EFFECTS OF SUPERVISED PRACTICE ON THE ACCURACY OF OBSERVERS FOR MANUAL SEGMENTATION OF SIMULATED ELECTROMYOGRAMS

Arthur de Sá Ferreira[1], Fernando Silva Guimarães[2], Regina Coeli Souza e Silva[1] and Manuel Armando Ribeiro Magalhães[1]

[1]*Laboratory of Computational Simulation and Modeling in Rehabilitation, Postgraduate Program of Rehabilitation Science, Centro Universitário Augusto Motta/UNISUAM, Rio de Janeiro, Brazil*
[2]*Laboratory of Cardiovascular and Respiratory Performance, Postgraduate Program of Rehabilitation Science, Centro Universitário Augusto Motta/UNISUAM, Rio de Janeiro, Brazil*

Original scientific paper
UDC: 577.35:612.766:004.94:796.015.868

Abstract:

Visual interpretation of electromyograms is common, but its accuracy is unknown. This study compared the accuracy curves of inexperienced observers in detecting muscular contractions from variable, simulated surface electromyogram signals. Accuracy was assessed both without feedback (unsupervised practice) and with feedback (supervised practice) to determine whether a training effect existed. Six observers performed manual segmentation in 300 simulated waveforms using a phenomenological model with a variable number of contractions (n=1, 2 or 3), smooth changes in amplitude, marked on-off timing, and a variable signal-to-noise ratio (0-39 dB). Segmentation was organized in two one-day sessions with 15 blocks of 20 signals each for the unsupervised and supervised practices, respectively. Supervised practice was provided by an immediate visual feedback on the manual segmentation. The accuracy curve showed no significant linear regressions for either unsupervised (R^2=.104, p=.241) or supervised practices (R^2=.153, p=.150). No significant difference in accuracy was observed between the unsupervised and supervised practices (85% [77; 99] and 88% [73; 97], respectively; p=.295). Unsupervised practice yielded low accuracy for one muscular contraction (AUC=.43; cut-off=12.8 dB) and increased with supervised practice (AUC=.63; cut-off=9.5 dB). Unsupervised practice resulted in high accuracy for two contractions (AUC=.88; cut-off=6.9 dB) and was similar to the supervised practice (AUC=.81; cut-off=6.3 dB). Supervised practice using visual feedback improved the accuracy of inexperienced observers in the segmentation of one muscular contraction in simulated electromyograms and did not influence the accuracy of two muscular contractions.

Key words: *electromyography, contraction detection, computer simulation, muscle activity*

Introduction

The shape-varying waveform exhibited by surface electromyograms (SEMG) remains a challenge for the scientific assessment of muscle functioning in either daily-living activities or dynamic sports. SEMG waveforms are related to the neural strategies for motor units' recruitment during muscle contractions and they therefore depend on the motor task being executed (Farina, Merletti, & Enoka, 2004; Merletti & Parker, 2004). The understanding of muscle function requires an accurate estimation of parameters related to its activity, which in turn depends on how accurately the SEMG is segmented into separated contractions (Ferreira, Guimarães, & Silva, 2010). On the one hand, automated methods are fast and accurate for detecting the on-off timing of contractions of SEMG exhibiting nearly constant amplitude as obtained during maximal isometric voluntary contractions (Abbink, van der Bilt, & van der Glas, 1998; Bonato, D'Alessio, & Knaflitz, 1998; Micera, Vannozzi, Sabatini, & Dario, 2001; Wilen, Sisto, & Kirshblum, 1999). On the other hand, they present poor performance in cases of shape-varying SEMG due to superposed activation patterns of motor units in more complex motor tasks (Staude & Wolf, 1999).

