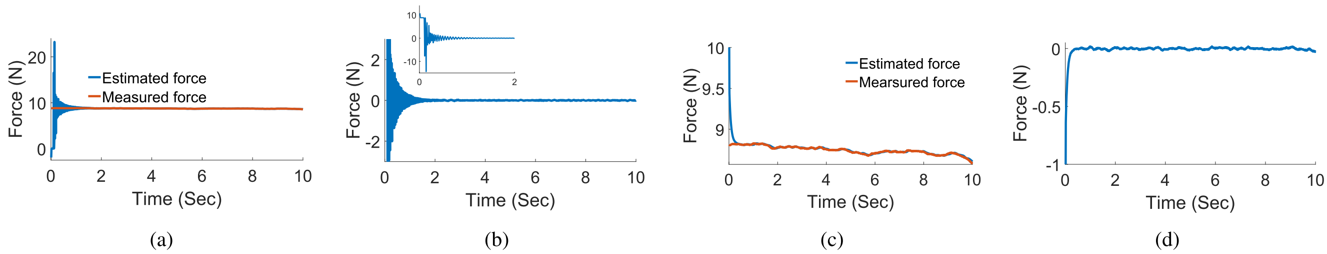

FIGURE 7. Estimated force by using neural network algorithms for case 1.

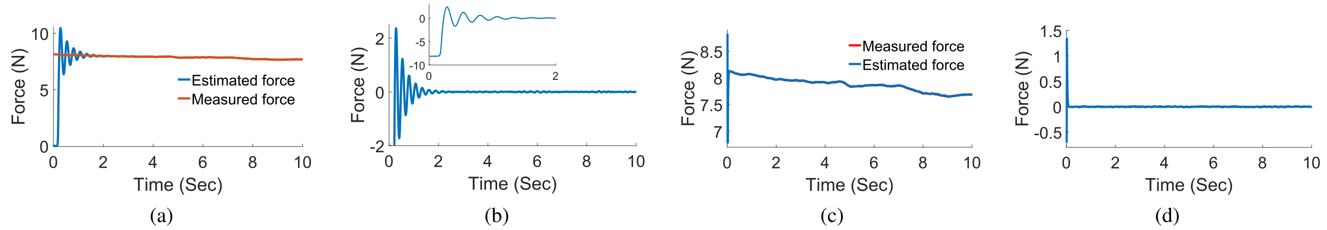

FIGURE 8. Estimated force by using neural network algorithms for case 2.

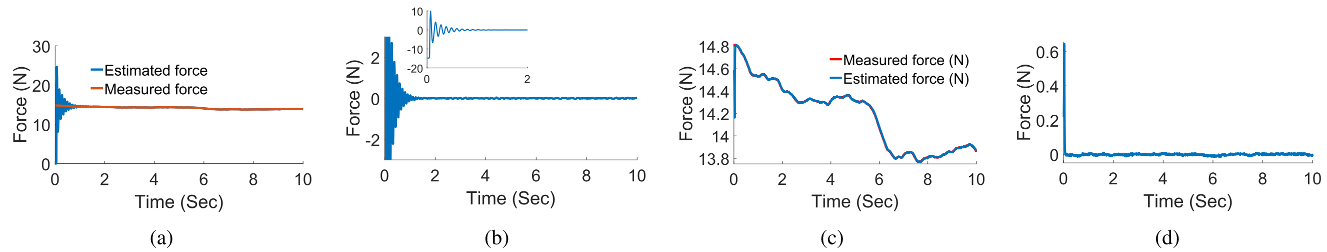

FIGURE 9. Estimated force by using neural network algorithms for case 3.

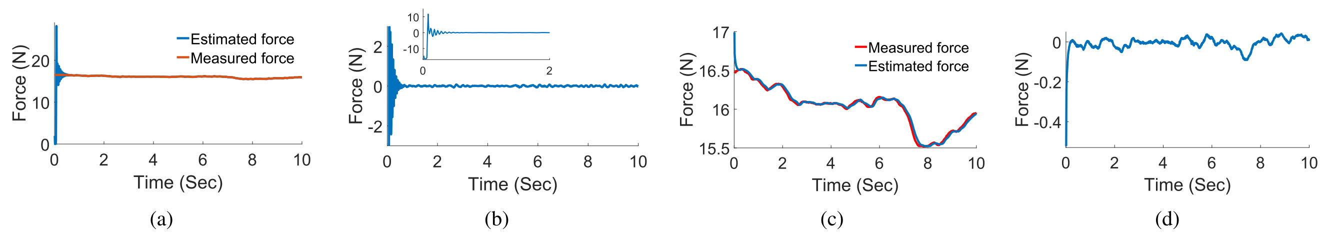

FIGURE 10. Estimated force by using neural network algorithms for case 4.

