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Multi-channel surface EMG classification using support vector machines and signal-based wavelet optimization

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Abstract

The study proposes a method for supervised classification of multi-channel surface electromyographic signals with the aim of controlling myoelectric prostheses. The representation space is based on the discrete wavelet transform (DWT) of each recorded EMG signal using unconstrained parameterization of the mother wavelet. The classification is performed with a support vector machine (SVM) approach in a multi-channel representation space. The mother wavelet is optimized with the criterion of minimum classification error, as estimated from the learning signal set. The method was applied to the classification of six hand movements with recording of the surface EMG from eight locations over the forearm. Misclassification rate in six subjects using the eight channels was (mean $\pm$ S.D.) 4.7 $\pm$ 3.7% with the proposed approach while it was 11.1 $\pm$ 10.0% without wavelet optimization (Daubechies wavelet). The DWT and SVM can be implemented with fast algorithms, thus, the method is suitable for real-time implementation.

Keywords: Multi-resolution analysis; Wavelet design; Multi-channel signal classification; Support vector machine; Electromyography; Myoelectric prostheses

1. Introduction

Surface electromyographic (EMG) signals are detected over the skin surface and are generated by the electrical activity of the muscle fibers during contraction. Since each movement corresponds to a specific pattern of activation of several muscles, multi-channel EMG recordings, performed with electrodes placed on the involved muscles, can be used to identify the movement. This concept has been applied for the development of myoelectric prostheses [1], where the control of the prostheses is obtained by classification of EMG signals. For this purpose, various pattern recognition schemes, consisting of feature extraction and classification, have been applied [2].

Surface EMG signals are the summation of motor unit action potential trains [3]. Motor unit action potentials are compact support waveforms which repeat with similar shape over time. Thus, classical representation techniques based on autoregressive modeling or time-frequency features (decomposition on time-windowed sine bases) may not be suited to this type of signals. For this reason, wavelets have been previously proposed as basis functions to project EMG signals for feature extraction and subsequent classification [4]. In the present study, the discrete dyadic wavelet transformation (DWT) will be applied with optimization of the corresponding representation space by signal-based selection of the mother wavelet.

The DWT projects a signal into a set of basis functions that are scaled and delayed versions of a prototype function, called mother wavelet. The mother wavelet determines the projection space, thus, infinite feature spaces can be obtained from the DWT with varying mother wavelet. The feature space may be chosen a priori using a particular standard mother wavelet (e.g., Daubechies), or selected based on optimal discrimination. It is expected that different mother wavelets would lead to different discrimination abilities between classes, thus, the need for signal-based wavelet selection. With the purpose of classification, a natural optimization criterion is the classification error

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estimated from a training set of signals and an efficient method for exploring a large family of wavelet functions is wavelet parameterization by imposing conditions on the scaling filter in a multi-resolution analysis (MRA) framework [6]. Signal-based optimization of DWT for pattern recognition has been previously proposed by our group for simulated EMG signals [7], where the focus was mainly on the feature space while a simple classification method (nearest representative) was applied in a single channel and bi-class context. In this study we propose a method based on the optimization of the representation space in combination with a robust classifier (support vector machine, SVM), in the case of multi-channel signals, in a multi-class context. Moreover, the method will be applied to experimental signals recorded during six movements of the hand. The main aims are (1) to prove that wavelet signal representation is a suitable space for control of myoelectric prostheses and (2) that selection of the mother wavelet has an impact in the discrimination ability of wavelet features, thus, the need for signal-based optimization.

2. Methods

In this section, we present the parameterization of the mother wavelet, the feature space used for the multi-channel signal, the multi-class decision rule, and the criterion that allows optimization of the mother wavelet.

2.1. Wavelet parameterization

The parameterization chosen for the mother wavelet, defined within the MRA framework [8–10], was previously used for signal classification [6], for biomedical signal compression [11,12], and for blind source separation [13]. It corresponds to a parameterization of the filter defining the wavelet, and is briefly recalled here.