Manual segmentation of SEMG by visual inspection is a valid alternative method to automated segmentation; it can be used for screening the signal in order to judge whether the SEMG represent meaningful physiological activity (Di Fabio, 1987). In spite of being an off-line and time-consuming method (Di Fabio, 1987; Staude & Wolf, 1999), manual segmentation still has important applications in movement sciences (Ferreira, et al., 2010) and other fields such as gynecology (Marques, Terrien, Rihana, & Germain, 2007; Moslem, Khalil, Marque, & Diab, 2010) and neurology (De Marchis, Schimd, & Conforto, 2012), where it is necessary to identify separated muscular contractions. Few studies investigated the accuracy of observers for manual segmentation of SEMG, with most of them analyzing the accuracy for on-off timing identification (Jesunathadas, Aidoor, Keenan, Farina, & Enoka, 2012). Our research group initiated a project aimed at assessing the accuracy of observers and automated methods for the detection of SEMG. The phase-I study (Ferreira, Guimarães, Magalhães, & Silva, 2013) investigated the accuracy and learning curves of observers for the segmentation of SEMG contractions using a phenomenological model developed to generate shape-varying SEMG signals. The results showed that inexperienced observers presented high accuracy – approximately 87% – for correct identification of muscular contractions on shape-varying simulated SEMG, and that their performance was faster but not more accurate in unsupervised practice. However, it remains uninvestigated whether supervised practice improves the accuracy of this signal processing in shape-varying SEMG signals.

Determination of the effects of supervised practice on accuracy curves of observers performing manual segmentation of SEMG might contribute to the establishment of practice parameters to achieve their optimal level of accuracy. Therefore, the aim of this phase-II study was to compare the accuracy curves of inexperienced observers to detect the number of muscular contractions in shape-varying SEMG under the unsupervised and supervised practice conditions, the latter being characterized by an immediate visual feedback. It was hypothesized that supervised practice might improve the accuracy of observers for the detection of SEMG contractions.

Methods

Participants

Six inexperienced participants (four women; 30±14 years) were recruited from the undergraduate and graduate academic community. They studied SEMG signals during graduation and post-graduation courses, but did not perform any manual segmentation of signals prior to this study. All participants were informed about the procedures and gave their written consent. The institutional ethics committee approved this study before its execution (CAAE-0011.0.307.000-11).

Simulation of shape-varying surface electromyograms

The computational procedure for SEMG simulation was fully described in a previous study (Ferreira et al., 2013) and is summarized here in Figure 1. The discrete raw *SEMG*(*i*) presenting a variable number of muscular contractions, smooth

