Feasibility of NeuCube Spiking Neural Network Architecture for EMG Pattern Recognition

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***Abstract*—Multichannel electromyography (EMG) signals have been used as human-machine interface (HMI) for the control of pattern-recognition based prosthetic system in recent years. This paper is a feasibility analysis of using recently proposed NeuCube spiking neural network (SNN) architecture for a 6-class recognition problem of hand motions. NeuCube is an integrated environment, which uses SNN reservoir and dynamic evolving SNN classifier. NeuCbube has the advantage of processing complex spatio-temporal data. The preliminary experiments show that Neucube is more efficient for EMG classification than commonly used machine learning techniques since it achieves better accuracy as well as consistent classification outcomes. The performance of NeuCube combined with TD features reaches up to 95.33% accuracy after a careful selection of the features. This paper demonstrates that NeuCube has the potential to be employed in practical applications of myoelectric control.**

Keywords—NeuCube architecture; spiking neural network; EMG; pattern recognition; hand motions

I. INTRODUCTION

The EMG signals, resulting from motor neuron impulses that activate the muscle fibers, can be correlated with the force produced by muscles [1]. The use of EMG signals is not only beneficial in medical diagnoses, but can also be helpful in controlling robot systems or prostheses.

To control multifunction prostheses, it is necessary to map the representative features extracted from the surface EMG to classes that represent different motions. This control strategy is mostly based on the pattern recognition approach. The feature extraction and classification portions of the pattern recognition system have been the subject of extensive research.

Some commonly investigated features include time-domain (TD) features [2], autoregressive (AR) coefficients [3], concatenated TD and AR (TD+AR) features [4], the short-time Fourier transform (STFT) [5], the wavelet transform (WT) [6], and the wavelet packet transform (WPT) [7]. Most modern classification methods also have been investigated such as Bayesian classifiers [8], artificial neural networks [3], Gaussian mixture models [9], hidden Markov models [10], fuzzy logic [11], multilayer perceptron (MLP) [12], and support vector machine [13].

However, current classifiers can only process temporal data, without considering the spatial structure of the data. Raw data usually need to remove noise firstly to achieve better accuracy. NeuCube is a 3-D spiking neural network (SNN) reservoir that specifically deals with spatio-temporal data proposed by N. Kasabov [14], [15]. It is an approximate map of human brain with its neurons assigned to particular locations based on brain coordinate systems. A SNN reservoir of 1000 (10 x 10 x 10) neurons is shown in Fig. 1. The size of the SNN reservoir can vary depending on the task and the data. It is capable of learning noisy data either on-line or with low amounts of training. These two main advantages make it useful to classification problems.

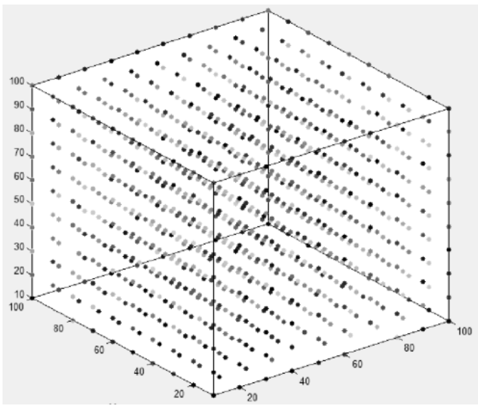

Fig. 1. A spiking neural network reservoir of 1000 neurons. [16]

In this study, the spatial structure of EMG data is considered, which is very different from previous work. As the EMG signals are generated from motor neuron impulses that activate the muscle fibers, it can be investigated whether connections between motor neurons are strengthened or weakened, and how the connections as well as neuron spiking activities change from random initialization to a stable pattern during training on a particular dataset through NeuCube.

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The accuracy of EMG recognition algorithm is also affected by the selection of EMG features. The features used in this study include both TD features and frequency-domain (FD) features. The performance of NeuCube combined with TD features reaches up to 95.33% accuracy after a careful selection of the features.

The remainder of this paper is organized as follows: Section II describes the structure of EMG acquisition device and experimental protocol. In Section III, the algorithms for EMG pattern recognition are proposed, including EMG signal processing, feature extraction, and the classifier description. In Section IV, the experimental results show that NeuCube has a good performance for EMG pattern recognition. Finally, Section V draws the conclusion and gives some future work.

