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REVIEW ON DEEP LEARNING APPROACHES TO THE CONTROL OF PROSTHETIC HANDS WITH ELECTROMYOGRAPHY SIGNALS

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ABSTRACT Natural control methods based on surface electromyography (sEMG) and pattern recognition are promising for hand prosthetics. Several efforts have been carried out to enhance dexterous hand prosthesis control by impaired individuals. However, the control robustness offered by scientific research is still not sufficient for many real life applications, and commercial prostheses are capable of offering natural control for only a few movements. This paper reviews various papers on deep learning approaches to the control of prosthetic hands with EMG signals and made a comparison on their accuracy.

KEYWORDS :

INTRODUCTION

The hand is one of the most complex and beautiful pieces of natural engineering in the human body. It gives us a powerful grip but also allows us to manipulate small objects with great precision. This versatility sets us apart from every other creature on the planet. Its loss not only causes physical illness but also it badly affects the mental state of the amputee. The studies in [1] [2] shows that the upper limb amputees in European states ranges from 50 to 270 per year. Upper limb amputation is mainly caused by cancer, trauma and also due to vascular complications of diseases.

In the past few years, there has been a tremendous increase in the controlling of artificial limbs. Expectations of upper limb prostheses have always been high because of the standard established by able-body dexterity. The two methods of upper limb prostheses that commercially available are either body-powered or electrical motor powered. The latter are controlled using electrical signals that are actually created by the body muscles. Specifically, these prosthetics works by using patient's existing muscles in their residual limb to control the functions of the prosthetic device itself. A sensor will be placed within the device which is able to (i) obtain electrical signals from the muscles, (ii) translate those signals into movements and (iii) execute the demand properly. The former method relies on the system of cables or harnesses (along with manual controls, in many cases) to control the limb itself. Essentially, the patient operates and controls the prosthetic arm using other parts of the body, such as shoulders, elbows or chest. Electrical motor powered prostheses method can be a great option for those who want a natural-looking prosthesis that utilizes existing nerves for functional use. But, this upper limb prosthesis tends to be more expensive than a body powered prosthesis, and it can take a longer adjustment period to become familiar to the body. Furthermore, the power source that operates the prosthesis does need to be charged regularly or may need battery replacement on occasion. For many patients, body-powered prostheses are practical option because they tend to be more affordable and do not rely on an outside power source to operate.

From the early 1960s, pattern recognition-based classification techniques started to attract the interest of research community working on controlling artificial limbs. The field of pattern recognition is concerned with the automatic discovery of regularities in data through the use of computer algorithms and with the use of these regularities to take actions such as classifying the data into different categories. Pattern recognition based control approach overcomes the drawbacks of conventional control mode of not able to reliably control multiple functions. This approach promises to deliver multifunction control of a myoelectric prosthesis. Pattern recognition based prosthetic control approach has usually four stages:

(i) EMG measurement
(ii) Feature extraction
(iii) Classification
(iv) Multifunctional prosthesis control

i.e., firstly the system captures many reliable myoelectric signals then retains the most important discriminating information from the measured EMG signals on which the classification is performed to predict one of the subset of intended movements which is then finally to implement the prosthetic operation of the predicted class of movement. However, it is a challenge to evaluate the real-time control performance of EMG pattern recognition based prostheses mainly in cases where there are unavailable multifunctional prosthetic systems. Currently, there is no any multifunctional myoelectric prosthesis system available for clinical use. Therefore the primary limitation of this approach may be lack of reliability and stability of current pattern recognition control. This has substantially hindered the technique from getting clinical applications.

Researchers have proposed various methods for controlling upper limb prostheses. But, a huge gap possessed between expected functionality and current state-of-the-art. Thus, controlling prosthetic hands seems to be an open challenge. Electric potential in the muscle cell and the nerves cell are highly correlated. Thus an EMG electrode reads electric potential which is generated in the muscle fibers when they contract. Surface electromyography (sEMG) and intramuscular electromyography (imEMG) are two types of EMG sensors. Even though the signal-to-noise ratios of imEMG are excellent to sEMG, those sensors are intrusive, painful, uncomfortable and also difficult to set up. Hence, we prefer sEMG over imEMG in this paper. sEMG signals are measured by placing electrodes on the surface of the skin just above the target muscles. They typically use silver electrodes. sEMG signals can get easily lost in the environmental noise as these signals have low signal to noise ratio. Therefore, in real time applications these signals need to be amplified to be able to read with the analog to digital converters (ADC).

METHOD

In this section, a method is proposed to control prosthetic hands with EMG signals in detail. Here, we proposed a novel method. The processes involved in the traditional method are preprocessing, feature extraction, dimension reduction and a classifier. But, in this proposed method, there is only a single novel convolutional neural network. This neural network takes raw EMG data as input.

