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EMG Signals based Human Action Recognition via Deep Belief Networks

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Abstract: Electromyography (EMG) signals can be used for action classification. Nonetheless, due to their nonlinear and time-varying properties, it is difficult to classify the EMG signals and it is critical to use appropriate algorithms for EMG feature extraction and classification. In previous studies various ML methods have been applied. In this paper, we extract four time-domain features of the EMG signals and use a generative graphical model, Deep Belief Network (DBN), to classify the EMG signals. A DBN is a fast, greedy deep learning algorithm that can find a set of optimal weights rapidly, even in deep networks with many hidden layers and a large number of parameters. To evaluate this model, we acquired EMG signals, extracted their features, and then utilized the DBN model as human action classifiers. The real data analysis results are presented to show the effectiveness of the proposed deep learning technique for 4-class recognition of human actions based on the measured EMG signals. The proposed DBN model has potential to be applied in design of EMG-based user interfaces.

Keywords: Deep learning; Deep Belief Network (DBN); Restricted Boltzmann Machine (RBM); Electromyography (EMG); Feature extraction; Human action recognition.

1. INTRODUCTION

The electromyography (EMG) signals reflect the physiological behavior of the neuromuscular system and have been widely used for diagnosis of neuromuscular disorders, prosthetics, control of human-machine interface, and human movement tracking (Taylor et al., 2010). The EMG pattern recognition algorithm can be applied to prosthesis control of patients with amputated limbs (Ajiboye and Weir 2005; Lorrain, Jiang and Farina 2011; Young, Smith, Rouse *et al.* 2013; Ning, Rehbaum and Vujaklija *et al.* 2014). Since mobile or wearable computing is gaining in visibility, there has been a revived interest in user interface/user experience (UI/UX) in recent years (Jaime, Israel and Luis *et al.* 2011).

The recent advance in EMG signal processing and analysis techniques has potential to be assistive to the disabled and elderly people with limited mobility. EMG pattern recognition consists of two core algorithms, i.e., feature extraction and classification. Some important performance indices for EMG pattern recognition include reproducibility, accuracy and precision.

However, in practice it is difficult to classify EMG signals because an EMG signal has nonlinear and time-varying characteristics. The quality of EMG signal acquisition and analysis performance can be influenced by many factors, such as measurement instruments, environmental condition, electromagnetic interference, and human factors. On the other hand, the user's age, muscle movement pattern, skin thickness, etc. may also influence, to certain degree, the signal quality.

Feature extraction may highly influence the computational complexity and classification accuracy of a machine learning (ML) algorithm. The gist of deep learning (DL) paradigm is to learn useful features and improve the classification accuracy by constructing a machine learning (ML) model with many hidden layers based on a large amount of training data (LeCun et al., 2015). Different from traditional shallow ML, DL is characterized by depth of the learning model as well as feature learning through layer-by-layer feature transformation. Compared with manual feature engineering, using big data to learn features can obtain more complete representation of the data.

In the past two decades, multi-channel EMG signals have been widely used to recognize limb movements in biology and clinical medicine and there has been a number of research on multichannel EMG signal classification. The general limitations of conventional classifiers include: 1) The data distribution of each class is overlapping; and 2) The classification accuracy is not stable across subjects, i.e., there are inter-subject variations in classification performance. Thus various ML methods have been applied recently. ML algorithms for classification task can be roughly categorized to shallow learning and DL. DL algorithms can be used to solve multi-dimensional, non-linear transformation problems. In general, DL comprises multiple layers, and each layer comprises many units. DL algorithms may suffer from slow learning rate and over-fitting issue.

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On the other hand, shallow learning algorithms, such as support vector machine (SVM) and linear discriminant analysis (LDA), are faster and have satisfactory classification performance in many applications (Subasi 2013; Young, Smith and Rouse *et al.* 2013). The performance of shallow learning algorithms, however, decreases with an increase in the amount and dimensionality of input data.

