Application of artificial intelligence in the decomposition of surface electromyography motor units

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Abstract

Surface EMG is the result of the integrated superposition of all activated muscle fiber action potentials at the skin surface electrodes when the muscle contracts. When skeletal muscle is functioning, the muscle fibers contract, and the contraction of the muscle has a series of biochemical changes within the muscle fibers, as well as action potential changes, reflecting the functional state of the nerve and muscle. If a real-time EMG electrode is used to display these action potential changes, a waveform is formed, called electromyogram. From the point of view of signal analysis, it can also be called EMG signal. Since EMG signals originate from a person's own electrical signals, EMG signals have a direct and natural character and are usually multi-channel measured from the skin of the muscle surface where the action takes place. Today, the use of EMG signals has become an important amount of information that can be used for research in muscle movement, clinical diagnosis, and rehabilitation medicine. Improved EMG such as multi-channel EMG and real-time EMG have been developed for practical needs, and the factor of muscle fatigue is also used as a consideration to improve the accuracy of EMG signal-based controllers. In conclusion, research on EMG signals is in high demand and developing rapidly.

Keywords ElEctromyogram; Motor unit; Decomposition

1 Background of the study

Surface EMG is the result of the combined superposition of all activated muscle fibre action potentials at the skin surface electrodes when the muscle contracts. When skeletal muscle is functioning, the muscle fibres contract and the contraction of the muscle has a series of biochemical changes within the muscle fibres, as well as action potential changes, reflecting the functional state of the nerve and muscle. If this action potential change is displayed using a real time EMG electrode, it forms a waveform called an electromyogram. In terms of signal analysis, this can also be called an EMG signal. Because EMG signals originate from a person's own electrical signals, they have a direct, natural character and are usually multi-channel measured from the skin of the muscle surface where the action takes place. Today the use of EMG signals has become an important amount of information that can be used for research in muscle movement, clinical diagnosis, rehabilitation medicine and more. Improved EMG such as multi-channel EMG and real-time EMG are being developed for practical needs and the factor of muscle fatigue is also taken into account to improve the accuracy of EMG signal-based controllers. In conclusion, research into EMG signals is in high demand and developing rapidly.

With the rapid development of artificial intelligence theory, motion recognition technology based on surface myoelectric signals is used in prosthetics and exoskeleton robots. The technology utilises powerful information sensing and data mining capabilities such as machine learning/deep learning models to decode human motion intent and achieve complex recognition tasks such as multi-degree-of-freedom discrete motion classification or joint continuous motion estimation, providing a natural and fluid human-machine interaction mode for the controlled device, thereby improving the quality of life of amputees and people with motor dysfunction. However, there are still many technical bottlenecks in the robustness, generalisation and reliability of existing EMG control systems, especially the real-time recognition capability of models in complex environments is significantly reduced, the market recognition is not high, and most of the results have not been able to get out of the laboratory.

2 Current status of research

2.1 Myoelectric control for prostheses

As every human movement is performed by a muscle contraction controlled by the central nervous system (CNS), the EMG signal accompanying the muscle contraction contains information about the muscles involved in that movement. If information about a person's intended action can be extracted from the EMG signal, it can be used as a novel interface tool for virtual reality and teleoperated devices, or as a communication tool for people with disabilities. For example, in a physically disabled person who has had an upper limb amputated as a result of an accident, if the central nervous system and some of the muscles driving the original limb are still present after the amputation, it can be expected that the EMG signal can be used to achieve a natural sensation of prosthetic control similar to that of the original limb.

However, due to the non-linear characteristics and large variability of the EMG signal, it is very difficult to achieve a high level of motor performance consistently, especially during rapid movements. The non-linear characteristics are caused by different muscles, as well as by variations in the signal source and recording electrode path. In addition, changes in EMG signals depend heavily on muscle fatigue, sweating and changes in electrode position. Some researchers such as Tsuji et al. have proposed a probabilistic neural network for the EMG pattern classification problem to improve back propagation learning. This network can improve the classification ability by learning to construct a statistical model of the EMG signal. However, the network does not take into account the time-varying characteristics of time-series EMG signals, so the classification performance may degrade with the non-stationarity of EMG signals.