The block diagram of the system that consists of a novel convolutional neural network is shown in fig. 1. This block diagram includes a FIFO memory, an aggregation unit and a look-up table.

First-in-first-out or FIFO in short are commonly used for buffering and flow control between hardware and software. In its hardware form, a FIFO primarily consists of a set of read and writes pointers, storage and control logic. Storage may be static random access memory (SRAM), flip-flops latches or any other suitable form of storage. The use of aggregation units avoids the need to aggregate all positions across the firm. Aggregation units are required to be supported by the following practices: A plan that identifies each unit, specifying its trading objectives, and supporting its separate identity. A look-up table is an array that replaces runtime computation with a simpler array indexing operation. The savings in processing time can be significant, because retrieving a value from memory is often faster than carrying out an "expensive" computation or input/output operation.

In this proposed method, we've obtained the data from an array of eight linearly spaced sensors regardless of their positioning relative to the muscle groups. Each sensor of this array captures signals from multiple muscles simultaneously. This is due to the fact that, when the sensors are exactly positioned above the targeted muscle, the accuracy from signals that captured from non-targeted muscles is close to the accuracy along with proper signal processing techniques and pattern recognition systems. Therefore, this method is more efficient, convenient and easy to implement for amputees for their repeated uses.

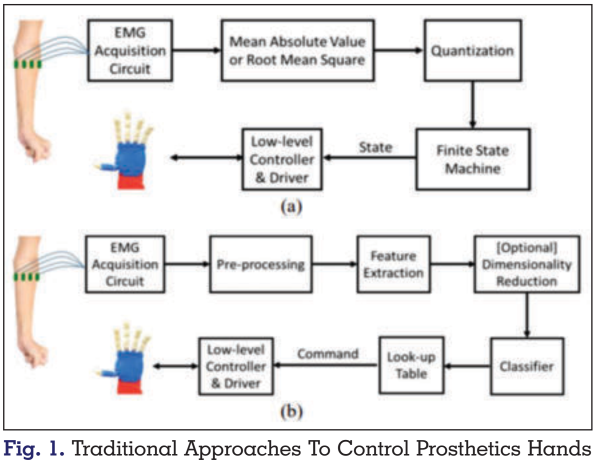

Fig. 1. Traditional Approaches To Control Prosthetics Hands With Emg Signals (a) Using Finite-state Machine And (b) Using Signal Processing And Pattern Recognition Methods.

A novel end-to-end network is developed for estimating the hand gesture class directly from raw EMG data. This is called novel because, it doesn't use any preprocessing subsystem and spectrograms. This method made use of 1-D convolutional layers. This method was not able to train very deep neural networks, i.e., it has access only to a limited number of datasets. In short, this method can train not more than 10 layers. The proposed network is shown in fig.2. It consists of 6 convolutional layers and 2 dense layers. There are 8 vectors in the input network, while each vector contains 200 elements. The number 200 stands for the sampled data points when the sliding window is 0.1s and the sampling rate is 2000 samples per second. One hot-encoding is performed in this method. So, the output of the network is a vector with number of element equal to the number of class. SoftMax is the activation function used in the last layer.

The initial step is selecting of the EMG dataset. The dataset used in this method consists of 8 subjects, with 3 repetitions of 15 hand positions. Each repetition is prolonged for 20s. Therefore, in total there are 45 data for each subject. Data from 2 subjects out of 8 subjects are used for testing and all the 3 repetitions from these 2 subjects were placed in the test set. Remaining 6 subjects are used for training and validation. Out of the 3 repetitions of each movement, 2 repetitions were chosen and placed into the training set, while the remaining repetition was placed in the validation set. The input of the proposed CNN is EMG measurement for 100ms time window. The window slides every 10ms. This dataset is chosen because it uses 8 dry, linearly and evenly spaced sensor arrangements and data are collected at a higher frequency of 4000 sample per second. Then this data is down-sampled to 2000 samples per second by jumping and not preprocessing. The second step is to select a high-performance GPGPU for training the networks. NVIDIA Tesla V100 GPGPU is chosen training data in this method. Therefore, we used V100 compute nodes in the Maverick2 at the Texas Advanced Computing Center (TACC), The University of Texas at Austin, Austin, TX, USA. The third step is selecting an appropriate developer kit which is required to communicate with the devices that drive the prosthetic hands. The proposed convolutional neural network was implemented in Python 3.5 using the TensorFlow library.