Deep belief network (DBN) was shown to be able to overcome the overfitting and local minima problems of the BP algorithm, reduce the training time, and improve the classification performance (Hinton, Osindero and Teh, 2006; Mohamed, Sainath and Dahl *et al.*, 2011; Mohamed, Dahl and Hinton, 2012; Shim and Lee, 2015; Abdel-Zaher and Eldeib, 2016). These characteristics are important in biosignal recognition applications, including an EMG-based user interface system. The major goal of this work is to develop an improved EMG classifier system on the basis of the DBN.

In order to achieve accurate recognition of limb movements from the EMG signals, it is essential to select appropriate feature extraction and classification algorithms. In this paper, we combine four time-domain features to select the best features of EMG signals. We use DBN to classify the EMG signals. The motion EMG data measured from 10 normal and 10 aggressive actions of three male and one female subjects was used to validate the proposed deep learning scheme. For each subject, 4-class classifier based on DBN was trained and tested.

2. DEEP BELIEF NETWORK

The Deep Belief Network (DBN) was proposed in Hinton et al. (2006). It is a generative model. By training the weights between the neurons in each layer, the features can be automatically learned to realize data classification and recognition.

DBN is composed of multiple layers of neurons. The explicit neurons are used to accept the signal input, while the hidden units (also called feature detector) are used to extract the features. The bottom layer represents the data vector, where each neuron represents one dimension of the data vector.

The basic components of DBN are the Restricted Boltzmann Machines (RBM). The training of DBN is performed layer by layer. Firstly, the RBM that constitutes the DBN is trained. The data layer is used to infer the hidden layer, which is treated as the data vector of the next layer. After each layer of the RBM training is completed, it is combined to form a DBN.

2.1 Deep Learning

The deep learning (DL) model consists of multiple hidden layers, which form abstract high-dimensional features through the combination of low-level features to learn the data distribution (Hinton et al., 2006). Through the stacking of multiple layers, the output of the previous layer is used as the input to the next layer to realize hierarchical representation of the input.

DL trains a ML model with multiple hidden layers using a large amount of data, learns representative features, and therefore can improve the classification accuracy of traditional shallow learning models. Different from the traditional shallow learning, DL places more emphasis on the depth of the model structure and can automatically learn the features. Through layer-by-layer feature transformation, the feature representation of the sample in the original space is transformed into a new feature space to facilitate the solution of regression/classification task. Using big data to learn features, one can obtain more comprehensive representation of the data.

2.2 Restricted Boltzmann Machine

The RBM is a component of the DBN, which is a probabilistic graphical model (Bielza, Moral, and Salmerón, 2015; Fischer and Igel, 2014). The outputs of random neurons have active and inhibited states. Neuronal states are determined by probabilistic rules. RBM consists of a visible layer and a hidden layer. There is no connection between the neurons in the same layer. The neurons are fully connected, that is, each neuron in the hidden layer is connected to the visible layer. The general structure of RBM is shown in Fig. 1.

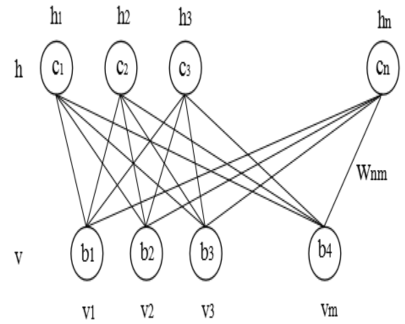

Fig. 1. The general structure of RBM.

The units in the visible layer of the RBM describe the features of the observed data. The units in the hidden layer is used to extract features and obtain the interdependency between the variables corresponding to the units in the visible layer.