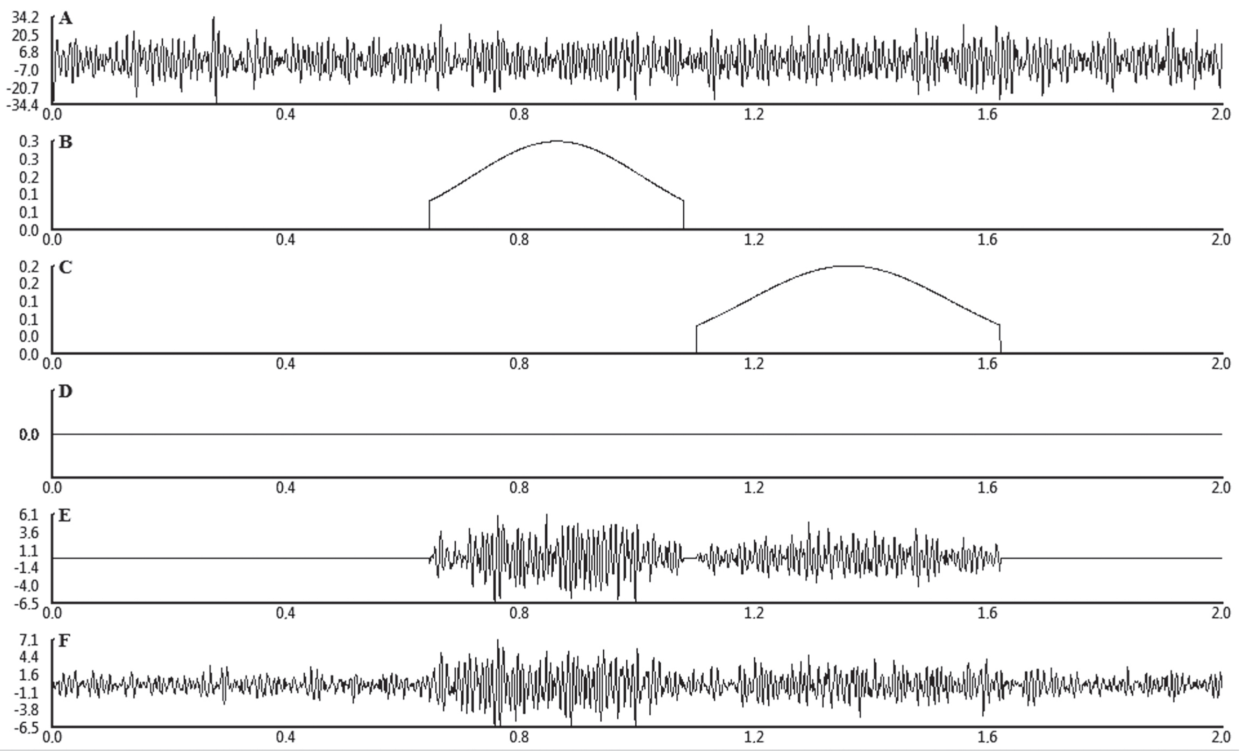

Figure 1. Steps for simulation of surface electromyograms (signal #229). A: Gaussian pattern representing an isometric contraction; B-D: three Gaussian patterns representing smooth muscle activity truncated by square patterns; E: simulated surface electromyogram; F: simulated surface electromyogram with additive noise used for manual segmentation.

changes in amplitude, marked on-off timing, and variable signal-to-noise ratio (SNR) is represented by equations 1-2:

$$(1)\quad SEMG(i) = y(i) + e(i)$$

$$(2)\quad y(i) = r(i) \cdot \sum_{n=1}^{3} g_n(i) \cdot \prod_{n=1}^{3} s_n(i)$$

where: i = sample number (1, 2,…, 2,000); n = muscular contraction (1, 2, or 3); $y(i)$ = noiseless SEMG for the i^{th} sample; $e(i)$ = background noise modeled as a band-limited (80-120 Hz, first-order Butterworth filter) pseudorandom pattern; $r(i)$ = isometric contraction modeled as a band-limited Gaussian-distributed pseudorandom pattern with standard deviation σ_r; $g_n(i)$ = n profiles of muscle activity modeled as n Gaussian functions with standard deviations σ_n and random amplitude factors in range [.1; 1]; and $s_n(i)$ = on-off periods modeled as n square patterns with time support α_n and unitary amplitude. Power-line interference and motion artifacts were not included since they could be satisfactorily removed before segmentation using other signal processing techniques (De Luca, Gilmore, Kuznetsov, & Roy, 2010; Lu, et al., 2009; Mewet, Reynolds, & Nazeran, 2004; Reaz, Hussain, & Mohd-Yasin, 2009). The SNR ratio per muscular contraction was calculated as the $10 \cdot \log_{10}(\sigma^2_y / \sigma^2_e)$, where σ^2_y and σ^2_e represent calculated variances of $y(i)$ and $e(i)$, respectively.

Three hundred SEMG signals were simulated using sets of uniformly distributed random values for σ_n (single contraction duration in range between 50 and 150 ms), α_n (1 to 2.5), and SNR (0 to 39 dB). All signals were simulated with a sampling frequency of 1.0 kHz and no further signal processing was performed before manual segmentation. The duration of contractions was chosen to match those observed in tremor detection (De Marchis, et al., 2012). The large range of SNR was also selected for comparison to other studies on SEMG simulation (5) and to generate muscular contractions that are either easy or difficult to find, so the performance of the observers could be distinguished. All components of the simulated SEMG – $r(i)$, $g_n(i)$, $s_n(i)$, and $e(i)$ – were stored as ASCII files in a database and are available upon request to the authors.

Manual segmentation in the unsupervised and supervised practices

Manual segmentation of SEMG signals was organized in two one-day sessions – unsupervised and supervised practices, respectively – separated by a two-week interval for washout. The session comprised 15 blocks of 20 signals each for analysis and the same 300 signals were evaluated during both practices, thus allowing a paired comparison of participants' accuracy.