II. EXPERIMENTAL PROTOCOL

An eight-channel EMG acquisition device has been developed at our laboratory, whose structure is indicated in Fig. 2. It consists of an amplifier, a linear isolation circuit and an analog/digital (A/D) converter. The amplifier employs differential-mode input with differential-mode amplification of 1000. The linear isolation circuit is used to achieve electrical isolation between the amplifier and the A/D converter. The analog EMG signal is sampled at 2048Hz and digitized with 12-bit conversion resolution using the A/D converter. The effective frequency band of EMG signal is distributed within 10-500 Hz, mostly within the range of 50-150 Hz. This device has designed with a 50 Hz notch filter and a 20-200 Hz band-pass filter in hardware, so as to remove most of the signal artifacts while retaining the information within the signals. After converted to digital signals, the raw EMG signals are transmitted to a PC for the following signal processing for pattern recognition.

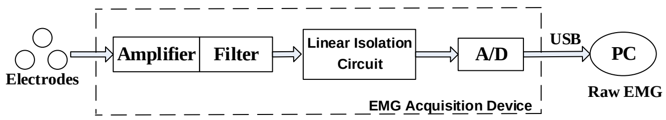


Fig. 2. Structure of EMG Acquisition Device.

One intact-limbed subject (male; 26 yrs) participates in the experiment. The experiment focuses on 6-class patterns shown in Fig. 3, which are hand grasp, hand open, wrist flexion, wrist extension, ulnar deviation, and radial deviation.

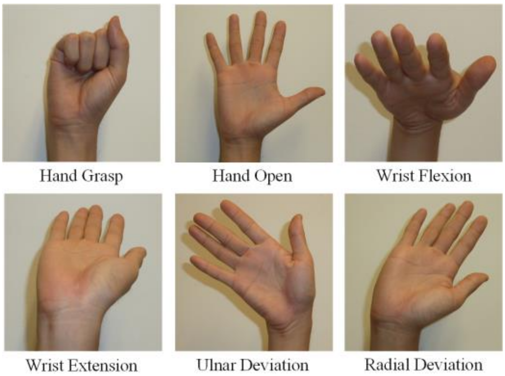


Fig. 3. The six classes of motion used in the experiment.

In this study, EMG signals are acquired from four muscles after a careful selection of relevant muscles coherently with the intended motions, which are flexor carpi radialis, extensor carpi ulnaris, extensor pollicis brevis, and flexor digitorum superficialis.

Most previous researches did a preparation work before placing electrodes, such as shaving and cleaning the skin surface, to reduce the input resistance and the external disturbance [17, 18]. Although this preparation work is beneficial to data acquisition, it confines the practicability of the classification method. So in this study, the electrodes are adhered to muscle surface directly without any disposal. Four pairs of Ag/AgCl electrodes are employed to measure the analog EMG signals. At each recording site, the electrodes are arranged in a differential configuration over the muscle belly and separated from each other by 2cm [19].

In the experimental session, the subject is instructed to perform 50 contractions per class. Each contraction is 2 s in duration, with a 2 s resting period between consecutive contractions. Stationary signals are acquired during each contraction. The order of motions is randomized and 300 contractions are performed by each subject totally.

III. PATTERN RECOGNITION METHODOLOGY

A. System flow chart

Fig. 4 shows the main steps of the pattern recognition system. The data processing, feature extraction and classification portions of the pattern recognition system have been the subject of extensive research. These three portions will be described in detail below.

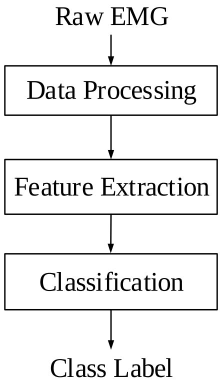


Fig. 4. Flowchart of the procedure for motion pattern recognition.

B. EMG signal processing

The raw EMG signal processing includes eliminating the signal offset and data windowing. Smoothing is not applied in this study so as to reduce the delay of signals. Before data windowing, the signal offset is subtracted from the signal in each channel. The offset is approximate equal to the resting state value of the baseline signal.

