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Original Research Article

# Electromyography and mechanomyography signal recognition: Experimental analysis using multi-way array decomposition methods

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ABSTRACT

In this study, we considered the problem of controlling a prosthetic hand with noisy electromyography (EMG) and mechanomyography (MMG) signals. Several dimensionality reduction methods were analyzed to assess their efficiency at classifying these signals, which were registered during the performance of grasping movements with various objects. Using the cross-validation technique, we compared various dimensionality reduction methods, such as principal components analysis, nonnegative matrix factorization, and some tensor decomposition models. The experimental results demonstrated that the highest classification accuracy (exceeding 95% for all subjects when classifying 11 grasping movements) and lowest computational complexity were obtained when higher-order singular value decomposition was applied to a multi-way array of multi-channel spectrograms, where the temporal EMG/MMG signals from all channels were concatenated.

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## 1. Introduction

The measurement and analysis of biosignals is used widely in medical diagnostics, sports, and rehabilitation. Computer recognition of biosignals provides significant support in these applications, thereby allowing the automation of human tasks. A new application of biosignal recognition is the control of machines, particularly processes in the human body that depend on the human will, such as the contraction of individual skeletal muscles. The accompanying myoelectric and myomechanic signals can be used to control a machine's action after recognition. In contrast to diagnostics, biosignal classification can be used to interpret human intentions. However, for both automatic diagnosis and automatic control, the efficiency of recognition depends on the methods used to analyze (representation and dimensionality reduction) and classify biosignals.

A particular challenge is the control of prosthetic hands. The human hand is capable of performing a variety of movements, thereby allowing gesticulation and the playing of musical instruments, but mainly grasping and manipulating objects. The hand is also a source of complex tactile sensations. The loss of a hand dramatically reduces the

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possibility of full human functioning in personal and professional life, and the loss of both hands practically excludes independent functioning. The aim of the prosthetic hand is to partially restore the function of the lost limb, especially its manipulating and prehensile functions. To achieve these needs, the prosthesis must have the ability to perform a variety of movements and to adopt different finger configurations. This requires the transmission of a wide range of control decisions to the prosthesis. Modern transradial prostheses are generally controlled via the recognition of hand stump muscle-derived signals. This type of control is possible after an upper limb is amputated below the elbow, where the forearm stump retains a significant part of the muscle that moves the fingers in the healthy hand. The movements of these muscles are still subject to the human will. During contraction, the muscles produce both electrical (myopotentials) and mechanical (myovibration) signals, which are referred to as electromyography (EMG) and mechanomyography (MMG) signals, respectively. These signals are associated with the movements of the healthy hand and fingers, and they can clearly represent the will of the user with respect to control of the prosthesis. It is essential that these signals are recorded non-invasively by suitable sensors placed directly above the muscles on the skin of a forearm. Therefore, prosthetic biocontrol involves measuring surface signals from the hand stump muscles and then recognizing the type of intended prosthesis action by classifying these observations [26,11,15,13].

For obvious reasons, the basic quality criterion for this type of control is the reliability of intent recognition (because the prosthesis cannot perform unintended movements). It is easy to show that this criterion is closely related to a fixed set of movements. Changing the repertoire of movements significantly affects the reliability of their recognition. Another criterion is the time required for recognition, which affects the prosthesis response time to control biosignals and it strongly influences agility. The response delay (also due to psychological reasons) results in a significant decrease in the precision of motion control. The third criterion is based on the requirements of the computer system resources (CPU and memory usage) used for running the algorithm. Clearly, this is not related to the synthesis stage of control (e.g., classifier training), but it is important for the action stage of control. Unfortunately, the number of recognition errors increases rapidly if more classes need to be recognized. This is partly because the information regarding human intentions contained in the registered signal is usually distorted by noise, and because the form in which it appears in the signal loads the classification process (disrupts the efficiency and reliability).

The preceding step of classification involves the process employed for analyzing biosignals. In our experiments, we measured the muscular activity using both EMG and MMG signals. To extract useful features for classifying various muscular activities, the temporal waveforms of the signals were transformed into the time-frequency domain. This transformation is usually performed with the short-time Fourier transform (STFT) but other transformations, such as the discrete wavelet transform (DWT) can be also used [5,16]. An appropriate transformation of the waveform into feature vectors can significantly decrease interference (in the raw signal). The set of features should retain information regarding human intention (human control decision). This part of the signal analysis process is referred to as feature extraction.

Most feature extraction methods produce redundant sets of features, but we should apply the next part of the signal analysis process to increase the efficiency of classification, i.e., selection/reduction of features, which yields a new optimal set of features (optimal in the sense of the minimum classification errors). Many of the methods for feature dimensionality reduction and selection can be applied to improve the classification of EMG/MMG signals [20]. One of the best-known techniques is principal components analysis (PCA) [9], which captures the orthogonal directions in the input data space where the variance is maximized. PCA works very well for time-series, but two important problems occur when it is applied to 2D data, such as spectrograms. First, the low-dimensional factors obtained with PCA contain negative entries, which substantially hinder their physical interpretation. Second, PCA loses information regarding the 2D interactions between the variables in a spectrogram or scalogram. Thus, the low-dimensional factors provided by PCA do not contain information regarding the local smoothness of spectrograms, which can considerably reduce the efficiency of classification.

Several approaches have been proposed to address these problems. To avoid the first problem, nonnegativity constraints can be imposed on all of the estimated factors to obtain the nonnegative matrix factorization (NMF) model [14,3]. Yazama et al. [28] first applied the NMF to the recognition of EMG signals. Subsequently, Theis and Garcia [22] compared various NMF algorithms in terms of their effectiveness at decomposing EMG signals. Recent advances in the use of the NMF for processing these signals include: the identification of EMG finger movements [1], separating ECG from a single-channel EMG signal [17], analysis of motor modules of human locomotion [18], coherence analysis of elbow and shoulder muscles [21], extraction of neural control information from EMG signals [8], and the classification of hand grip configurations [15].

Despite the undoubted advantages of the NMF for processing EMG signals, the other problem cannot be alleviated if a 2D representation is vectorized, but multi-way array decomposition methods [3] can be used to avoid this issue, which provide multi-linear features that capture the nature of the high-dimensional data along each mode. After the decomposition of a multi-way array of ordered spectrograms, the separate features reflect the temporal and frequency structures, as well as the discriminant features corresponding to the mode of ordering in the spectrograms. If nonnegativity constraints are imposed on each estimated factor, these methods can be regarded as extensions of NMF. In particular, nonnegative tensor factorization is a simple extension of NMF to multi-way nonnegative data. The strategies used in its application to model dimensionality reduction and the classification of multi-way array data were presented by [3,19]. According to a strategy based on core tensor classification, Xie and Song [27] performed experiments with two-channel EMG signals, where they successfully classified two hand actions: full elbow flexion and full elbow extension. EMG-based experiments with multi-way array decomposition methods were also performed by Kim et al. [11], where EMG

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