Observers were instructed to take the necessary time for analyses and were informed that each signal might present up to three muscular contractions. The detection procedure started with the observers selecting the current block of signals and running a dedicated, user-friendly algorithm to open-read-display the SEMG signal in the same sequence as stored in database. It is worth noticing that only the composite $SEMG(i)$ was displayed on the screen so observers were blinded to simulation patterns (Figure 2). The screen for signal segmentation contained buttons for representing the number of contractions and corresponding pairs of movable cursors to separate them all. Observers were asked to accurately detect the number of contractions by visual inspection and to mark the corresponding button on the screen. Subsequently, the algorithm displayed pairs of cursors for each visually detected muscular contraction to allow observers to accurately mark separate on-off timings for each

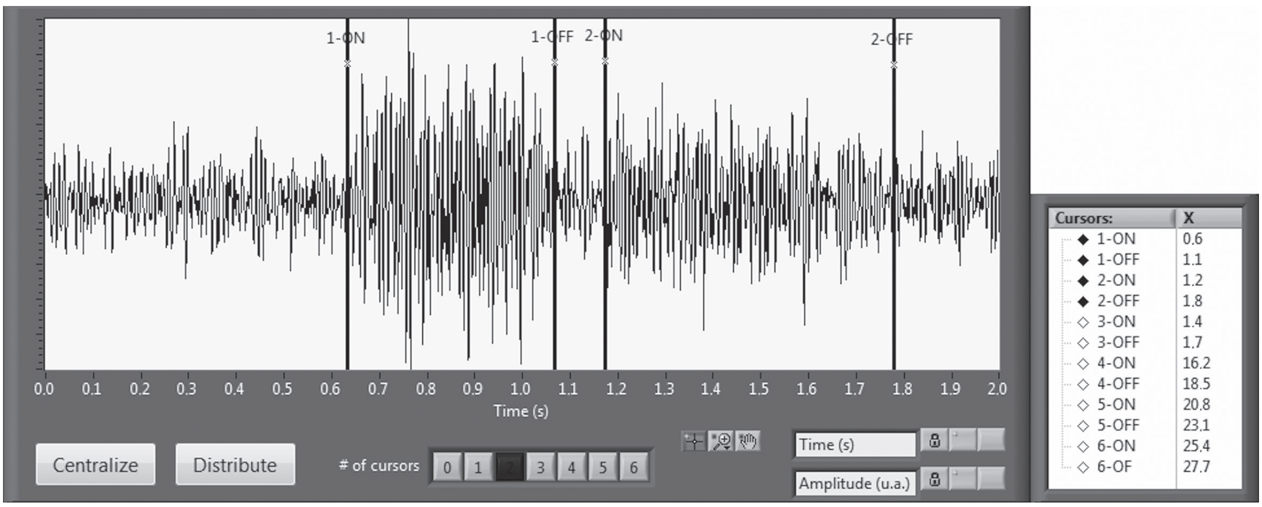

Figure 2. Computer screen for manual segmentation of simulated surface electromyograms. The observer marked the number of pairs of cursors for delimiting each muscular contraction (#2 in this example) and moved the on-off cursors for the corresponding locations of each contraction.

contraction. When a block of signals was completed, the number of contractions of each signal and their respective on-off timing were digitally stored as ASCII files for comparative analysis per block and per observer. A five-minute rest was allowed between sequential blocks. Total session time was approximately between two and three hours including the rest period.

Unsupervised practice was performed as follows. When the observer completed the manual segmentation of each signal, the software window was manually closed and the next signal in the block was automatically displayed. No information regarding the previous segmentation was provided to the observer before the next SEMG signal was presented for analysis.

Supervised practice was characterized by an immediate visual feedback after the observer closed the window. In such practice, the same window was automatically opened after manual segmentation showing the same SEMG signal just analyzed and the correct number of muscular contractions and respective on-off times. After manually closing the feedback window, the observer automatically received the next signal in the block for segmentation until finishing the block.