In order to perform a continuous classification, the classifier acts upon a sliding window of data, producing a class decision (an estimate of the intended motion) from each window. In this study, a 128-sample data analysis window (corresponding to 62.5 ms) is employed to extract features. Consequently, the offset-removed data are segmented in 128-sample windows, with an overlap of 64 samples between two consecutive windows. Hence, there is a 64-sample delay between two consecutive windows. The classification is performed for each window. These choices make the response time much less than 300 ms, which is widely used as an acceptable delay for a real-time myoelectric control system [20].

C. *TD and FD feature extraction*

TD and FD features were both employed in this study. These features were extracted within the 128-sample data analysis window. TD features include the mean absolute value (MAV), waveform length (WL), variance (VAR), and AR coefficients. FD features include the power spectrum (PS) and WT coefficients.

MAV represents the absolute mean amplitude of EMG signal and it is a direct reflection of muscle contraction level. WL provides a measure of the complexity of the signal. It is defined as the cumulative length of the EMG signal within the analysis window. VAR is the measure of the EMG signal's power, which uses the mean value of the square of the deviation of that variable in statistics. Mathematical definitions of these features are given by

$$MAV = \frac{1}{N}\sum_{k=1}^{N}|x_k| \tag{1}$$

$$WL = \sum_{k=1}^{N}|\Delta x_k| \quad where\ \Delta x_k = x_k - x_{k-1} \tag{2}$$

$$VAR = \frac{1}{N-1}\sum_{k=1}^{N}x_k^2 \tag{3}$$

where x_k is the *k*th sample of EMG signals in the analysis window, N is the length of the data analysis window.

The AR feature models individual EMG signals as a linear autoregressive time series and provides information about the muscle's contraction state [21]. It is defined as

$$x_k = \sum_{i=1}^{\rho}\alpha_i x_{k-i} + \xi_k \tag{4}$$

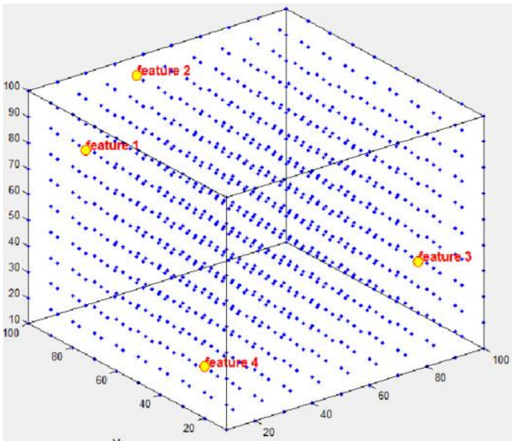
where α_i represents autoregressive coefficients, ρ is the AR model order, and ξ_k is the residual white noise [22]. A 4th-order AR model is employed in this study to extract AR coefficients.

The choice of the mother wavelet is critical in signal processing, and several standard wavelets are tested to determine which wavelet produces best detection result. In preliminary studies, the Daubechies wavelet shows a better result amongst the Daubechies, Coiflet and Symmlet wavelets, and thus it is selected as the mother wavelet. The "approximation" coefficients of wavelet decomposition retain the important signal characteristics and store the main energy of the signal, which is used as the frequency-domain (FD) feature in this study using Daubechies wavelet of order 5 at level 3.

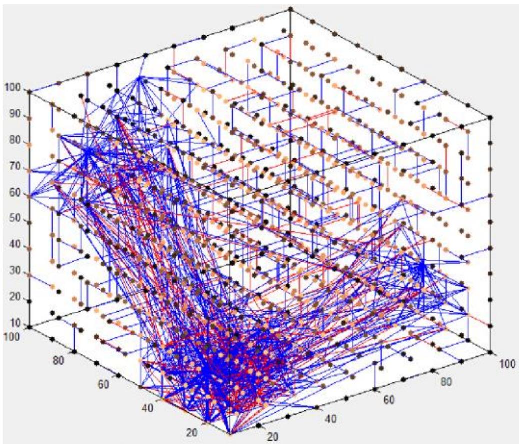
D. *Classifier description*

Each neuron in NeuCube belongs to a specific functional and structural area as in a human brain according to its (x, y, z) coordinates. NeuCube was initially for processing brain data such as EEG data and functional magnetic resonance imaging (fMRI) data. While EMG data are generated from motor neuron impulses, the connections of relevant motor neurons during hand motions may be strengthened or weakened. NeuCube maybe can explore how the connections change from random initialization to a stable pattern.