The visible units $\mathbf{v} = [v_1, \cdots, v_m]$ represents the visible data, while the hidden units $\mathbf{h} = [h_1, \cdots, h_n]$ are used to obtain the relationship between the observed variables. The random vector $(\mathbf{v}, \mathbf{h}) \in \{0,1\}^{m+n}$, the joint probability distribution of the model is given by Gibbs distribution (also called Boltzmann distribution) $p(\mathbf{v}, \mathbf{h}) = \left(1/Z \right) \cdot e^{-E(\mathbf{v}, \mathbf{h})}$, where the normalization denominator Z is the canonical partition function resulted from the constraint that the probabilities of all accessible states must add up to 1, and the energy function is:

$$E(\mathbf{v},\mathbf{h}) = -\sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij}h_i v_j - \sum_{j=1}^{m} b_j v_j - \sum_{i=1}^{n} c_i h_i \qquad (1)$$

As shown in Fig. 1, for all $i \in \{1,2,\cdots,n\}$ and $j \in \{1,2,\cdots,m\}$, w_{ij} denotes the connection weight between v_j and h_i, b_j and c_i are the biases of the j-th visible variable and the i-th hidden variable, respectively. Different from the standard Boltzmann machine, there are only connections between the hidden and visible layers in the RBM (i.e., no connections within a layer). Therefore, the hidden variables can be given by the states of the visible variables, which in turn can be reconstructed from the inferred hidden variables. Then we have the probabilities:

$$p(\mathbf{h} \mid \mathbf{v}) = \prod_{i=1}^{n} p(h_i \mid \mathbf{v}) \qquad (2)$$

$$p(\mathbf{v} \mid \mathbf{h}) = \prod_{j=1}^{m} p(v_i \mid \mathbf{h}) \qquad (3)$$

Since there is no connection in either the hidden layer or the visible layer, the conditional distribution $p(\mathbf{h} \mid \mathbf{v})$ and $p(\mathbf{v} \mid \mathbf{h})$ can be perfectly decomposed. The conditional independency of the variables in a layer makes the Gibbs sampling very simple (Gelfand, 2000): The variables in the same layer are jointly sampled without the need to sample the new values for all variables in turn. As a result, the Gibbs sampling consists of only two steps:

Step 1: Based on $p(\mathbf{h} \mid \mathbf{v})$, sample the new states of the hidden units $\mathbf{h}$; and

Step 2: Based on $p(\mathbf{v} \mid \mathbf{h})$, sample the states of the visible layer $\mathbf{v}$.

The distribution of the vector $\mathbf{v}$ on $\{0,1\}^m$ can be formed by the RBM with the marginal distribution:

$$\begin{aligned} p(\mathbf{v}) &= \sum_{h} p(\mathbf{v},\mathbf{h}) \frac{1}{Z} \sum_{\mathbf{h}} e^{-E(\mathbf{v},\mathbf{h})} \\ &= \frac{1}{Z} \sum_{h_1}\sum_{h_2} \cdots \sum_{h_3} e^{\sum_{j=1}^{m} b_j v_j} \prod_{i=1}^{n} e^{h_i (c_i + \sum_{j=1}^{m} w_{ij} v_j)} \\ &= \frac{1}{Z} e^{\sum_{j=1}^{m} b_j v_j} \sum_{h_1} e^{h_1 (c_1 + \sum_{j=1}^{m} w_{1j} v_j)} \cdots \sum_{h_n} e^{h_n (c_n + \sum_{j=1}^{m} w_{nj} v_j)} \\ &= \frac{1}{Z} e^{\sum_{j=1}^{m} b_j v_j} \prod_{i=1}^{n} e^{h_i (c_i + \sum_{j=1}^{m} w_{ij} v_j)} \\ &= \frac{1}{Z} \prod_{j=1}^{m} e^{b_j v_j} \prod_{i=1}^{n} (1 + e^{c_i + \sum_{j=1}^{m} w_{ij} v_j}) \end{aligned} \qquad (4)$$

2.3 Deep Belief Network

The DBN is a combination of simple learning modules, restricted Boltzmann machines (RBMs). Each RBM is composed of a visible layer and a hidden layer. The two layers are connected through a symmetric weight matrix, and the units within a layer are not connected.

