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Automatic segmentation of surface EMG images: Improving the estimation of neuromuscular activity

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ABSTRACT

Surface electromyograms (EMGs) recorded with a couple of electrodes are meant to comprise representative information of the whole muscle activation. Nonetheless, regional variations in neuromuscular activity seem to occur in numerous conditions, from standing to passive muscle stretching. In this study, we show how local activation of skeletal muscles can be automatically tracked from EMGs acquired with a bi-dimensional grid of surface electrodes (a grid of 8 rows and 15 columns was used). Grayscale images were created from simulated and experimental EMGs, filtered and segmented into clusters of activity with the watershed algorithm. The number of electrodes on each cluster and the mean level of neuromuscular activity were used to assess the accuracy of the segmentation of simulated signals. Regardless of the noise level, thickness of fat tissue and acquisition configuration (monopolar or single differential), the segmentation accuracy was above 60%. Accuracy values peaked close to 95% when pixels with intensity below ~70% of maximal EMG amplitude in each segmented cluster were excluded. When simulating opposite variations in the activity of two adjacent muscles, watershed segmentation produced clusters of activity consistently centered on each simulated portion of active muscle and with mean amplitude close to the simulated value. Finally, the segmentation algorithm was used to track spatial variations in the activity, within and between medial and lateral gastrocnemius muscles, during isometric plantar flexion contraction and in quiet standing position. In both cases, the regionalization of neuromuscular activity occurred and was consistently identified with the segmentation method.

1. Introduction

Surface electromyography advanced rapidly in the last decade, in particular regarding the development of sophisticated detection systems, which currently comprise grids with hundreds of electrodes (Merletti et al., 2009).

The conventional bipolar configuration may suffice for identifying gross activation of skeletal muscles in specific motor tasks (Danion et al., 2002; McLean and Goudy, 2004), or in response to stretching stimuli (Schieppati et al., 2001). Conversely, this configuration provides unrepresentative electromyograms (EMGs) if the location of surface electrodes is not chosen properly. Indeed, variations in amplitude and spectral features of surface EMGs, with respect to the position of electrodes, have been extensively studied using arrays of electrodes (Farina et al., 2002; Mesin et al., 2009; Merletti et al., 2003; Zwarts and Stegeman, 2003). Spurious changes in EMG traces hinder the observation of neuromuscular activity when surface electrodes are placed close to the innervation zone or the tendon locations (Mesin et al., 2009).

Quantifying muscle activity with a linear array or pairs of electrodes presumes that the whole muscle is activated homogeneously. Such an assumption is particularly relevant when estimating muscle forces with analytical models (Lloyd and Besier, 2003; Zajac, 1989). Nonetheless, compelling evidences indicate that skeletal muscles are functionally divided into compartments, activated selectively in voluntary contractions (Danion et al., 2002; McLean and Goudy, 2004), during the control of quiet standing posture (Vieira et al., 2010), and even in response to muscle stretching (Eng and Hoffer, 1997). Therefore, the assessment of neuromuscular activity in different motor tasks would benefit from the use of bi-dimensional arrays of electrodes, allowing for the identification of localized EMG activity within and between muscles.

In this study, we propose and validate a method for the automatic identification of local variations in surface EMG activity with a bi-dimensional array of electrodes. Initially, the generation of scaled images from the surface EMGs is outlined. Then, EMG

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images are segmented with the watershed algorithm (Vincent and Soile, 1991). The performance of our method is assessed using simulated EMGs. Finally, we applied the method to segment experimental signals recorded from the gastrocnemius muscles. We chose these muscles because of their high degree of compartmentalization (English et al., 1993) and our interest in understanding how such a partitioning might affect the control of human standing posture (Vieira et al., 2009, 2010). The segmentation method proposed here is expectedly useful to study localized muscle activity, the load sharing between synergists and to predict muscle force using EMG-driven models.

2. Methods

2.1. Generating images from surface EMG signals

When electromyograms are recorded with a bi-dimensional grid of electrodes, each electrode may be conceived as a pixel p with coordinates x and y given by the rows and columns in the grid. EMG activity is often represented with its average rectified value (ARV) or its root mean square (RMS). For EMG images generated with the ARV descriptor, pixels intensity is computed as

$$I_{emg}[x,y,\ i]=\frac{1}{N}\sum_{n=1+(i-1)N}^{iN}|EMG[x,y,n]| \tag{1}$$

where i and N stand for the epoch number and the number of samples in each epoch, respectively. In a grayscale EMG image, dark and light pixels indicate low and high EMG amplitudes, respectively (Fig. 1).

The cluster of pixels with high intensity in Fig. 1 means a group of electrodes detecting high EMG activity and likely reflects the spatial selectivity of muscle activation.

2.2. Segmenting EMG image with watersheds

The watershed technique segments grayscale images by considering pixels with high intensity as elevated surfaces and pixels with low intensity as catchment basins. Similarly, the intensity of pixels in EMG images can be represented as a topographical relief (Fig. 2). The algorithm identifies the location of ridges (watersheds) in the grayscale image and labels each catchment basin (group of pixels), surrounded by such ridges, with a different number (Vincent and Soile, 1991).