Statistical analysis

Descriptive values are presented as medians [minimum; maximum]. Graphs display group-average values and error bars represent ±SD. Signals were considered as correctly identified if the number of muscular contractions marked by the observer matched the number estimated from the Boolean OR comparison of $s_n(i)$ signals (the gold-standard of the activation pattern). Accuracy for quantification of events was computed as the proportion between the total of signals correctly identified to the total of signals per block. The accuracy curve per observer under the unsupervised and supervised practice conditions were modeled by a linear regression model (H_0: ß =0; intercept=0) and tested for difference between sessions using the Wilcoxon's test. P values and 99% confidence interval (99% CI) of nonparametric tests were estimated by bootstrap procedure by using Monte Carlo method with 800 samples. Statistical significance was considered at $p<.05$ (two-tailed; H_0: there is no difference in accuracy estimated during supervised or unsupervised practices).

Receiver-operating characteristic (ROC) curves (Hanley & McNeil, 1982) were used to determine the accuracy, sensitivity, specificity, and cut-off for SNR to a successful detection (binary variable: correct=1). The AUC as surrogate measure of accuracy varied from 0 to 1 and can be likewise interpreted from *no apparent accuracy* (AUC≤.5) to *perfect accuracy* (AUC=1). The group-median area under the ROC curve (AUC), sensitivity, specificity, and cut-off values for SNR were estimated separately for signals that were simulated with one and two muscular contractions (249 and 49 signals, respectively).

Computational resources

Two computers with the same configuration (Intel® Core 2 Duo, Windows® XP) were used in this study and observers used the same computer throughout the study. Algorithms for SEMG simulation and manual segmentation by observers were implemented in LabVIEW 8.0 (National Instruments, Texas, USA) and were fully automated. Statistical analyses were conducted in SPSS 17 (SPSS Inc., Illinois, USA) and LabVIEW 8.0 (National Instruments, Texas, USA).

Results

Figure 3 presents the group-average accuracy curves obtained from the unsupervised and supervised practices. The accuracy curve showed a positive trend in accuracy throughout the session for both practices, but without significant linear regressions for either the unsupervised (r=.323, R^2=.104, p=.241) or supervised practice (r=.391, R^2=.153, p=.150).

Figure 4 exhibits the group-median accuracy per block for comparison between practices. No significant difference (p=.595 [.550; .640]) in accuracy was observed between the unsupervised (85% [77; 99]) and supervised practices (88% [73; 97]) (Figure 2).

The ROC curves are displayed in Figure 5 and present distinct behaviors considering the quantity of simulated contractions under both practice conditions. Regarding the signals for one contraction, unsupervised practice yielded no apparent accuracy and was largely affected by SNR (AUC=.43; sensitivity=45%; specificity=39%; cut-off=12.8 dB), although the accuracy increased with supervised practice and was less affected by SNR (AUC=.63; sensitivity=62%; specificity=62%; cut-off=9.5 dB). Regarding the signals for two contractions, unsupervised practice resulted in high accuracy that was even less affected by the SNR (AUC=.88; sensitivity=81%; specificity=80%; cut-off=6.9 dB) and was similar to supervised practice (AUC=.81; sensitivity=72%; specificity=73%; cut-off=6.3 dB).