Therefore, some researchers have proposed a new neural network for the pattern classification problem of time-series EMG signals. For time-series EEG signals, a pattern classification method using a network structure combining probabilistic neural network and recurrent neural network is proposed, which improves the classification ability by considering the time-varying characteristics of the neural system. In order to classify non-smooth EMG signals accurately, it is difficult to learn non-smooth EMG signals with one network alone for reasons such as local minima problems and classification accuracy problems. Therefore, the signal processing is divided into two parts: (1) pattern processing within each time interval, and (2) filtering based on the time course of the pattern sequence. Then, a network structure combining BPN and NF is proposed for these two parts. As a result, the whole process can be performed efficiently, although the structure can become quite complex. The proposed network is combined into two different neural networks:one is a normal back-propagation neural network and the other is a recursive neural filter. In addition, a terminal learning method was developed in order to regulate the convergence time and to make the learning process smoother. With this method, the dynamics of the energy function always converges steadily to the equilibrium point in finite time. In addition, the learning process of multiple networks can be synchronised. The convergence time is always less than a predetermined upper limit, which reduces the mental stress of the operator while waiting for convergence. Also, several subjects were selected to be tested using smooth/non-smooth EMG signals. This developed time series EMG signal can accurately predict the continuous motion of the operator and the operator's EMG signal can control the prosthetic hand, and the neural filter during the study can take into account the time history of the input signal to improve the classification accuracy. In particular, for non-smooth EMG signals, the classification rate was improved by 20 - 30% using this NF. In addition, the entropy value of the network output was defined, and misclassification was reduced by suspending classification of network outputs with high entropy

2.2 Interpretable artificial intelligence models and EMG signals

For people with disabilities, wearable prostheses are an optional safety device in which an EMG sensor is usually used, which predicts movement in a very short time. In general there are two different methods to record EMG signals: surface EMG (non-invasive) and intramuscular ECG (invasive), in comparison, the surface EMG signal sensor is an external safety device that simplifies the signal acquisition process. Assistive devices based on surface EMG signals can be used to improve the quality of daily life of unhealthy people. Orthoses are used to help people with weak joints move more easily, while prostheses are used to replace missing limbs. Electromechanical robotic devices include an instrument for signal measurement, a machine learning (ML) algorithm for recognising EMG patterns, and a mechanical frame for control. Although some signal conditioning systems and high level EMG signal acquisition devices are available, such as BIOPAC and BIONOMADX, they are expensive.Pradhan et al. proposed a two-channel EMG biopotential amplifier that captures EMG signals while performing seven gestures by deploying an INA128 instrumentation amplifier.Guo et al. developed a two-channel EMG biopotential amplifier by using an instrumentation amplifier (INA326) and an operational amplifier (AD8603) to smooth the raw signal, a four-channel EMG acquisition system was developed. However, the system was complicated by the fact that each channel required its own ADS8603 and INA326 for regulation. Pancholi and Joshi demonstrated signal recognition using EMG data by designing an 8-channel, low-cost data acquisition system.

Despite many successful applications, identifying leg activity with surface EMG signals remains a challenge due to the noisy nature of the signal. The prevalence of multiple artefacts, such as environmental noise, intrinsic noise and motion artefacts mixed together, makes it difficult to distinguish the actual surface EMG signal of the muscle from other artefacts. The use of new methods such as wavelet denoising, Wigner-Ville distribution and empirical mode decomposition (EMD) to effectively minimise these artefacts in surface EMG signals has recently been demonstrated in several studies.

There have been many attempts by researchers over a long period of time to use surface EMG signals to detect human activity. Li et al. investigated the recognition of nine different types of activity using surface EMG signal data recovered from the forearm. Using support vector machine and general regression neural network algorithms, the recognition rates were 98.64% and 96.27% respectively. This was done to achieve accuracy and control of the smart prosthesis. khemraj et al. used convolutional neural networks, k-nearest neighbour classifiers and support vector machines to classify various lower limb activities. In this experiment, a large number of healthy individuals were invited to participate in a series of tasks to collect data from accelerometer and gyroscope sensors.Gautam et al developed a unique classification method that considers lower limb motion when calculating prognosis for knee angles.Naik et al used independent component analysis (ICA)-entropy limit minimisation (EBM) to classify healthy and knee deformity patients with three different Lower limb movements were classified by approximating the entropy of a large range of distributions by EBM and decomposing the surface EMG signal using ICA.

