Ankle Joint Torque Prediction Based on Surface Electromyographic and Angular Velocity Signals

CHANJUAN SU,1, SHURONG CHEN1, HAIYAN JIANG2,3, AND YAN CHEN2,3
1Rehabilitation Department, Fuzhou Second Hospital Affiliated to Xiamen University, Fuzhou 350007, China
2College of Electrical Engineering and Automation, Fuzhou University, Fuzhou 350108, China
3Fujian Key Laboratory of Medical Instrumentation and Pharmaceutical Technology, Fuzhou University, Fuzhou 350108, China
Corresponding author: Haiyan Jiang (e-mail: jianghaiyan@fzu.edu.cn)

This work was supported by the Fuzhou Key Specialty Construction Project of China under Grant 201710272.

ABSTRACT Joint torque prediction plays an important role in quantitative limb rehabilitation assessment and exoskeleton robot, and it is essential to acquire feedback or feedforward signal for adaptive functional electrical stimulation (FES) control. The Surface electromyography (sEMG) signal is one of the basic processing techniques to detect muscle activity, and also one favorable technique to estimate joint torque. In order to predict joint torque in a wide range of real time convenient applications, it is necessary to fuse sEMG signals with other convenient physical sensors such as accelerometers and gyroscopes, herein, we use a time delay artificial neural network to predict human joint force of ankle eversion and inversion based on sEMG and angular velocity signals. We testify our method on the data recorded from 8 subjects (5 healthy subjects and 3 patients) who are on isokinetic ankle eversion and inversion. The results show that the mean Cross-correlation coefficients (ρ) and the mean normalized root-mean-square deviation (NRMSE %) calculated between the prediction and the real value for isokinetic contraction is 0.966±0.019 and 7.9%±0.026. Compared with artificial neural network (ANN) and support vector regression (SVR), the proposed method can predict the joint torque effectively. For the future application, the method has the potential to be employed to predict the ankle moments in real-time application for quantitative lower limb rehabilitation assessment and exoskeleton robot control.

INDEX TERMS Joint force, angular velocity Signals, artificial neural network, surface electromyography (sEMG).

I. INTRODUCTION

Joint torque prediction plays an important role in quantitative limb rehabilitation assessment and exoskeleton robot [1], [2], especially in the closed-loop control of functional electrical stimulation (FES) [3] and the control of transhumeral prosthetic. A number of kinematics and noninvasive methods have been proposed to estimate the lower limb muscle activities, but most of these require special measuring apparatus, such as isokinetic dynamometers, which made these methods unsuitable for application in patients’ daily lives and operations outside the lab. The Surface electromyography (sEMG) signal is the sum of the action potentials generated by the active motor units and detected over the skin, the signal contains a wealth of information about muscle functions, and it is one of the basic processing techniques to detect muscle activity and provide the motion intentions of the user. Because of the significant advantages such as noninvasive, real-time, and multi-point measurement, sEMG has been widely used in medical [4], [5], engineering studies [6], [7], control of prosthesis [8], biomechanics and movement analysis [9]–[11], genomics and exoskeleton robot control. In recent years, the recording and analysis of sEMG signals provide important information to the field of limb joint force prediction [9], [12], used as a feedback prediction controller of FES [3] and provide continuous real-time control signal for human musculoskeletal system.

Because of the nonlinear relationship between the recorded sEMG signals and joint force, nonlinear torque estimation methods were introduced for the study of torque prediction. Zhang et al. [13] proposed an EMG-based torque prediction method for time-variant muscle fatigue tracking in spinal cord injured patients with surface FES, the results represent a feasible and effective torque prediction performance under
Ankle Joint Torque Prediction Based on Surface Electromyographic and Angular Velocity Signals

C. Su et al.: Ankle Joint Torque Prediction Based on Surface Electromyographic and Angular Velocity Signals

isometric condition. Sun et al. [14] has focused on the human ankle torque estimation according to the EMG signals and the design of the controller. Dasanayake et al. [15] utilized independent component analysis (ICA) to isolate the EMG signals from each muscle and proposed a novel kinematic model to measure the actual torque. However, artificial neuron network (ANN) as a computational model based on the structure and functions of biological neural networks, has been still by far the most successful and popular used method in torque prediction [16], [17].