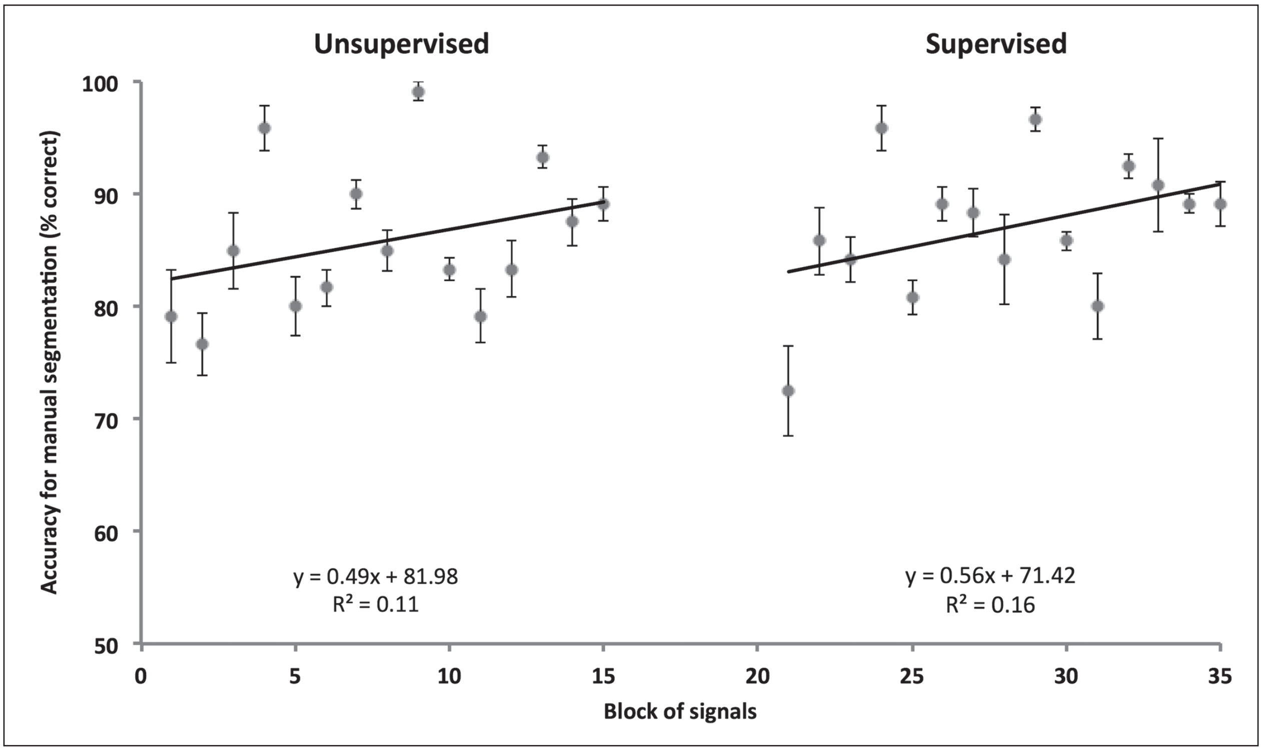

Figure 3. Accuracy curves for manual segmentation of simulated surface electromyograms under unsupervised (left) and supervised (right) practices. Circles and errors bars are represented as group-average±SD values per block.

