Study of the SEMG probability distribution of the paretic tibialis anterior muscle.

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Abstract. The surface electromyographic signal is a stochastic signal that has been modeled as a Gaussian process, with a zero mean. It has been experimentally proved that this probability distribution can be adjusted with less error to a Laplacian type distribution. The selection of estimators for the detection of changes in the amplitude of the muscular signal depends, among other things, on the type of distribution. In the case of subjects with lesions to the superior motor neuron, the lack of central control affects the muscular tone, the force and the patterns of muscular movement involved in activities such as the gait cycle. In this work, the distribution types of the SEMG signal amplitudes of the tibialis anterior muscle are evaluated during gait, both in two healthy subjects and in two hemiparetic ones in order to select the estimators that best characterize them. It was observed that the Laplacian distribution function would be the one that best adjusts to the experimental data in the studied subjects, although this largely depends on the subject and on the data segment analyzed.

1. Introduction

Surface electromyogram (SEMG) is an electrical manifestation of the muscular activity recorded by means of surface electrodes. The amplitude of this signal is the result of the spatial and temporal integration of the action potentials of a great number of elemental sources: the muscular fibers.

It is believed that the SEMG signal generated at a constant force, a constant angle and in contraction without muscular fatigue is originated from a group of independent and lineally superposed generators. Thus, this signal may be modeled by means of a stochastic process, with a Gaussian probability distribution function (PDF) [1]. However, experimental studies carried out for different muscular contraction levels have shown that the PDF of the SEMG signal would be closer to a Laplacian type distribution [2]. The approximation to either one or the other PDF would depend on the level of muscular activation [2]-[5].

To analyze the amplitude of the SEMG signal, temporal parameters such as the root mean square (RMS) and the absolute mean value (VMA) among others, are generally used. The decision to use either one or the other parameter as the best estimator of the signal amplitude depends on its PDF. RMS is the most suitable estimator when the signal has a Gaussian distribution, while VMA is best when the PDF is Laplacian. Taking this and the muscular force level into account, either RMS or VMA can be used as SEMG amplitude estimators. These estimators are used alone or in combination to carry out the analysis and detection of changes in the amplitude of the muscular signal, the analysis of the human gait or to trigger and control motor neuroprothesis. [6][9].
In subjects with muscular paresis owing to lesions to the central nervous system, the muscle activation patterns that participate in the different phases of the gait cycle are altered. It has been noticed that the activity level of the tibialis anterior muscle (TA) in people with this type of lesions, quantified according to RMS or VMA, differs from the one registered in healthy subjects. These changes can be observed especially during the oscillation phase of the gait cycle which corresponds to an activation period of that muscle. However, the specificity of RMS or VMA, as detection parameters of changes in the muscular activity, will depend not only on the activation patterns, but also on the distribution function of the amplitude of the paretic EMG signal. For these reasons, in this work we analyze the approximation degree of the amplitude distribution of the SEMG of the TA to a Gaussian PDF for different phases of the gait cycle associated to an increase and or decrease of the TA activity, both in healthy subjects and in those with muscular paresis. Furthermore, the experimental distribution obtained for the different phases and cases is compared to the Gaussian and to the Laplacian PDFs.

2. Materials and methods

2.1. EMG Recordings

EMG signals from the tibialis anterior muscle registered from two subjects without neurological disorders and from two with hemiparesia, which were registered with Ag-ClAg surface electrodes displayed according to the SENIAM recommendations [14] were analyzed.

The signals obtained were filtered analogically between 5 and 500 Hz and digitally between 10 and 400 Hz. The signal sampling frequency was 2 KHz.

The subjects walked on a treadmill, at a comfortable rate. A minimum of 18 steps were recorded for each subject. A switch was fitted on the metatarsus to relate the TA activation segments to the normal gait phases.

Out of each step, the following analysis segments were selected: the initial contact phase (FIA), the mid stance phase (FMA), the terminal stance phase (FFA) and the oscillation phase (FO) [13]. The fact that the SEMG signal can be considered stationary for sections smaller than 400 mseg [16] was taken into account for the selection of these segments.