In the earlier works, although the performance of these methods is satisfactory, the predicting joint torque is under laboratory conditions. Therefore, fusing sEMG signals with other convenient physical sensors such as accelerometers and gyroscopes, to predict joint torque in a wide range of real time applications is essential. In fact, due to transmission time, sEMG is generated 30-150ms earlier than human muscle movements, joint moment is a sum of series action potentials generated by the active motor units. Time delay artificial neural network (TDNN) is an artificial neural network model in which all the neuron-like units (nodes) are fully connected by directed connections. Each unit has a time-varying real-valued activation and each connection has a modifiable real-valued weight. A TDNN can be viewed as a special structure of recurrent neural networks and have typically been reported to be successful for time series prediction. Because of the hysteresis of muscle movements, it is related to a time series sEMG signals, in this article, TDNN is used as a predictor model of the joint force. The input of TDNN consisted of multi-channel sEMG signals and the angular velocity information. The advantages of our proposed method are demonstrated on the data recorded from 8 subjects (5 healthy subjects and 3 patients) who are on ankle eversion and inversion isokinetic contractions at three different angular velocities. The diagram of joint torque prediction strategy is illustrated in Fig. 1. The performance of the TDNN network was subsequently tested by comparing predicted joint torque values from the model with the real joint torque values. Three accuracy metrics were used to evaluate the performance of the models: the cross-correlation coefficient ($\rho$), the root-mean-square deviation (RMSE) and the normalized root-mean-square deviation (NRMSE %). The experiment results such as the mean (±SD) $\rho$ and NRMSE, were analyzed by IBM SPSS Statistics subscription software.

II. MATERIALS AND METHODS

A. DATA ACQUISITION

Fig. 2 illustrates the system setup for data collection. To develop and test a new sEMG-based real time human joint force predictor of ankle eversion and inversion, both Delsys Trigno Wireless System (Delsys, Inc, Natick, USA) and BIODEX System 4 Pro Strength Testing System (Biodex, Inc., Shirley, NY, USA) were used to record sEMG signals, accelerometer signals and the angular velocity data. Trigno EMG sensors employ 4 silver bar contact for detecting the sEMG signal at skin surface. BIODEX System 4 is used as a reliable method for ankle eversion and inversion isokinetic contractions. Analog Signal Access Interface of BIODEX System provides real time analog voltage outputs of joint torque, angular velocity and position from the dynamometer, and Delsys Trigno Analog Adapter is used to collect and transmit those data connected to a base station.

A total of 8 subjects (3 females, 5 males), ranging in age from 17–50 years old participated in this study, including 5 healthy subjects and 3 three patients in rehabilitation training. A total of 5 sEMG sensors are placed on the subjects' muscles of gastrocnemius, tibialis anterior, peroneus Longus, extensor hallucis longus, extensor digitorum longus. These muscles are selected based on their importance for motor control of the ankle, the sensors are placed over target muscles as described in Fig. 3.

During the acquisitions, subjects are seated at BIODEX System 4 Pro Strength Testing System, to perform ankle
eversion and inversion isokinetic contracts at 3 different angular velocities, i.e. 30, 60, and 90 deg/s. Angular velocity, joint torque (in Nm), position and sEMG signals are recorded simultaneously. All sensor sites are initially cleansed using alcohol pads to mitigate sources of sEMG noise at the skin electrode interface. The raw data from the sEMG and position sensors are sampled at rate of 2000Hz and 418Hz using a 16 bit A/D converter, respectively.

