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Spectral Collaborative Representation based Classification for hand gestures recognition on electromyography signals

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ABSTRACT

The classification of the bio-signal has been used for various purposes in the literature as they are versatile in diagnosis of anomalies, improvement of overall health and sport performance and creating intuitive human computer interfaces. However, automatic identification of the signal patterns on a streaming real-time signal requires a series of complex procedures. A plethora of heuristic methods, such as neural networks and fuzzy systems, have been proposed as a solution. These methods stipulate certain conditions, such as preconditioning the signals, manual feature selection and large number of training samples.

In this study, we introduce a novel variant and application of the Collaborative Representation based Classification (CRC) in spectral domain for recognition of hand gestures using raw surface electromyography (EMG) signals. The CRC based methods do not require large number of training samples for an efficient pattern classification. Additionally, we present a training procedure in which a high end subspace clustering method is employed for clustering the representative samples into their corresponding class labels. Thereby, the need for feature extraction and spotting patterns manually on the training samples is obviated.

We presented the intuitive use of spectral features via circulant matrices. The proposed Spectral Collaborative Representation based Classification (SCRC) is able to recognize gestures with higher levels of accuracy for a fairly rich gesture set compared to the available methods. The worst recognition result which is the best in the literature is obtained as 97.3% among the four sets of the experiments for each hand gestures. The recognition results are reported with a substantial number of experiments and labeling computation.

1. Introduction

Electromyographic (EMG) signal based applications beyond clinical and rehabilitation purposes have been extensively studied in the literature. The classification of EMG signals in the kinesiological field has been investigated to analyze and improve sport [1,2], art [3] and occupational [4] performance. Human Computer Interface research field is another niche where the EMG signals have been utilized including, but not limited to control of exoskeletons, robotic prosthetic arms and hands.

The success of the EMG signal classification highly depends on three stages which are pre-processing, feature selection and the classification. In the pre-processing stage, noise and artifacts are removed from the signals. In [5], the authors propose a time lagged Recurrent Neural Networks (RNN) to eliminate the noise on the EMG signals. Wavelet transforms [6], higher order statistics [7,6] and empirical mode decomposition [8] method have also shown to be effective for removing artifacts and noise from the EMG signals.

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Feature extraction deals with extracting discriminating information hidden in the data which require experience in the field and tedious investigation of all possible features. Statistical features such as mean, variance and zero-crossing and derivatives have been predominantly examined and used in the bio-signal studies. No matter how pure the signal and how accurate the classification method is, without discriminating features it is difficult to obtain

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reliable classification results for any signal. In recent years, with the introduction of the auto-encoders and new network architectures [11], the dormant neural network has been revived in the burgeoning deep learning researches. The premise of this field is the self-learning neural networks which learn the features in an unsupervised manner from the big data.

Heuristic methods and variants of classical neural networks have been extensively used in classification of the stochastic biosignals [12–16]. The authors in [12] use a classical neural network and statistical features for classification of the EMG signals obtained on from the face muscles to steer a power wheelchair. A feed-forward error backpropagation and wavelet neural networks were trained in [13] with a relatively sufficient number of the training samples with respect to that in [12]. In the studies [14,15] a combination of fuzzy and neural network methods was used to classify EMG signals.

Depending on the number of signal patterns to be classified, various kinds of features and methods for pre-processing and filtering, the accuracy of the classification methods ranges between 88 and 99.75% [17,10]. The common points of the listed methods are the large number of procedures to obtain a substantial recognition accuracy and the difficulty in the implementation. On the other hand, neural network can only result in a generative model provided that a sufficient number of training samples are fed through.

The EMG signal measured on skin surface is not a mere signal but rather the superposition of the Motor Unit Action Potential (MUAP) of the many tiny muscle fibers [18,19]. Due to the stochastic nature of MUAPs, the EMG signal pattern might exhibit intra and interpersonal variations for the same muscle activity. These variations make the EMG pattern classification an intricate task for creating robust classifiers.

In concert with the advancements in pervasive computing technologies, the wearable gadgets in which high grade sensors embedded have been released to the market. Thalmic Labs' MYO armband [20] is one of the state of the art sensors which consists of eight surface EMG sensors. The sensor kit contains an inertial measurement unit as well. Inevitably, accessibility to such kind of devices with an affordable price tag garnered public attention both from academic and non-academic environments.