The FIA segment corresponds to the TA activation responsible of absorbing the impact of the foot drop during the plantar stand. This segment corresponds to the initial 10% of the stance phase. The FMA and FFA segments are related to gait stages where the TA muscular activity is diminished. The FMA begins at 20% of the stepping phase and has a of 150 mseg duration. The FFA segment was considered at the 150 final mseg of the stepping phase. Finally, the FO segment is associated to the TA activation stage present during the swing phase, which is in charge of maintaining an adequate foot-floor distance at the moment of initiating a step. This segment was established as the 150 mseg that follow the initiation of the TA muscular activity in the swing phase. This initial stage was visualized in the majority of the recordings at 30% of the beginning of the swing phase. Thus, this percentage was considered as a fix value for all the trials.
Figure 1. TA electromyographic recording of a hemiparetic subject corresponding to a gait cycle, where the following segments can be identified: initial contact phase (FIA), mid stance phase (FMA), terminal stance phase (FFA) and oscillation phase (FO).

2.2. Evaluated SEMG density of probability
For each of the selected segments the distributions of the SEMG amplitudes were obtained and their adjustment, both to the Gaussian PDF and to the Laplacian one, was evaluated.

The Gaussian PDF is calculated as follows:

\[
 f(x) = \frac{1}{\sigma \sqrt{2\pi}} \exp\left(\frac{-(x-\mu)^2}{2\sigma^2}\right),
\]

where \(\mu\) is the mean and \(\sigma^2\) is the distribution variance.

The Laplacian PDF is described by the following formula:

\[
 f(x) = \frac{1}{2b} \exp\left(-\frac{|x-\mu|}{b}\right) = \frac{1}{2b} \begin{cases} 
 \exp\left(\frac{-\mu-x}{b}\right) & \text{if } x < \mu \\
 \exp\left(\frac{-x-\mu}{b}\right) & \text{if } x \geq \mu 
\end{cases},
\]

where \(\mu\) is the mean and its variance is \(2b^2\).

By means of the chi-squared test, with \(p<0.05\), the adjustment of the experimental distribution to the Gaussian PDF was evaluated for the analyzed segments in each one of the obtained recordings.

The mean squared error (MSE) analysis was carried out between the distributions of the equations (1) and (2) and the mean PDF (averaged out from all the recordings) for each of the segments.

3. Results
As an example, figure 1 shows the recording of the SEMG signal corresponding to a step of one of the hemiparetic subjects studied, where the segments of the analyzed data can be identified.

In figure 2 the histograms obtained during the FIA and FO segments of one of the healthy subjects are shown. In this figure the mean PDF for all the recordings obtained for each segment can be seen in a full line. The dotted lines correspond to the Gaussian PDF and the dashed lines show the Laplacian PDF.
Figure 2. Distribution of the normalized amplitudes of the SEMG signal from a healthy subject in the segments corresponding to the FIA and the FO segments. The full line indicates the average experimental PDF of the recordings. The grey zone represents a standard deviation above and below average. The dotted line shows the Gaussian distribution and the dashed line represents the Laplacian distribution.

The histograms obtained for the analyzed segments, corresponding to one of the hemiparetic subjects are shown in figure 3. The average PDF for each of the segments of all the recordings are represented with a full line. As shown in the previous figure, the dotted line represents the Gaussian PDF and the dashed line represents the Laplacian PDF.

Figure 3. Distribution of the normalized amplitudes of the SEMG signal from a hemiparetic subject for the four segments studied. The full line shows the average experimental PDF of the recordings. The grey zone indicates a standard deviation above and below average. The dotted line represents the Gaussian distribution and the dashed line shows the Laplacian distribution.