In the MRA, the filters h and g are associated to the scaling function φ and wavelet ψ through the two-scale relations: $\varphi(t/2)=\sqrt{2}\sum_n h[n]\varphi(t-n)$ and $\psi(t/2)=\sqrt{2}\sum_n g[n]\varphi(t-n)$. In the case of orthogonal wavelets, the wavelet filter g can be deduced from h by $g[k]=(-1)^{1-k}h[1-k]$ and then the mother wavelet is completely defined by the scaling filter h coefficients. However, to generate an orthogonal MRA wavelet, h must satisfy some conditions. For a Finite Impulse Response (FIR) filter of length L_h, there are $L_h/2+1$ sufficient conditions to ensure the existence and orthogonality of the scaling function and wavelet [14,15]. Thus, $L_h/2-1$ degrees of freedom remain to design the filter h. The lattice parameterization described by Vaidyanathan and Hoang [16] offers the opportunity to design h with $L_h/2-1$ new free parameters, called parameter vector θ. If $L_h=4$, the design parameter vector $\theta=[\alpha]$ is reduced to a scalar parameter:

$$
\begin{aligned}
i=0,3: h[i] &= \frac{1-\cos(\alpha)+(-1)^i\sin(\alpha)}{2\sqrt{2}} \\
i=1,2: h[i] &= \frac{1+\cos(\alpha)+(-1)^{i-1}\sin(\alpha)}{2\sqrt{2}}
\end{aligned} \tag{1}
$$

If $L_h=6$, we need a two-component design vector $\theta=[\alpha,\beta]$, and h is given by:

$$
\begin{aligned}
i=0,1: h[i] &= \frac{[(1+(-1)^i\cos\alpha+\sin\alpha)(1-(-1)^i\cos\beta-\sin\beta)+(-1)^i 2\sin\beta\cos\alpha)]}{(4\sqrt{2})} \\
i=2,3: h[i] &= \frac{[1+\cos(\alpha-\beta)+(-1)^i\sin(\alpha-\beta)]}{(2\sqrt{2})} \\
i=4,5: h[i] &= \frac{1}{\sqrt{2}-h(i-4)-h(i-2)}
\end{aligned} \tag{2}
$$

For other values of L_h, expressions of h are given in Refs. [10,17].

2.2. Multi-channel feature space

We consider a multi-channel signal x composed of K channels x_k: $x=\{x_1,\ldots,x_k,\ldots,x_K\}$. Given a mother wavelet ψ, the DWT decomposes the channel x_k on the corresponding discrete wavelet basis, where all the wavelets are dyadic dilated and translated versions of ψ. It provides a set of coefficients $d_{x_k}(s,u)=\langle x_k(t),\psi_{s,u}(t)\rangle$ where $\psi_{s,u}(t)=2^{-s/2}\psi(2^{-s}t-u)$. The N coefficients $d_{x_k}(s,u)$ of the decomposition of the discrete channel x_k of length N are computed by Mallat's algorithm using h and g [8].

The waveforms are supposed to occur at unknown instants, randomly distributed inside a class. In order to be insensitive to occurrence instants, we use the marginals of each level of the decomposition as the channel features. We define the marginals of the DWT as:

$$
m_{x_k}(s)=\sum_{u=0}^{N/2^s-1}|d_{x_k}(s,u)|, \quad s=1,\ldots,S
$$

where S is the deepest level of the decomposition ($S=\lfloor\log_2 N\rfloor$). The features representing the channel x_k are the components of the vector $M_{x_k}=[m_{x_k}(1),\ldots,m_{x_k}(S)]$. The vector M_{x_k} allows the representation of the channel by the contributions of each dyadic scale.

The multi-channel representation space is defined by the set of the mono-channel feature spaces. In this space, the signal x is represented by:

$$
M_x=[M_{x_1},\ldots,M_{x_k},\ldots,M_{x_K}]
$$

2.3. Multi-class decision rule using SVM

The classification is based on the SVM approach, using a two-class SVM discrimination for each of the n_c classes [5]: each class ω_{+i} against the rest of the population ω_{-i}, $i=1,\ldots,n_c$. After training, a discriminant function f_i is obtained for each two-class SVM separation problem. For a given signal x, the final decision is taken from the n_c discriminant functions f_i:

$$
\text{``}x\text{ belongs to }\omega_j\text{''} \text{ with } j=\underset{i=1,\ldots,n_c}{Arg\max}\ f_i(x) \tag{3}
$$