However, machine learning performance is improved by increasing the complexity of the model, and machine learning algorithms do not provide interpretable AI models, which are generally difficult to trust for accuracy. While the motivation for predictive modelling is to improve model performance, the lack of interpretability means that the models are inadequate for qualitative evaluation of their intended tasks, so some researchers are now focusing on 'interpretable AI'. For example, Ankit Vijayvargiya et al. have used the ESP32-Wroom-32 module connected to the output of two MyoWare muscle sensors (a two-channel system), a low-cost python-based channel data acquisition system that can be used to measure EMG signals on the surface of lower limb muscles in five different scenarios. Test data from test subjects of varying degrees of health and gender were collected, signal denoising and segmentation based on WD-EEMD, feature extraction and classification from the surface EMG signal data using an overlapping window approach, quantitative evaluation of algorithm performance and predictive analysis using an easily interpretable XAI model. This predictive model uses a complex model to predict new data by disrupting existing samples, calculating the difference between the alignment and the original data, selecting the best features of the complex model results obtained from the aligned data, fitting a simple model to the aligned data using the features selected in the previous step and the similarity score as weights, and explaining the local behaviour of the complex model using the feature weights of the simplest model.

In addition, most analyses of EMG signal maps are based on discrete models that have been used for training, which are inadequate for the relatively dexterous manipulative movements of robotic prostheses. For example, HyunIn Lee et al. designed experiments to record training data and test data from subjects and processed the data accordingly, trained three different neural network models, compared their effects, and proposed a post-training attention matrix interpretation model to achieve an interpretation of the correspondence between finger muscle flexion angle and EMG signals.

2.3 Deep learning and electromyographic signals

Artificial intelligence has been developing rapidly for a long time and some scholars such as Bengio, Arel, Goodfellow and Schmidhuber have applied AI and deep learning to most fields. In the deep learning research community scholar Krizhevsky achieved a breakthrough when he first introduced AlexNet to solve the ImageNet classification challenge in 2012. Deep learning is capable of solving complex problems with high accuracy. It is helping researchers discover more salient hidden information in big data with higher accuracy. sapsanis (2013) used surface EMG signals based on empirical pattern decomposition to classify basic hand movements. bitzer et al. (2006) added a support vector machine (SVM) based method which can detect finger opening and closing movements. Reference (Kim et al 2019) attempted to find a relationship between hand force output and surface EMG signals. Their algorithm is based on tensor algebra and is able to accurately predict grasp force using surface EMG signals. In another study, the authors highlight that haptic feedback may allow for better interaction in controlling and manipulating a robotic hand (Li et al 2018,2017). Kayabasi et al (2018) compared the performance of artificial neural networks (ANNs) and extreme learning machines (ELMs) on an epimyographic signal dataset and concluded that ELMs may be a better option than using ANNs to quickly and accurately analyse responses.

Both robotic and prosthetic hands are used in the intelligent robotics industry to perform human-like physical functions, which can improve their dexterity and maneuverability and have been studied by a number of scholars.Ouyang et al. (2014) used an adaptive neuro-fuzzy interference system to classify four hand motions.Ju (2014) proposed a fuzzy Gaussian mixture model to classify 10 hand motions. Kakoty and Hazarika (2011) classified six hand movements using a support vector machine based on a radial basis function kernel.Khezri and Jahed (2008) used a wavelet thresholding approach to classify three hand movements.Akben (2017) used consistent correlation values for feature extraction and a cascaded structural classifier to classify six hand movements. ruangpaisarn and Jaiy (2015) used different classifiers such as radial basis function, k-nearest neighbour, decision tree, sequential minimum optimization and plain Bayes to classify six different hand movements. nishad et al. (2019) used Kraskov entropy for feature extraction and k-NN classifier to classify hand movements.

Most of the aforementioned studies have used traditional machine learning methods and more electrodes to analyse surface EMG signals. As it takes more time to adopt manual feature extraction methods, some researchers have started to use deep learning models, such as Musab Cosku et al. proposed a new 1D-CNN model that automatically extracts features from surface EMG signals for the classification of handgrip types. A model for non-manual extraction of surface EMG signals based on an 11-layer complete end-to-end 1D neural network is proposed, where the first layer of the model contains the original EMG signal. The convolutional layer follows the input layer and performs convolutional operations on the input data with 3 step intervals and 32 3-element filters. Feature maps of the input data are generated after the convolution process. The 2-cell region on these feature maps is reduced to the maximum value of the MaxPooling layer. As a result, the size of the feature maps is reduced and determined by the stride and pooling size values. the Dropout layer is used to prevent overfitting by ignoring certain units in the training phase for a certain group of randomly selected neurons. Dimensional transformations are performed in the flattening layer to be able to process the attributes in the previous layers in the dense layer. softmax layer is the final layer of the model and completes the classification process of the model. In this layer, the input surface EMG signal data is classified as spherical, tip, palmar, lateral, cylindrical and hooked. The classification is also performed using a softmax classifier. The classification process is performed on the overt surface EMG signals of the basic hand movement dataset. This dataset uses only two electrodes to acquire surface EMG signal data. Based on this a novel and cost effective robotic prosthetic hand can be designed using only one channel of data.