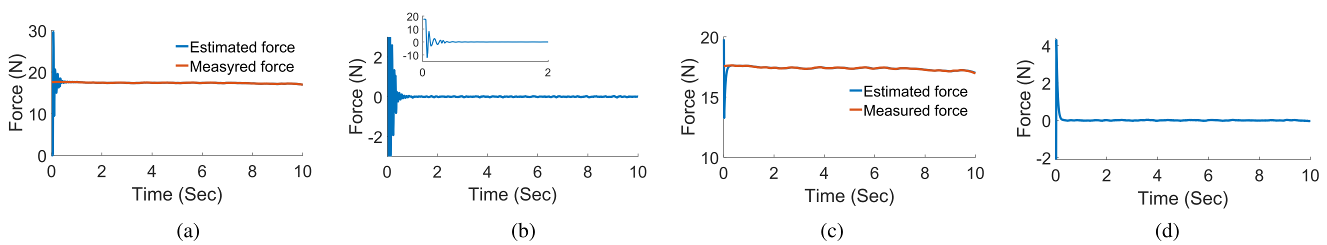

FIGURE 11. Estimated force by using neural network algorithms for case 5.

while the curves of error are stable after 0.5s for TDFWNN. It is also noted that the rate of convergence of TDFWNN is faster than that of RBFNN.

C. EVALUATION OF EXPERIMENTAL RESULT

From Tables 2-3 and Figures 17-18, the MSE of TDFWNN is much smaller than that of the RBFNN for estimat-