In this article, we introduce a signal pattern classification method in spectral domain and training procedures to classify the forearm EMG signals. The signals are obtained by 8-channel MYO armband real-time. The classification method is based on the Collaborative Representation based Classification (CRC) [21] which competes with the Sparse Representation based Classification (SRC) [22] with the same accuracy levels but much faster computation times. The drawback of the CRC compared to the SRC is that the CRC requires the observed and training signal patterns to be of equal length. This restricts the use of CRC methods for gesture and posture recognition in which the duration of the gestures might vary for each repetition. On the other hand, the SRC methods rely on the representation fidelity, whereas the CRC data fidelity. Therefore, the CRC methods lead lower recognition accuracy levels, if the data do not exhibit fidelity [23]. As the EMG signals are the products of complex stochastic processes, the performance of the CRC methods is low as we detail comparisons in the proceeding sections.

The Spectral Collaborative Representation based Classification (SCRC) proposed in this paper overcomes these drawbacks and yields high recognition accuracy for a fairly rich hand gesture set. Since the observed and training signal patterns must have equal lengths, a special training scheme is adapted to build a training dictionary. Therefore, the need for spotting signal patterns and manual feature selection is automatically eliminated and the boundary of the representative columns is implicitly embedded in the training matrix.

The contributions of this study to the literature are:

- The spectral content; complex conjugate eigenvalue pairs are obtained from 1D vectors by converting the observed signal pattern to a trajectory or a circulant matrix to capture the representative features of the EMG signals.
- The gesture and posture recognition is performed in a continuous manner eliminating the requirements for spotting or picking the signal patterns on the streaming signals due to the proposed training scheme which implicitly embeds the signal boundaries on the representative columns.
- The training phase is easy to implement; thus the end user can obtain a training dictionary on the spot. The flexibility in building a training dictionary paves the way for the use of the procedures and methods introduced here to implement different applications, such as control of a bionic prosthesis.
- The number of hand gestures are the highest among the similar studies. Our worst recognition result is over 97% with a substantial number of gesture labeling computation.

The rest of the paper is organized as follows. In Section 2, a brief review of the CRC method is given and then the circulant matrix approach is detailed. In Section 3, after giving the technical details of the MYO armband, training phase for the gestures and SCRC is elaborated. The experiment and simulation results are discussed in Section 4. The paper ends with conclusion and future works in Section 5.

2. Spectral Collaborative Representation based Classification

2.1. Collaborative representation based classification

Spectral methods have been used for decades in variety of science disciplines where random signal or stochastic processes are involved.

Although randomness in the systems might render analysis of the features difficult in time domain, the spectral features such as eigenvalues and frequencies might reveal valuable information of the underlying processes [24]. Fourier analysis is the widely used spectral analysis method for this purpose. In this study, as the EMG signals show randomness, we exploit the spectral analysis by employing the circulant matrix structure for eigenvalue decomposition.

Both of the methods, the SRC and CRC address finding the linear representation coefficients vector x for the observed pattern $y = Ax$ where $A = [A_1, A_2, \ldots, A_n] \in \mathbb{R}^{mxn}$ is the dictionary matrix. The representative samples are stacked as column vectors in the dictionary. In the objective function of the solution (Eq. (1)) different vector norms are utilized depending on the methods and requirements.

$$\hat{x} = \arg\min_{x} \|y - Ax\|_p + \sigma \|x\|_q \quad (1)$$

In the SRC solution ℓ_1 regularization is used ($p = 2, q = 1$), whereas the norms p and q become 1 or 2 in the CRC methods depending on the requirements such robustness of the classifier. If the objective function is solved by Regularized Least Square (RLS) in which ℓ_2 norm used for both terms of the objective function the solution turns out the ridge regression.

We used the least square version of the CRC method which is dubbed as CRC_RLS by the authors in [23]. The ridge regression solution of Eq. (1) is obtained as $\hat{x} = Py$ where $P = (A^T A + \sigma I)^{-1} A^T$ and σ is the regularization parameter. Once the solution vector $\hat{x}$ is obtained the label of the observed signal is computed evaluating the minimum representation residuals r_i given in Eq. (2) where $\delta_i : \mathbb{R}^n \to \mathbb{R}^n$ is the selection operator that selects the coefficients of