3 Summary

In conclusion, recent research on artificial intelligence in the decomposition of EMG signals has yielded good results, such as the use of different neural networks to classify non-smooth EMG signals in the case of continuous motion, such as the use of interpretable artificial intelligence to establish reliable predictive modelling results for EMG signals, such as efficient multi-tiring classification of EMG signals using single channel data through deep learning. In the future, machine learning and muscle signals can be combined to solve existing problems regarding prosthetic dexterity, using machine learning algorithms to help implement translation of human signals to prosthetic commands, etc.

[Reference]

[1] Toshio Tsuji, Osamu Fukuda, Makoto Kaneko, Koji Ito. Pattern classification of time-series EMG signals using neural networks. IEEE Control Signal Process. 2000; 14:829-848

[2] Ankit Vijay vargiya, Puneet Singh, Rajesh Kumar, Nilanjan Dey. Hardware Implementation for Lower Limb Surface EMG Measurement and Analysis Using Explainable AI for Activity Recognition. TRANSACTIONS ON INSTRUMENTATION AND MEASUREMENT, VOL. 71, 2022

[3] J. Li et al. ”Using body sensor network to measure the effect of rehabilitation therapy on improvement of lower limb motor function in children with spastic diplegia,” IEEE Trans. Instrum. Meas., vol. 69, no. 11, pp. 9215-9227, Nov. 2020.

[4] P. K. Shukla, A. Vijayvargiya, and R. Kumar, ”Human activity recognition using accelerometer and gyroscope data from smartphones, ” in Proc. Int. Conf. Emerg. Trends Commun., Control Comput.(ICONC), Feb. 2020, pp. 1-6.

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[6] A. Gautam, M. Panwar, D. Biswas, and A. Acharyya, ”MyoNet: A transfer-learning-based LRCN for lower limb movement recognition and knee joint angle prediction for remote monitoring of rehabilitation progress from sEMG,” IEEE J. Transl. Eng. Health Med. vol. 8, pp. 1-10, 2020. -10, 2020.

[7] G. R. Naik et al. ”An ICA-EBM-based sEMG classifier for recognizing lower limb movements in individuals with and without knee pathology,” IEEE Trans. Neural Syst. Rehabil. Eng. vol. 26, no. 3, pp. 675-686, Jan. 2018.

[8] Musab Coskun, Ozal Yildirim, Yakup Demir3, Rajendra Acharya. Efcient deep neural network model for classifcation of grasp types using sEMG signals. Journal of Ambient Intelligence and Humanized Computing (2022) 13:4437-4450

[9] Arel I, Rose DC, Karnowski TP. Deep machine learning-a new frontier in artifcial intelligence research IEEE Comput. Intell Mag 5(4):13 -18

[10] Bengio Y. Learning deep architectures for AI Foundations and trends in Machine. Learning 2(1):1-127. https://doi.org/10.1561/ 2200000006

[11] Goodfellow I, Bengio Y, Courville. A Deep Learning Book in preparation for MIT Press

[12] Schmidhuber J. Deep learning in neural networks: an overview. Neural Network 61:85-117

[13] Krizhevsky A, Sutskever I, Hinton GE. ImageNet classifcation with deep convolutional neural networks. adv Neural Inf Process Syst 25:1 -9

[14] Sapsanis C, Georgoulas G, Tzes A, Lymberopoulos D. Improving EMG based classifcation of basic hand movements using EMD. In: 35th annual international conference of the IEEE engineering in medicine and biology society (EMBC), Osaka, pp. 5754-5757

[15] Bitzer S, van der Smagt P. Learning EMG control of a robotic hand: towards active prostheses. in: Proceedings 2006 IEEE international conference on robotics and automation, 2006. ICRA 2006, Orlando, FL, pp. 2819-2823

[16] Kim S, Kim J, Kim M, Kim S, Park J (2019) Grasping force estimation by sEMG signals and arm posture: tensor decomposition approach. J Bionic Eng 16(3): 455-467

[17] Kayabasi A, Yildiz B, Aslan M F, Durdu A. Comparison of ELM and ANN on EMG signals obtained for control of robotic-hand. in: 10th international conference on electronics, computers and artifcial intelligence (ECAI), Iasi, Romania pp. 1-5