The probability of the generated visible vector is:

$$p(\mathbf{v}) = \sum_{n} p(\mathbf{h} \mid W) p(\mathbf{v} \mid \mathbf{h}, w) \qquad (5)$$

The weight between visible and hidden units is updated by:

$$\Delta w_{ij} = \varepsilon (< v_i, h_j >^0 - < v_i, h_j >^1) \qquad (6)$$

where 0 and 1 denote the network state and reconstructed state, respectively.

DBN can be implemented as a deep neural network with many hidden layers and was shown by many studies to be superior to traditional ML models, such as back-propagation (BP) network, K-Nearst Neighbor (KNN), and support vector machine (SVM) (Mnih, Zhang, and Hinton, 2009; Lecun, Bottou, Bengio and Haffner, 1998; Cristianini and Schölkopf, 2002; Erhan, Bengio, and Courville et al., 2010).

3. FEATURE EXTRACTION

The common feature extraction methods include time-domain analysis (Knox et al, 1993), frequency-domain analysis (Carlo et al., 1981), parametric models (e.g., ARMA), and dual spectral analysis (Sezgin, 2012).

3.1 EMG Datasets

This paper uses the EMG Physical Action Dataset downloaded from UCI Machine Learning repository (data contributed by University of Essex, UK). Three subjects were male (sub1, sub2, sub3) and one were female (sub4), aged 25-30 y/o. Each subject's EMG signals, corresponding to 10 normal and 10 aggressive actions, were recorded by using Delsys EMG device. There are eight EMG signal measurement electrodes (CH1-CH8). One female and three male subjects were used in the experiments (sub1-3 male, sub4 female). For each action, about 10,000 samples were collected with a sampling rate of 1k Hz. The relevant information concerning the dataset (8 measurement channels from different parts of body) is given in Tables 1 and 2.

Table 1. The EMG dataset.

Type of data	Type of attribute	# samples	# attributes
Time series	Real-valued	10,000	8

Table 2. The eight channels of EMG signal measurement.

R-Arm		L-Arm		R-Leg		L-Leg	
CH1	CH2	CH3	CH4	CH5	CH6	CH7	CH8
R-Bic	R-Tri	L-Bic	L-Tri	R-Thi	R-Ham	L-Thi	L-Ham
Right bicep	Right tricep	left bicep	left tricep	Right thigh	Right hamstring	Left thigh	Left hamstring

The EMG signal processing and analysis can be divided into feature extraction and model training/testing. Appropriate features must be selected to characterize the data. This paper used selected four salient time-domain features of EMG signal. The methods and data analysis results will be described below.

The raw EMG signals are classified into normal and aggressive, each including 10 actions. The normal actions include bowing, clapping, handshaking, hugging, jumping, running, seating, standing, walking, and waving. The aggressive actions include elbowing, front-kicking, hammering, headering, kneeing, pulling, punching, pushing, side-kicking, and slapping. For each action, there were approximately 10,000 sample data per channel. As an example, the raw EMG signal (9,930 sampling data points) due to the *bowing* action of sub1 is shown in Fig. 2.

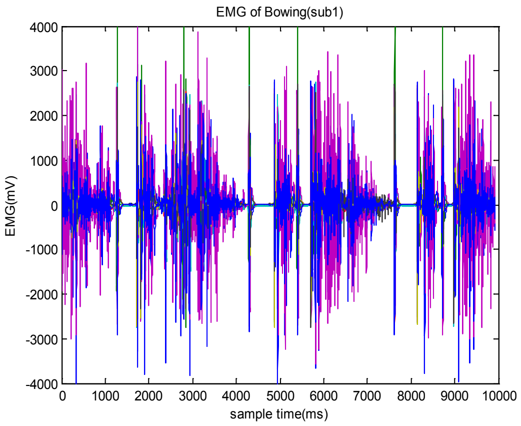

Fig. 2. The measured EMG signal of *bowing* action (sub1).