After data acquisition, a time serial of sEMG Signals can be collected, which are shown in Fig. 4. In Fig. 4, the sEMG signals of the gastrocnemius muscle, tibialis anterior muscle, peroneus Longus muscle, extensor halluces longus muscle, extensor digitorum longus muscle are shown from top to bottom. The angular velocity Signals during ankle eversion and inversion isokinetic contractions are shown in Fig. 5, and the joint force Signals are shown in Fig. 6.

B. METHODS

1) FEATURES EXTRACTION
sEMG can be seen as zero-mean Gaussian in time domain. Its amplitude is random and vibrates frequently across zero. There are a number of methods to calculate the power of random sEMG [18]. In our study, in order to predict joint force of ankle eversion and inversion based on sEMG signals in real-time, the root mean square (RMS) value of the raw sEMG signals is used to as the feature vectors. It has the advantages, for instance, it can be used in real-time application, required low computational complexity, easy implementation and has a good performance in low noise environment. After filtered by a 10-500 Hz band-pass filter, the sEMG signals are processed using a moving window root mean square (RMS) algorithm. The RMS is calculated using (1):

\[
RMS = \sqrt{\frac{1}{L} \sum_{i=1}^{l} x_n^2}
\]

where, RMS is the RMS of the nth sEMG data segment, xn is the n-th sample of the raw sEMG signal, L is the length of sEMG signal. The parameter L indicates the moving window width. If a large window width L is utilized, the sEMG smoothness will be increased. While, the large L will introduce signal processing delay. On the contrary, a small window width L can reduce the signal delay but still leaves some high frequency noise.

The length of the moving window L is set to be 100 points, overlapped by 30 samples each time. Fig. 7 shows sEMG sampled from the gastrocnemius muscle of a volunteer and its RMS during the exercise. As it can be seen, the RMS of sEMG still contains some high frequency noise and the signal...
smoothness is poor for the reason of utilizing a small integral width W. To remove the high frequency noise, the data are smoothed by a 10-point moving average and 10-point median filtering. After the processing of the sEMG signals, the data is shown in Fig. 8, from top to bottom is the gastrocnemius muscle, tibialis anterior muscle, peroneus Longus muscle, extensor halluces longus muscle, extensor digitorum longus muscle. The filtered RMS is smooth enough and can be used as the envelop of the raw sEMG. It should be noted that the low-pass filtering operation with cutoff frequency of 5–10Hz can cause sEMG signal delay.

Because the sampling frequency of sEMG (2,000 Hz) is higher than that of joint angle and joint force, in order to match the length of the sEMG signal in time-domain, the joint torque data are also resampled and are then smoothed by a 10-point moving average and 10-point median filtering.

2) TIME DELAY ARTIFICIAL NEURAL NETWORK

The schematics of the developed time delay artificial neural network is shown in Fig. 9. The TDNN take joint angular velocity and the RMS value of the sEMG signals as input, and the joint torque signals as output.

As Fig.9 shows, it is a three-layer regression fitting neural network, consisting of input nodes, a hidden, and an output layer, the number of hidden layer is 10. The backpropagation learning algorithm is used to optimize the neural networks and the Levenberg–Marquardt algorithm (LM) algorithm is applied for training of the network.

In the networks, Let $W(i)$ be the vector of weights between the input submatrix and the $i$th hidden layer. The output of the $i$th hidden neurons $h(i)$ can be calculated as follows:

$$h_i = \sigma \left( \sum_{k=1}^{n} W(k)I(k) + b_i \right)$$  \hspace{1cm} (2)

where $\sigma$ is the nonlinear activation function and $b(i)$ is the bias of the $i$th hidden neuron. (2) represents the output of each hidden neuron for a particular submatrix $I$.

$$y(k) = f \left( \sum_{i} W_0 h_i + b_0 \right)$$  \hspace{1cm} (3)

where $W_0$ and $b_0$ is the weight and bias of the hidden layer into the output layer, respectively. The function $f$ represents a nonlinear sigmoid function.
3) PREDICTION EVALUATION