Since pixels with high ARV amplitude would be conceived as elevated surfaces, clusters of these pixels would be partitioned if the watershed algorithm was applied directly to EMG images (Fig. 2a). In this case, pixels with high gray intensity (i.e. high neuromuscular activity) would constitute the watershed line, which is not desired. Rather, watershed lines could be estimated by processing the gradient of I_{emg}. Assuming that pixels represent the spatial sampling of I_{emg}, the edges of subsets with low and high EMG activities are computed as the Euclidean norm of I_{emg} gradient (g_{emg}), which gives the rate of change in gray intensity (Fig. 2b)

$$\begin{gathered}g_x[m,\ n;i]=F^{-1}\left[S^T\sum_{m=1}^{N_r}\sum_{n=1}^{N_c}I_{emg}[m,n;\ i]e^{-j2\pi\left(\frac{k_xm}{N_r}+\frac{k_yn}{N_c}\right)}\right]\\ g_y[m,n;i]=F^{-1}\left[S\sum_{m=1}^{N_r}\sum_{n=1}^{N_c}I_{emg}[m,n;\ i]e^{-j2\pi\left(\frac{k_xm}{N_r}+\frac{k_yn}{N_c}\right)}\right]\\ g_{emg}=\sqrt{g_x^2+g_y^2}\end{gathered} \tag{2}$$

where F^{-1} is the inverse of the Fourier transform operator, k_x and k_y indicate the spatial frequencies, N_r and N_c stand for the number of rows and columns of electrodes, T indicates the transpose operator, and S is the bi-dimensional Fourier transform of the zero-padded Sobel operator

$$s=\begin{vmatrix}+1 & +2 & +1\\ 0 & 0 & 0\\ -1 & -2 & -1\end{vmatrix} \tag{3}$$

As the number of clusters produced by the watershed segmentation depends on the number of regional minima in the gradient, the problem of over-segmentation (Fig. 2b) can be minimized by flattening sharp transitions of gray intensity in g_{emg} with image opening followed by image closing operation (Heijmans, 1995). Opening and closing can be envisaged as the attenuation and intensification of pixels with intensity exceeding or not reaching some threshold, respectively. Opening and closing g_{emg} by the structuring element ν are defined as (Heijmans, 1995)

$$g_{emg}\circ\nu=(g_{emg}\ominus\nu)\oplus\nu \tag{4}$$

$$g_{emg}\bullet\nu=(g_{emg}\oplus\nu)\ominus\nu \tag{5}$$

where $\circ$ and $\bullet$ indicate opening and closing, respectively. $\oplus$ and $\ominus$ are the Minkowski operators for addition and difference, defined as

$$(g_{emg}\oplus\nu)(p)=\max_{z\in D_\nu}\{g_{emg}(p+z)\} \tag{6}$$

$$(g_{emg}\ominus\nu)(p)=\min_{z\in D_\nu}\{g_{emg}(p+z)\} \tag{7}$$

where D_ν is the domain of the structuring element ν, which was chosen as a square grid (3×3) of zeros (which means that $z\in[-1,0,1]\times[-1,0,1]$).

The opened–closed gradient of I_{emg} provided a flattened surface for the segmentation. Clusters of EMG activity were then identified properly with the watershed algorithm (Fig. 2c).

Enhancing the contrast of EMG image with histogram equalization (Kim et al., 2001), before computing its gradient, emphasized groups of pixels with similar intensity and further improved the watershed segmentation (Fig. 2d).

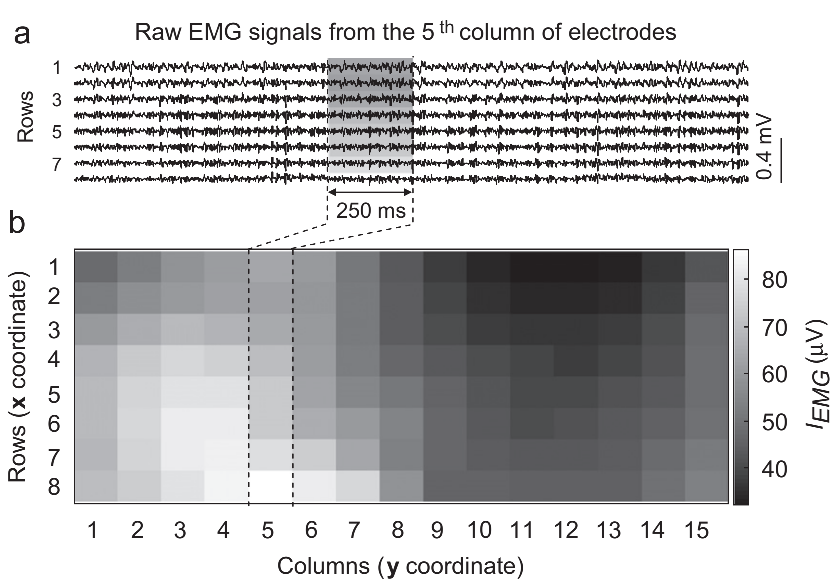

Fig. 1. Grayscale image (bottom panel) created with intensity values (I_{emg}) computed for experimental EMGs recorded from the gastrocnemius muscles during isometric plantar flexion (Section 2.3.2). A matrix of 120 electrodes, disposed into 8 rows and 15 columns, was used for the EMGs acquisition. Pixels intensity corresponds to ARV amplitudes computed for an epoch of 250 ms (dashed lines).