Fig. 5(a) shows the location of EMG acquisition sites in NeuCube. Fig. 5(b) shows the connections between neurons and the weight adjustment during training. This is very different from traditional methods, which offers facilities to trace the learning process for the sake of data understanding. After training, the SNN reservoir has captured spatial and temporal relationships from the data.



(a)



(b)

Fig. 5. Snapshots from a dynamic visualization of a SNN reservoir: (a) Initialization of neuron states; (b) Neuron connections change during training.

IV. RESULTS AND DISCUSSION

Classification accuracy is used as the main index to show the performance of EMG pattern recognition.

The 3-fold cross-validation procedure is applied to each combination of feature set and classifier. Original EMG datasets are randomly partitioned into 3 equal size sub-datasets. In each fold, a single sub-dataset is retained as testing data and the remaining 2 sub-datasets are used as training data for the classification model. Each classification accuracy is produced by averaging across the cross-validation results.

Table I shows the classification accuracy ranging from 68.7-95.3%. It is clear from the results that the (MAV+WL) features performed significantly better than the other features with the highest overall accuracy. Moreover, MAV and WL are both time-domain features and they are easily real-time processed with lower time-consumption.

TABLE I. COMPARISON OF OVERALL ACCURACY USING DIFFERENT FEATURES WITH NEUCUBE

	Features	Overall Accuracy (%)
Time-Domain	Raw Data	68.7
	MAV	90.7
	WL	91.3
	VAR	78.7
	AR	88.6
	MAV+WL	**95.3**
Frequency-Domain	PS	76.0
	WT	78.0

In terms of the comparison with other classification approaches, NeuCube is compared to some popular machine learning methods: multiple linear regression (MLR), support vector machine (SVM), and multilayer perceptron (MLP). The SVM method uses a polynomial kernel; the MLP method uses 30 hidden nodes with 1000 iterations for training. The overall accuracy of each method with the MAV feature is shown in Fig. 6.

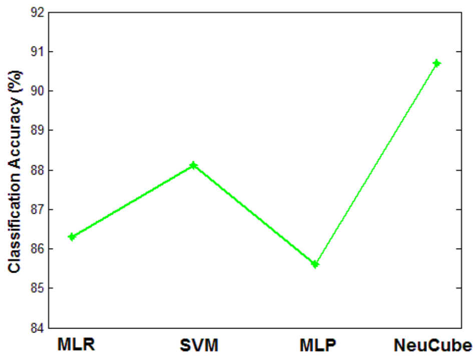


Fig. 6. Comparison of different classifiers when using MAV feature.

It can be determined that NeuCube achieves the highest overall accuracy of 90.7% when using MAV feature for the 6-class recognition problem of hand motions. While the closest competitor is SVM with the second highest accuracy of 88.1%. MLP is the poorest performing with an overall accuracy of 85.6%. In summary, the performance of NeuCube is superior to other three classification methods with better accuracy as well as consistent classification outcomes, which has potential applications in EMG pattern recognition.

Major factor that prevents high technology from intervening into rehabilitation practice is cost. Though the EMG acquisition devices commonly used in research and clinical situations have better performance, they are expensive and unlikely to be widely available to patients. A relatively cheap and accessible EMG acquisition device may serve to improve the current situation, which is beneficial to the extensive adoption of high technology.

V. CONCLUSION

The results of this study support the premise that NeuCube is feasible to use in EMG pattern recognition. Additionally, the abilities of NeuCube to both spatially and temporally represent data and provide visualization of the data could be useful in future applications. The large number of parameters that need to be optimized limits the extensive application of NeuCube. Efficient parameter optimization algorithm remains to be investigated. Future work will concentrate on the implement of prosthetic system based on NeuCube.

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