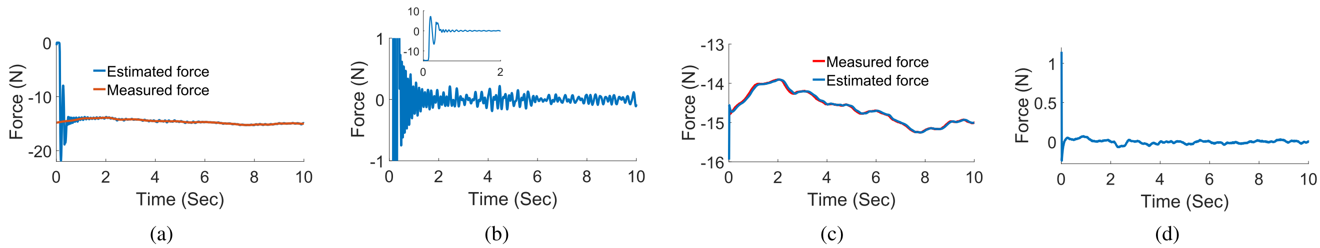

FIGURE 12. **Estimated force by using neural network algorithms for case 6.**

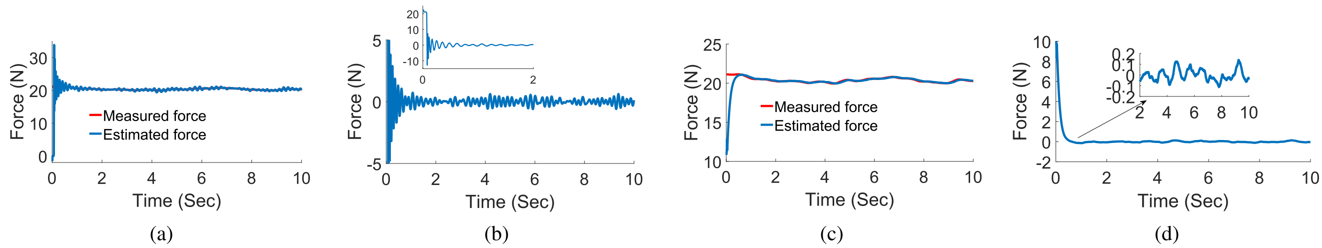

FIGURE 13. **Estimated force by using neural network algorithms for case 7.**

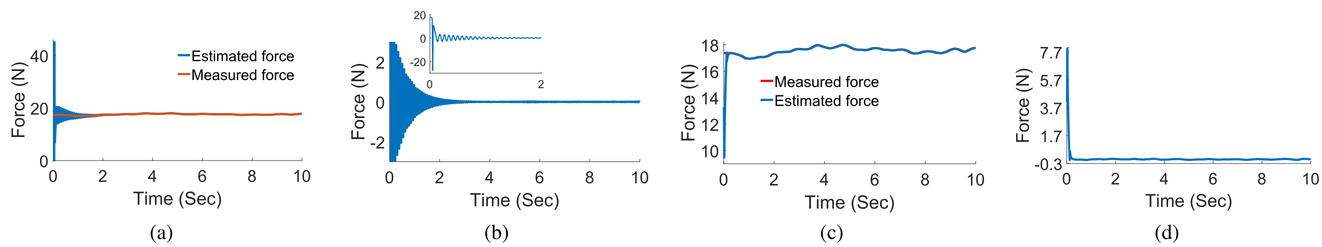

FIGURE 14. **Estimated force by using neural network algorithms for case 8.**

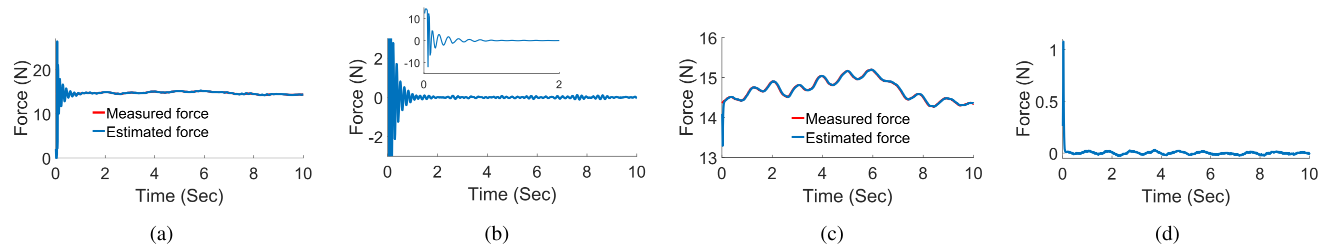

FIGURE 15. **Estimated force by using neural network algorithms for case 9.**

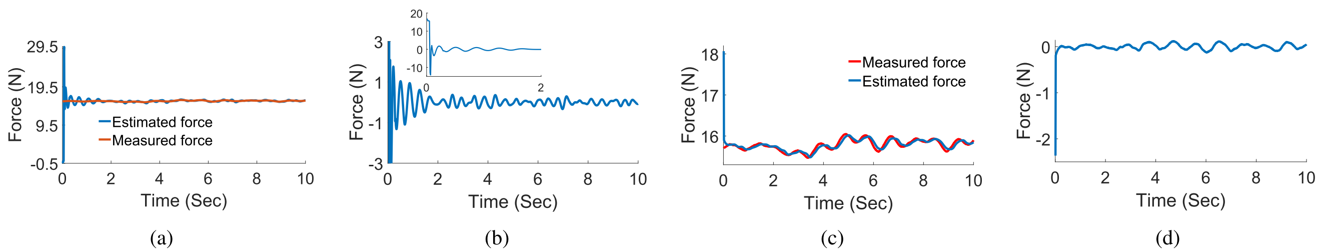

FIGURE 16. **Estimated force by using neural network algorithms for case 10.**

ing the potential model of sEMG-force in cases 1-10 for 2 subjects.

In Table 4, for subject 1, the average MSE for TDFWNN and RBFNN are $(0.0034 + 0.0030 + 6.6673 \times 10^{-4} + 0.0011+0.0623)/5$ and $(1.3434+1.3053+1.5011+1.7935+1.8992)/5$, respectively. The average MSE of TDFWNN is $(0.0021+0.2032+0.1980+0.0038+0.0085)/5$ for subject 2, that of RBFNN is $(3.5240 + 3.7098 + 2.4734 + 1.5729 +$

TABLE 2. MSE of force estimation algorithms.

Algorithms	RBFNN	TDFWNN
Case 1	1.3434	0.0034
Case 2	1.3053	0.0030
Case 3	1.5011	6.6673×10^{-4}
Case 4	1.7935	0.0011
Case 5	1.8992	0.0623

TABLE 3. MSE of force estimation algorithms.