A time delay artificial neural network is designed and trained with all three angular velocity (30, 60 and 90 deg/s), and the joint torque prediction ability of the TDNN is evaluated. In the test, we randomly selected 80% data for training and verification, 20% data for testing. The performance of trained models was subsequently tested by comparing predicted torque values from the model and the measure torque values. RMSE, $\rho$, and NRMSE (%) between the predicted joint torque and the measure joint torque data are used to evaluate network performance. RMSE is a measure of the difference between the measured and predicted values. The calculation is as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (T_e_i - T_m_i)^2}$$  \hspace{1cm} (4)

$$\text{NRMSE} = \frac{\text{RMSE}}{T_m_{\text{max}} - T_m_{\text{min}}}$$  \hspace{1cm} (5)

$$\rho = \frac{\sum_{i=1}^{n} (T_m_i - \bar{T}_m_i)(T_e_i - \bar{T}_e_i)}{\sqrt{\sum_{i=1}^{n} (T_m_i - \bar{T}_m_i)^2 \sum_{i=1}^{n} (T_e_i - \bar{T}_e_i)^2}}$$  \hspace{1cm} (6)

In the above formulas, $T_m(i)$ is the measured and $T_e(i)$ is the predicted joint torque value for sample $i$, $n$ corresponds to the total number of samples tested, $T_{m_{\text{max}}}$ and $T_{m_{\text{min}}}$ represent the maximum and minimum of $T_m$.

III. RESULTS

A. CONVERGENCE CURVE OF THE DESIGNED TDNN

Simulations show the designed TDNN can converge rapidly and the training time is less than one second. Fig.10 shows the tracking error convergence curve of the designed TDNN.

As shown in the performance plot, in which the epochs the Mean Square Error (MSE) of the TDNN has decreased, and have a very low MSE at the end of the training phase.
B. PERFORMANCE OF SUBJECT 1 AT DIFFERENT ANGULAR VELOCITIES

Fig. 11 shows the Regression coefficients of training samples, validation samples and test samples. As can be seen, the correlation coefficient of all sample are higher than 0.99.

The joint force prediction results of subject 1 at different angular velocities 30, 60, and 90 deg/s are shown in Fig. 12 (a), (b) and (c) respectively. For each subfigure, the red dot is the measure joint torque and the blue star is the prediction joint torque estimated by TDNN. The RMSE, NRMSE (%) and $\rho$ of subject 1 at different angular velocities (i.e. 30, 60, and 90 deg/s) are shown in Table 1.

C. ACCURACY OF PREDICTION

The statistical estimation results by TDNN for the healthy subjects and patients at different angular velocities (i.e. 30, 60, and 90 deg/s) are shown in Fig.13. The average $\rho$, RMSE and NRMSE (%) calculated from the predicted results are shown in Fig. 13 (a), Fig. 13(b) and Fig. 13(c) respectively. For the healthy subjects, the mean correlation coefficient $\rho$ and NRMSE is 0.968±0.015 and 7.3% ±0.0192, respectively; while for the patients, the mean $\rho$ and NRMSE (%) is 0.960±0.025 and 9.17% ±0.0355, respectively. For all the subjects the mean (±SD) RMSE, NRMSE (%), and $\rho$ for isokinetic contraction is 1.19±0.500, 7.9% ±0.026 and 0.966±0.019 respectively. The result shows that TDNN has good adaptability to predict the joint force at different angular velocities for either healthy or patient.

IV. DISCUSSION

To compare TDNN with other methods, we used the most common artificial neural network (ANN) and support vector regression (SVR). ANN is a feedforward structure with input, hidden, and output layers. The sigmoid activation functions were used to capture the nonlinearities of inputs. SVR maps input data using a nonlinear mapping to a higher dimensional feature space. We used epsilon support vector regression ($\varepsilon$-SVR) and the Gaussian kernel for estimation of joint force. The Performance of the TDNN, traditional ANN and SVR are shown in Fig. 14.