There are differences in EMG signals between different movements. There are also individual differences in EMG signals across subjects, but there is a certain relationship between the EMG signal and the tension and relaxation of the muscle. The noised contained in the original/raw signals may strongly affect the action classification accuracy.

This paper extracted four significant time-domain features from the EMG signals. With the deep learning algorithm, the 4-class subject-specific and subject-independent classifiers are trained respectively.

3.2 Time-domain Features

Features can be calculated by time series analysis. This paper selects four time-domain features, including the number of Zero Crossings (ZC), Mean Absolute Difference (MAD), Mean Absolute Value (MAV), and Sign Change Slope (SCS). ZC is the number of zero crossings of the signal. For two consecutive sampling points x_k, x_{k+1}, if the following condition is fulfilled, the value of ZC is increased by 1:

$$\begin{cases} |x_{k+1} - x_k| \geq \delta \\ ZC = \sum_{i=1}^{N} \mathrm{sgn}(-x_{k+1}x_k) \end{cases} \tag{7}$$

where the threshold δ is used to reduce the noise and the sign function is given by:

$$\mathrm{sgn}(x) = \begin{cases} 1, x > 0 \\ 0, \text{otherwise} \end{cases} \tag{8}$$

If we have N sampling data points, MAD represents the average of the absolute difference between two consecutive samples and is defined by:

$$MAD = \frac{1}{N}\sum_{k=1}^{N}|x_{k+1} - x_k| \tag{9}$$

MAV is defined by:

$$MAV = \frac{1}{N}\sum_{k=1}^{N}|x_k| \tag{10}$$

For three consecutive sampling points x_{k-1}, x_k, x_{k+1}, if the following condition is satisfied, the value of SCS is increased by 1:

$$(x_k - x_{k-1})(x_k - x_{k+1}) \geq \omega, k = 1, 2, \cdots, N \tag{11}$$

4. CLASSIFICATION RESULTS AND ANALYSIS

4.1 Structure and Parameters of Classifier

In normal and aggressive movements, there are hand and leg movements respectively. We divide these movements into 4 classes: *normal hand* movement (Clapping, Handshaking, and Waving (swinging)), *normal leg* movement (Jumping, Running, and Walking), *aggressive hand* movement (Hammering, Punching, and Slapping), and *aggressive leg movement* (Frontkicking, Kneeing, and Sidekicking). The classifier network structure is shown in Fig. 3, where the input of the network is the features from the eight channels CH1-CH8, and the outputs are the four class labels: Hand_Normal (Normal Hand action), Hand_Aggressive (Aggressive Hand action), Leg_Normal (Normal Leg action), or Leg_Aggressive (Aggressive Leg action).

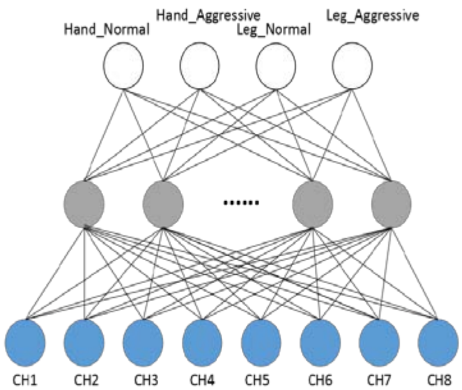

Fig. 3. Configuration of 4-class action classifier system.

The number of hidden units in the RBM (grey units in Fig. 3) is 50, the number of RBM training iterations is 300, and there is only a single hidden layer in the DBN. Fifty percent of sample data is chosen randomly for training, while the remaining 50% sample data for testing. When training the subject-specific classifiers, there are 57 data points of normal hand movement, aggressive hand movement, normal leg movement, and aggressive leg movement, among which 114 were selected randomly as training samples, and the remaining 114 were used as test samples. When training a generic classifier using all the EMG signals from the four subjects, there are 228 data points for normal hand movements, aggressive hand movements, normal leg movements, and aggressive leg movements, among which 456 were selected randomly as training samples, and the remaining 456 were used as test samples.