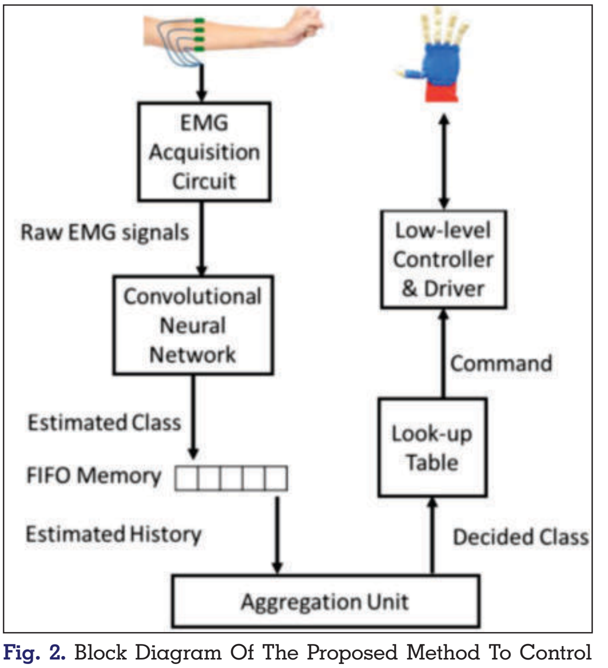

Fig. 2. Block Diagram Of The Proposed Method To Control Prosthetics Hands With Raw EMG Signals Using A Convolutional Neural Network.

In Atzori et al [3], convolutional neural networks is applied to the classification of 50 hand movements in 67 intact subjects and 11 transradial hand amputees. This work made use of NinaPro datasets. A comparison between the results of proposed method and those obtained with classical machine learning methods on three NinaPro datasets are done. NinaPro database is particularly useful for this analysis this is because it provides publicly available data and reference classification performances with classical machine learning procedures.

The total analyzed data includes EMG of hand movements of 78 subjects consists of 11 transradial amputees and 67 intact subjects. This total data is divided into three datasets. Dataset 1 includes data acquisitions of 27 intact subjects of 2 left handed and 25 right handed from 7 females and 20 males of age 28 ± 3.4 years. Dataset 2 includes data acquisitions of 40 intact subjects of 6 left and 34 right-handed from 12 females and 28 males of age 29.9 ± 3.9 years. Dataset 3 includes data acquisitions of 1 left and 10 right-handed from 11 males of age 42.36 ± 11.96 years. Several repetitions of entire acquisition protocol have done. Particularly, dataset 1 is repeated for 10 times while dataset 2 and dataset 3 is repeated for 6 times. Muscle activity is recorded using two types of double differential sEMG electrodes. 10 OttoBock MyoBock 13E200-50 (Otto Bock HealthCare GmbH) is used for dataset 1 which were fixed on the forearm using an elastic armband while dataset 2 and 3 are recorded using 12 electrodes from a Delsys Trigno Wireless System which were fixed on the forearm using their standard adhesive bands and a hypoallergenic elastic latex-free band.

The results show that convolutional neural networks with a very simple architecture are comparable to the average machine learning classification methods and also show that several factors are fundamental for the analysis of sEMG data. The average results are comparable to the average results obtained with the reference classical classification, but lower than the results obtained with the best classical classification techniques.

Table 1: The Average Classification Accuracy Obtained Using Three Methods On Three Datasets.

	Using convolutional neural network	Using all classical methods	Using the best classical classification method
Dataset 1	66.59 ± 6.40%	62.06 ± 6.07%	75.32 ± 5.69%
Dataset 2	60.27 ± 7.7%	60.28 ± 6.51%	75.27 ± 7.89%
Dataset 3	38.09 ± 14.29%	38.82 ± 11.99%	46.27 ± 7.89%