Algorithms	RBFNN	TDFWNN
Case 6	3.5240	0.0021
Case 7	3.7098	0.2032
Case 8	2.4734	0.1980
Case 9	1.5729	0.0038
Case 10	1.7749	0.0085

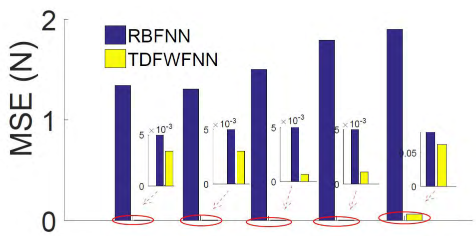

FIGURE 17. Evaluation criterion (MSE) of force estimation algorithms for cases 1-5.

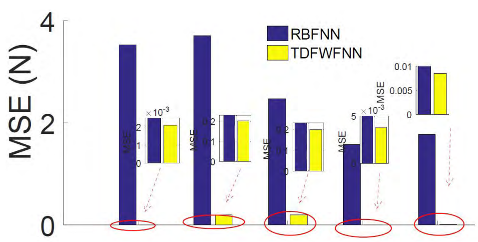

FIGURE 18. Evaluation criterion (MSE) of force estimation algorithms for cases 6-10.

TABLE 4. Average MSE of force estimation algorithms.

Algorithms	RBFNN	TDFWNN
Subject 1 (Cases 1-5)	1.5671	0.0141
Subject 2 (Cases 6-10)	2.611	0.0831

1.7749)/5. It verities that the TDFWNN algorithm is superior to the RBFNN method in estimating the potential model of sEMG-force when the signal is relative stable.

Figure 19 shows the coefficient of determination R^2 of TDFWNN and RBFNN. It can be seen that the values of R^2 of TDFWNN are larger than that of RBFNN, which means that the regression performance of TDFWNN is superior to the RBFNN.

V. DISCUSSION

In this study, we carried out experiments of 10 trials for 2 subjects with absolute average force varing from

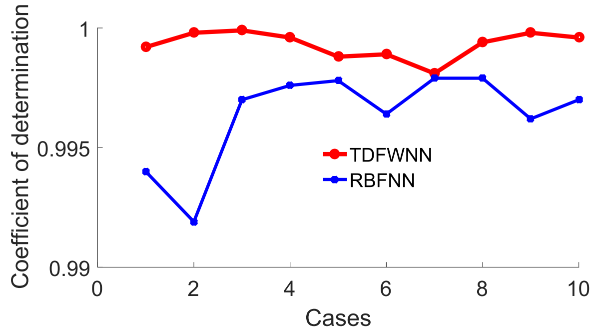

FIGURE 19. Evaluation criterion (R2) of force estimation algorithms for cases 1-10.

7.8749N to 20.3994N. According to the experimental results, it is observed that the rate of convergence of TDFWNN is faster than that of RBFNN, which is clearly shown in Figures 7-16. In Figure 19, it can be seen that the values of R^2 for both are larger than 0.99. This means that the RBFNN and TDFWNN are both effective in estimating the relationship between sEMG signal and generated force. However, compared with the RBFNN method, the TDFWNN has better convergence rate and precision which can be explained by the higher determination coefficient R^2 of the TDFWNN as shown through the experiment.

Because of the complexity of the model of sEMG-force, richer information should be taken into account in order to improve the modeling accuracy and robustness. For example, the kinematic motion of humans' hand, interactive payload, and so on [41], [42]. These factors would be considered in our future work. The obtained sEMG-force model will be implemented and verified in human-robot interaction applications [43] as our continuous work as well.

VI. CONCLUSION

In this work, we proposed a force estimation algorithm to build a relationship between measured sEMG signal and generated hand force. Considering the advantages of neural network techniques for non-linear regression, a TDFWNN algorithm was employed. In the experiments, we utilized the MAV of sEMG signals as the input of TDFWNN. The experiments were carried out with 2 subjects for 10 trials. As the experimental results confirmed, the hand force can be estimated accurately based on the measured sEMG signals using the TDFWNN method. And the comparison with conventional RBFNN shows that the presented TDFWNN algorithm provides a better estimation performance in terms of both convergence rate and estimation error.

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