4.2 Performance Metric

The classification testing accuracy is evaluated by:

$$ACC = \frac{\text{\# of correctly classified samples}}{\text{\# of all samples}} \times 100\% \qquad (12)$$

The training and test samples were partitioned at random. The same training procedure is repeated 5 times, and the corresponding testing classification accuracies are saved. The mean and standard deviation (s.d.) are finally calculated.

4.3 Results and Analysis

The task is to train classifier to classify 12 actions into four classes: Hand_Normal, Leg_Normal, Hand_Aggressive, and Leg_Aggressive. Different combinations of the four time-domain features, i.e., MAV, [MAV, SCS], [MAD, SCS], [MAD, SCS, ZC], are explored to design the classifier. The accuracy of the 4-class subject-specific and generic classifiers is presented in Tables 3 and 4, respectively.

Table 3. The percentage accuracy of subject-specific classifiers.

Features	sub1	sub2	sub3	sub4
MAV	97.66±1.83	**92.11**±2.32	93.57±1.02	90.06±2.68
[MAV, SCS]	**98.58**±1.76	88.39±2.54	**99.71**±0.51	99.12±0.88
[MAD, SCS]	97.67±2.68	85.96±0.88	98.56±0.48	**100**
[MAD, ZC, SCS]	94.15±2.20	86.81±1.07	93.67±2.92	97.66±2.00

Table 4: The percentage accuracy of generic classifier, trained using EMG signals from all four subjects.

Features	*ACC*
MAV	74.59±3.15
[MAV, SCS]	89.53±1.36
[MAD, SCS]	87.03±1.05
[MAD, ZC, SCS]	**90.66**±1.47

We can see that for the subject-specific classifier, the feature sets [MAV, SCS] and [MAD, SCS] lead to better classification performance. For the generic classifier, the classification accuracy of feature set [MAD, ZC, SCS] is the best. These results show that the multi-classification problem can be effectively solved by selecting appropriate feature set. With an increase in the amount of sampling data, DL is more efficient than shallow learning because BP algorithm could get stuck in the local minima. DBN is shown to be more stable than BP and be able to circumvent over-fitting.

5. SUMMARY AND CONCLUSIONS

This paper uses a DBN-based EMG pattern classifier to classify the EMG signals. We combined four time-domain features, i.e., MAD, MAV, ZC, and SCS, to form different feature sets. The best feature set is found to design a 4-class EMG signal classifier. The subject-specific and generic classifiers were trained and tested. The results showed the effectiveness of the DBN model for design of EMG-based user interface systems. The developed DL method have potential applications in such areas as rehabilitation and enhancement of user experience.

This work proposed a general method for EMG signal classification based on DBN. However, the real-time multi-class EMG signal recognition is still challenging. The datasets used in this work cover 20 actions. The training of multi-classifier (e.g., more than four classes) is more difficult than the binary or 4-class recognition. Moreover, the data measured from four subjects may be too small to select the best classification algorithm since the EMG signals are highly variable across different limb movements and different subjects. Therefore, in the future we need to pursue the following research directions:

1) To further enhance the classification performance, more investigations on extraction of salient (or dominant) features and optimization of the DBN structure is warranted. The nonlinear and time-varying characteristics of the EMG signals make the classification problem less amenable to conventional classifiers. Many hidden layers contribute to extraction of the dominant features and reduced number of misclassifications. However, too deep layers may engender divergence. Therefore, it is important to optimize structural parameters of the DBN, such as the number of hidden layers, number of units in each layer, and the learning rate.
2) EMG signals are usually highly noisy and nonlinear, therefore we need to develop more sophisticated real-time EMG multi-classification method.
3) Use more subjects to examine individual differences due to gender, age, health condition, etc.

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