The mean $\rho$, RMSE, and NRMSE calculated from the prediction result are shown in Fig. 14 (a), Fig. 14(b) and Fig. 14(c) respectively. In Fig. 14 (a). The mean $\rho$ between actual joint torque and predicted joint torque obtained by TDNN, ANN and SVR are 0.966±0.019, 0.951±0.249, and 0.954±0.037 respectively. In addition, according to the pictures (c), the mean NRMSE between real joint torque and predicted joint torque obtained by TDNN, ANN and SVR are 7.9%±0.026, 9.8%±0.045 and 9.07%±0.036, respectively. In conclusion, it can be seen that the TDNN, which take joint angular velocity and the RMS value of the sEMG signals as input, is better than the traditional ANN algorithm and SVR.

This article has presented a TDNN network to predict lower limb joint force, which used the time series data sEMG and angular velocity as input to predict lower limb joint force in real-time. The results show that the mean prediction RMSE and NRMSE (%) for isokinetic contraction is 1.19±0.500 and 7.9%±0.026 respectively, achieved by the proposed method. The mean (±SD) $\rho$ between the prediction and the real value
was calculated to be $0.966 \pm 0.019$. The results show that the proposed TDNN methods represent an efficient way to the joint force prediction, the predictor has several advantages such as good generalization universality and rapid learning speed and convergence. For the future application, TDNN is likely to be employed to predict the ankle moments in daily life to control exoskeleton robot. Moreover, the obtained results in this article can be used in a wide range of clinical and engineering applications.

REFERENCES

[1] T. Kikuchi, C. Sato, K. Yamabe, I. Abe, T. Ohno, S. Kugimiyu, and A. Inoue, “Upper limb training/assessment program using passive force controllable rehabilitation system,” in Proc. IEEE Int. Conf. Rehabil. Robot., Jul. 2017, pp. 505–510.

[2] B. Xiong, N. Zeng, H. Li, Y. Yang, Y. Li, M. Huang, W. Shi, M. Du, and Y. Zhang, “Intelligent prediction of human lower extremity joint moment: An artificial neural network approach,” IEEE Access, vol. 7, pp. 29973–29980, 2019.

[3] Q. Zhang, M. Hayashi, and C. Azevedo-Coste, “Evoked electromyography-based closed-loop torque control in functional electrical stimulation,” IEEE Trans. Biomed. Eng., vol. 60, no. 8, pp. 2299–2307, Aug. 2013.

[4] E. E. A. Cabral, G. A. F. Fregonezi, L. Melo, N. Basoudan, S. Mathur, and W. D. Reid, “Surface electromyography (sEMG) of extradiaphragm respiratory muscles in healthy subjects: A systematic review,” J. Electromyogr. Kinesiol., vol. 42, Oct. 2018, Art. no. S105064117304595.

[5] D. Barmpakos, P. Kaplanis, S. A. Karkanis, and C. Pattichis, “Classification of neuromuscular disorders using features extracted in the wavelet domain of sEMG signals: A case study,” Health Technol., vol. 7, no. 1, pp. 33–39, Mar. 2017.

[6] R. Akhundov, D. J. Saxby, E. Edwards, S. Snodgrass, P. Clausen, and L. E. Diamond, “Development of a deep neural network for automated electromyographic pattern classification,” J. Experim. Biol., vol. 222, no. 2, pp. 160–167, 2019.

[7] K.-S. Lee, “EMG-based speech recognition using hidden Markov models with global control variables,” IEEE Trans. Biomed. Eng., vol. 55, no. 3, pp. 930–940, Mar. 2008.

[8] M. Atzori, A. Gijsberts, C. Castellini, B. Caputo, A.-G. M. Hager, S. Elsig, G. Giatisidis, F. Bassetto, and H. Müller, “Clinical parameter effect on the capability to control myoelectric robotic prosthetic hands,” J. Rehabil. Res. Develop., vol. 53, no. 3, pp. 345–358, 2016.