Zhai et al. [4] proposed a CNN based classifier for short latency hand movement classification using sEMG spectrogram as feature. Then, a self-recalibrating CNN classification system is investigated. This classification system is continuously fine-tuned using prediction results from recent testing session after processed through a label correction mechanism. NinaPro database is used for this study. The NinaPro Database2 (DB2) contains sEMG data recordings from 40 intact subjects. Each subject is required to perform 49 types of hand movement including 8 isometric and isotonic hand configurations; 9 basic wrist movements; 23 grasping and functional movements and 9 force patterns. Each movement was repeated 6 times with a 3 s rest in between. The 12-channel sEMG signal was sampled at 2,000 Hz and filtered with a Hampel filter to remove 50 Hz power line interference. NinaPro Database 3 (DB3) comprises data of 11 trans-radial amputated subjects with disabilities of the arm, shoulder and hand (DASH) scores ranging from 1.67 to 86.67 (scale 0–100) performing the same 50 hand movements as the intact subject. sEMG signals are sectioned into 200 ms (400 samples) segments with 100 ms (200 samples) increments. The spectrogram for each segment of each channel is computed using a 256-point fast Fourier transform (FFT) with a Hamming window and 184-point overlap. Thus, each segment results in a spectrogram calculated at 129 different frequencies (0–1,000 Hz) with 3 time bins. To improve computational efficiency and performance, the normalized spectrogram matrices are vectorized channel by channel and then apply PCA to it. The proposed CNN model contains 1 convolutionl layer (Conv Layer), 2 fully connected layers (FC Layers) with dropout and a softmax loss layer. The softmax loss layer computes the cost function using the normalized exponential function. It also outputs the probabilities of all movement types considered in the current prediction. Each layer is trained by back-propagation. An open source MATLAB toolbox MatConvNet was used to implement the CNN classifier (Vedaldi and Lenc, 2015). Before inputting into the CNN, the resultant vectors of PC scores are first rearranged in to a 2D matrix such that, for each channel, the 25 × 1 vector becomes a 5 × 5 matrix. In this way, each of the sEMG segments is treated like a 2D image and the 12 channels mimic the RGB channels in a color image. The dropout method was applied to reduce over-fitting (Hinton et al., 2012b). In each training echo, 50% of the neurons in the fully connected layers will be randomly dropped from error propagation and weight update.

Cote-Allard et al. [5] proposes leveraging inter-user data using transfer learning on a Convolutional Neural Network (CNN) to introduce a more accurate classifier. For this study, two set of datasets are used. First set of dataset comprises of 18 able-bodied subjects, each performing one round of seven gestures for 20s long. The second set of dataset or the evaluation dataset includes 17 healthy, able-bodied subjects, those performing three rounds of seven gestures for 20s long. First among the three rounds serves as training/validation set while the remaining two rounds are test set. Data acquisition was approved by the Laval University Ethics committee (approbation number: 2017-026/21-02-2016) and written informed consent was obtained from all subjects. A Myo Armband is used for recording each subject's forearm electromyography. It is a low cost, 8-channel, dry electrode, consumer grade sEMG device with low sampling rate of 200 Hz. The armband will be tightened to its maximum and slid up the user's forearm until the circumference of the armband matched that of the forearm. Input latency is an important factor to consider for real-time control in a closed loop. [6] recommends a maximum time latency of 300ms while [7] suggest that latency should be keep between 100-125 ms. Pre-processing is reduced into simply calculating the spectrograms of the raw sEMG data. Spectrograms are particularly well suited to capture non-stationary signals as is the case with the sEMG data. For each of the eight channels of the armband, 52 samples (260 ms) per spectrograms are leveraged using Hann windows of 28 points per FFT and an overlap of 20. This yields a matrix of 8x4x15 (Channels x Time bins x Frequency bins). The axes are then rearranged to be 4x8x15 in order to be suitable to be fed to the CNN. Finally, to reduce baseline drift and motion artifact, the lowest frequency bin is removed. The final generated matrix is thus of shape 4x8x14. The non-linear activation function is the parametric rectified linear unit (PReLU) [8] and ADAM [9] is employed for the optimization of the CNN. The deactivation rate for MC Dropout is set at 0.65 and was found using cross validation on the pre-training set. Finally, to further avoid over-fitting, early stopping is utilized by saving 10% of the training data which is randomly chosen at the beginning of the training in order to periodically test the network. The proposed classifier was shown to be robust enough to control a 6 DoF robotic arm with the same speed and precision as with a joystick. Additionally, the target network yielded an average accuracy of 97.81% on the evaluation dataset when trained on 4 cycles.

Table 2: Comparison Between Convolutional Neural Network And Other Methods

Method	sensors	Length (ms)	Input	Accuracy
Atzori et al. [36]	12	150	Pre-processed	70%
Zhai et al. [37]	12	200	Pre-processed	78%
Cote-Allard et al. [38]	8	260	Spectrogram	97.81%
Proposed CNN	8	100	Raw	91.26%

CONCLUSION

In this paper, we reviewed various deep learning techniques to control hand prostheses using EMG signals. Accuracy between all methods is verified. Methods using spectrogram best results than those using preprocessing. While the proposed CNN method gives better results than preprocessed techniques but lower than spectrogram based method. This method is easy to implement and less complex compared to others.

The proposed post-processing subsystem makes our system error-free. In the future, first, we will collect more EMG data from many people. After that, we will be able to study deeper neural networks. The low-test accuracy (48.40%) can be addressed by a higher amount of data. Then, we will compare recurrent neural networks with the proposed post-processing subsystem. The main disadvantage of the proposed method is that it is limited to a finite number of hand gestures. In the future, we will study deep imitation learning and deep reinforcement learning to address continues control of prosthetic hands with EMG signals.

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