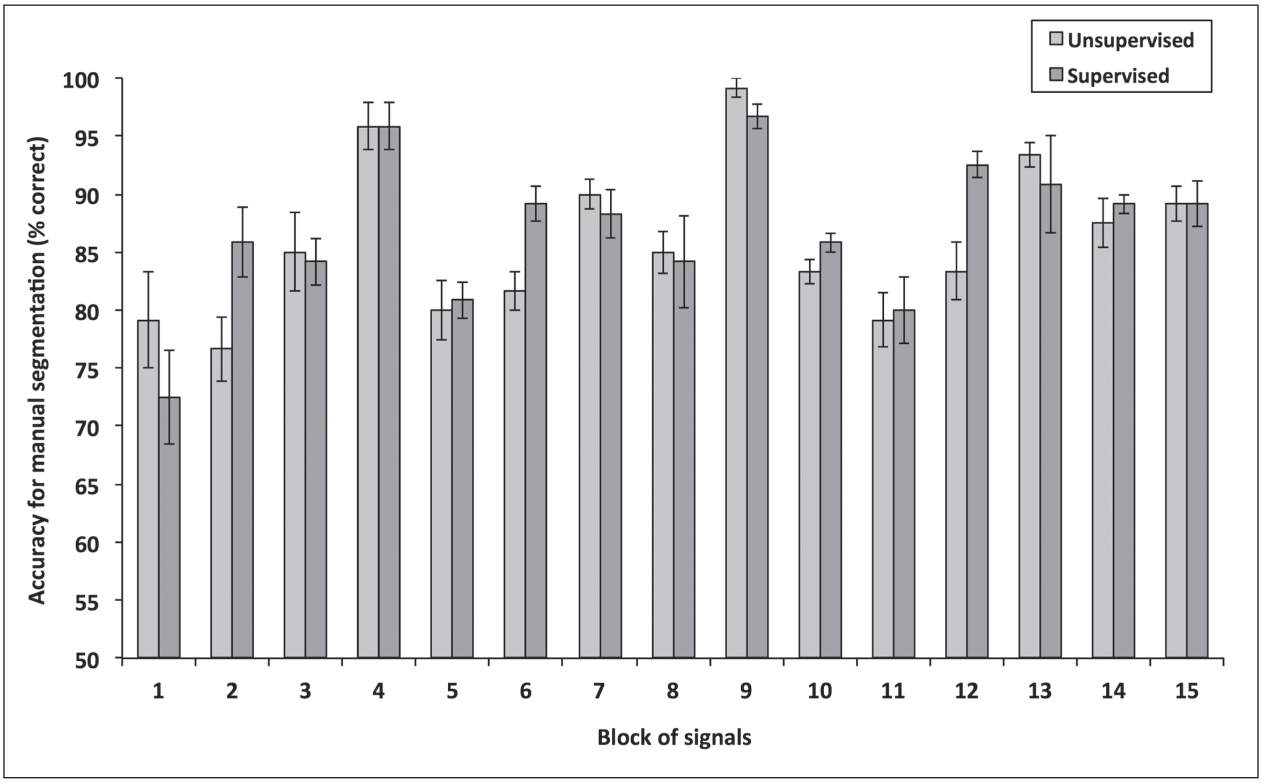

Figure 4. Comparison between accuracy for manual segmentation of simulated surface electromyograms under unsupervised (light grey) and supervised (dark grey) practices. Bars and errors bars represent group-averages±SD values.