The results of the chi-squared test (p<0.005) for each of the subjects studied are shown in Table 1. The number of recordings that best adjust to the Gaussian distribution in each of the selected segments can be observed in each column. This table shows that, for all the subjects, the experimental PDF during FO does not adjust to the Gaussian distribution.

| Subject         | Amount of steps | FIA | FMA | FFA | FO |
|-----------------|-----------------|-----|-----|-----|----|
| Healthy 1       | 30              | 7   | 13  | 19  | 3  |
| Healthy 2       | 30              | 13  | 5   | 19  | 9  |
| Hemiparetic 1   | 18              | 4   | 8   | 3   | 0  |
| Hemiparetic 2   | 22              | 5   | 10  | 8   | 3  |
The total ECM (average of all the trials) between the mean PDF estimated for each of the segments and the Gaussian and Laplacian PDF, corresponding to the four subjects that were studied. In general, it can be observed that this error is smaller in the case of the Laplacian distribution. In Table 2 the numbers in bold correspond to those exceptions, when the total ECM is smaller for the Gaussian distribution. This can be seen in the case of segments FIA, FFA and FO that correspond to our healthy subject 2 and of segments FMA and FFA of hemiparetic subject 2.

Table 2. Mean quadratic error of the analyzed segments, average of all the steps, between the estimated mean pdf and the gaussian and laplacian pdf.

| Subject     | Segment | Error with respect to FDP |
|-------------|---------|--------------------------|
|             |         | Gaussian | Laplacian |
| Healthy 1   | FIA     | 0,26724  | 0,10825  |
|             | FMA     | 0,19031  | 0,10473  |
|             | FFA     | 0,15964  | 0,14430  |
|             | FO      | 0,33001  | 0,08443  |
| Healthy 2   | FIA     | 0,14342  | 0,17322  |
|             | FMA     | 0,15301  | 0,11434  |
|             | FFA     | 0,13949  | 0,23361  |
|             | FO      | 0,16202  | 0,19389  |
| Hemiparetic 1 | FIA   | 0,19268  | 0,16823  |
|             | FMA     | 0,25477  | 0,21364  |
|             | FFA     | 0,19581  | 0,11933  |
|             | FO      | 0,39591  | 0,18128  |
| Hemiparetic 2 | FIA   | 0,22855  | 0,16954  |
|             | FMA     | 0,12594  | 0,20146  |
|             | FFA     | 0,17802  | 0,20653  |
|             | FO      | 0,16810  | 0,13255  |

4. Discussion and conclusions
The detection of changes in muscular activity involves the analysis of the signal in order to determine which estimators show greater specificity for detection. These estimators depend on the probability distribution of the signal.

In this work it was demonstrated that in the SEMG from both the healthy and hemiparetic subjects studied, the distribution of amplitudes corresponding to the FIA and FO segments relates better to the Laplacian PDF. These segments correspond to gait phases in which a greater TA activity is normally evidenced. In the case of the rest of the studied segments, the distribution showed an irregular behaviour.

The results obtained indicate that the distribution of the probability of the SEMG signal does not fit into a unique distribution model. However, these results suggest that the segments related to important moments of TA activity are closer to a Laplacian PDF, not only in healthy volunteers, but also in
hemiparetic subjects. This conclusion coincides with other studies reported on healthy subjects [2][5]. Nevertheless, this SEMG characterization as a process with Laplacian distribution is valid in the case of the analyzed segments that were supposed to be stationary. In this sense, it is believed that during the gait cycle the SEMG distribution changes when a series of situations vary, e.g. the muscular contraction level, the muscle length, the speed at which this length changes, the relative movement of the electrodes with respect to the generating source, among others.

According to what has been stated above, for the selection of estimators of amplitude change of the SEMG signal it is necessary to take a particular gait model into account. Such a model should incorporate physiological aspects related to the way the signal is generated, i.e., the way in which the potentials of the motor units are recluted, aspects related to the method by which the signal is recorded and the consequent alterations arisen from pathology. Furthermore, as the level of muscular contraction affects the way in which the distribution of the SEMG amplitude occurs, the model should take dynamic aspects related to changes in muscular contraction that can be seen during the gait cycle into account.

The contribution of this work was to study signals not only from healthy people, without sequels, who will not need the help of technology, but also from those potential users in need of it. Our future steps are focused on the exploration of a greater number of pathological cases that may help us understand the differences between them and healthy subjects in order to conceive commands based on the electromyography signal under real situations with actual users.

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