[9] C. Li, Y. Zhou, and Y. Li, “The signal processing and identification of upper limb motion based on sEMG,” Wireless Pers. Commun., vol. 103, no. 1, pp. 887–896, Nov. 2018.

[10] A. A. Al-Tae and A. Al-Jumaily, “Optimal feature set for finger movement classification based on sEMG,” in Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), Jul. 2018, pp. 5228–5231, doi: 10.1109/EMBC.2018.8513436.

[11] R. Crepin, C. L. Fall, Q. Masclet, C. Gosselin, A. Campeau-Lecours, and B. Gosselin, “Real-time hand motion recognition using sEMG patterns classification,” in Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), Jul. 2018, pp. 2655–2658, doi: 10.1109/EMBC.2018.8512820.

[12] M. Roberto and P. Philip, Electromyography: Physiology, Engineering, and Non-Invasive Applications. New York, NY, USA: IEEE Press, 2004, pp. 381–425.

[13] Q. Zhang, M. Hayashi, P. Fraisse, and D. Guiraud, “FES-induced torque prediction with evoked EMG sensing for muscle fatigue tracking,” IEEE/ASME Trans. Mechatronics, vol. 16, no. 5, pp. 816–826, Oct. 2011.

[14] Z. Li, H. Cheng, H. Guo, and X. Sun, “Compliant training control of ankle joint by exoskeleton with human EMG-torque interface,” Assem. Autom., vol. 37, no. 3, pp. 349–355, Aug. 2017, doi: 10.1108/AA-12-2016-161.

[15] W. D. I. G. Dassanayake, R. A. R. C. Gopura, V. P. C. Dassanayake, and G. K. I. Mann, “Surface EMG signals based elbow joint torque prediction,” in Proc. IEEE 8th Int. Conf. Ind. Inf. Syst., Dec. 2013, pp. 110–115.

[16] Y. Liu, S.-M. Shih, S.-L. Tian, Y.-J. Zhong, and L. Li, “Lower extremity joint torque predicted by using artificial neural network during vertical jump,” J. Biomech., vol. 42, no. 7, pp. 906–911, May 2009.

[17] M. H. Jali, T. A. Izzuddin, Z. H. Bohari, M. F. Sulaiman, and H. Sarkawi, “Predicting EMG based elbow joint torque model using multiple input ANN neurons for arm rehabilitation,” in Proc. 16th Int. Conf. Comput. Modeling Simulation (UKSim-AMSS), Cambridge, U.K., Mar. 2014, pp. 189–194.

[18] Q. L. Li, Y. Song, and Z. G. Hou, “Estimation of lower limb periodic motions from sEMG using least squares support vector regression,” Neural Process. Lett., vol. 41, no. 3, pp. 371–388, Jun. 2015.

CHANJUAN SU received the B.S.M. degree in rehabilitation science from Fujian Medical University, Fuzhou, China, in 2009. Since 2009, she has been an Attending Physician of rehabilitation with the Rehabilitation Department, Fuzhou Second Hospital Affiliated to Xiamen University. Her research interests include the rehabilitation of the nervous systems and common diseases in orthopedics.

SHURONG CHEN received the degree from the College of Traditional Chinese Medicine of Fujian, in 2007. He is currently the Deputy Chief Physician of the Fuzhou Second Hospital Affiliated to Xiamen University. His research interest includes the rehabilitation of orthopaedic diseases.

HAIYAN JIANG received the B.E. degree in electrical engineering from the Shandong University of Science and Technology, Qingdao, China, in 1998, and the M.E. and Ph.D. degrees in electrical engineering from Fuzhou University, Fuzhou, China, in 2005 and 2013, respectively. She is currently an Associate Professor with the Department of School of Electric Engineering and Automation, Fuzhou University. Her research interests include biomedical detection and signal processing.

YAN CHEN received the B.E. degree in electrical engineering from the Xiamen Institute of Technology, Fujian, China, in 2018. She is currently pursuing the master’s degree with Fuzhou University, Fuzhou, China. Her research interests include biomedical detection and signal processing.