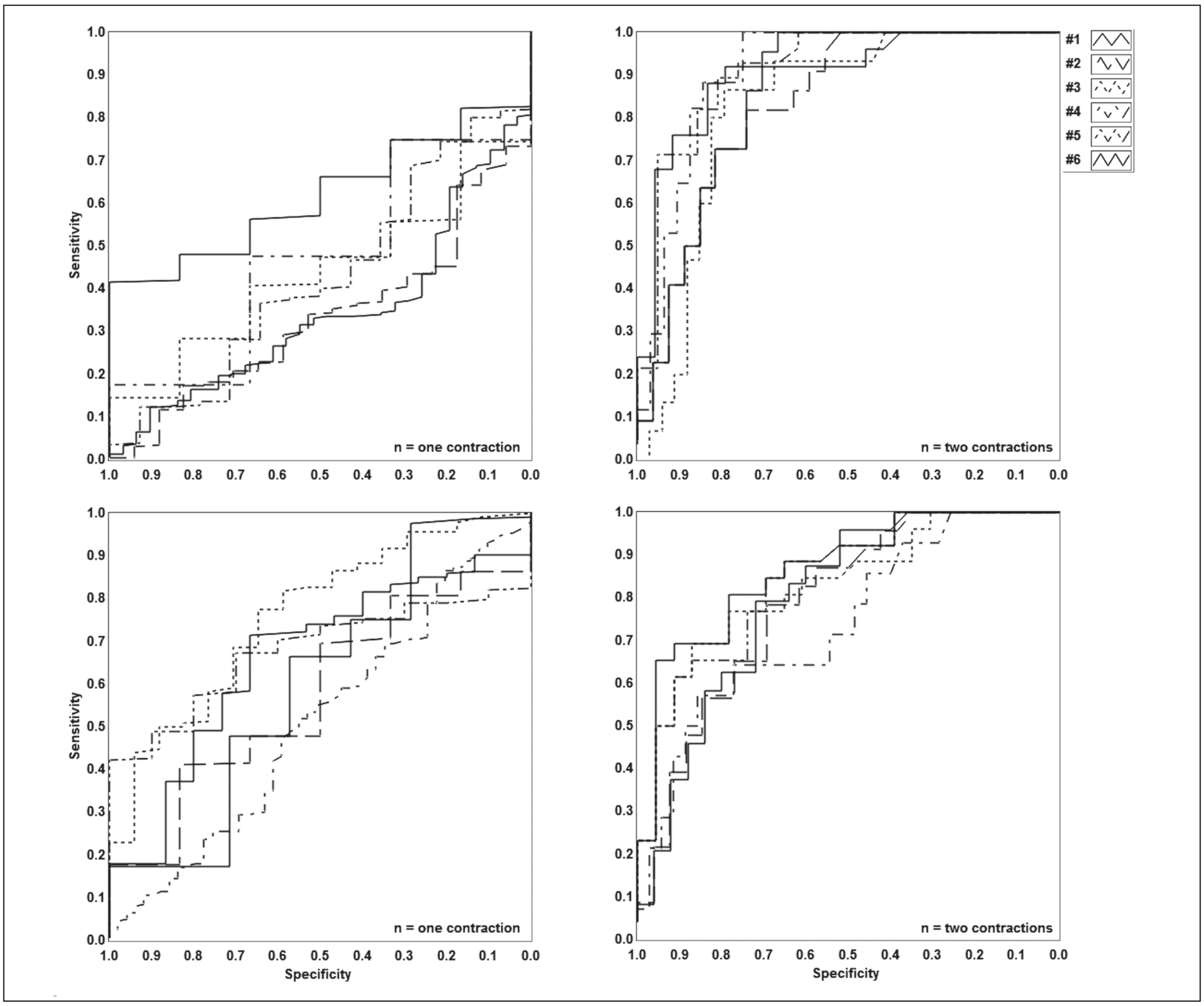

Figure 5. Receiver operating characteristic curves for accuracy estimated for quantification of n=1 (left panels) and n=2 (right panels) contractions as obtained from unsupervised (top panels) and supervised practices (bottom panels). Lines represent each observer.

Discussion and conclusions

This study compared the accuracy curves, segmented by inexperienced observers, obtained under unsupervised and supervised practices to detect the number of contractions in shape-varying simulated SEMG. The results of this study confirm our hypothesis that supervised practice improves the accuracy of observers for detection of SEMG contractions only in specific conditions, but not for all signals. More specifically, immediate visual feedback improved manual segmentation of one muscular contraction, although it did not change the accuracy when two contractions were present in the SEMG. To the best of our knowledge, this is the first study to quantify the accuracy curve of inexperienced observers for manual segmentation of shape-varying SEMG with supervised practice. In contrast to the phase-I study (Ferreira, et al., 2013), there was no learning curve investigation and the observers were informed about their performance immediately after the segmentation of the signal.

The group-average accuracy curves suggested that observers performed manual segmentation progressively better in each block of signals until the plateau of performance was achieved. This improvement in accuracy may be attributed to familiarization with the procedure, best use of equipment, or to the discovery of 'shortcuts' to complete the procedure (Anzanello & Fogliatto, 2007). However, the learning effect may be considered as negligible for one session of SEMG, since no significant linear trend was observed. The level of accuracy observed in this study using manual segmentation under variable SNR is similar to that reported in recent studies using manual segmentation (Ferreira, et al., 2013; Malone, Meldrum, Gleeson, & Bolger, 2011), and therefore the results of this study are considered as representative.

During unsupervised practice, observers were not aware of their accuracy in segmenting previous signals. Such a lack of feedback on their performances does not simulate a real scenario (i.e.

real SEMGs do not have gold-standards), but it also tests whether inexperienced observers can intuitively learn how to detect muscular contractions better. In contrast, during supervised practice the feedback available from the previous signal provided an opportunity to the observers to extract relevant information from SEMG to significantly improve their accuracy and learn from their performance. Although the absence of significant differences between unsupervised and supervised practices reinforces the former case, it was sufficient to improve the accuracy for detection of one but not two muscular contractions.

In-deep analysis of ROC curves showed that observers exhibited low statistical performance for detection of one contraction at a high SNR but performed better for detection of two muscular contractions at lower SNR under both practices. Most importantly, these results suggest that the performance for detection of one contraction can improve after supervised practice. The results from the ROC curves with two muscular contractions were the most stable and may be explained by the experimental procedure; signals with two contractions may have induced the observers to miss a contraction with a smaller amplitude despite previous experience on the possible existence of other contractions. On the contrary, signals simulated with one contraction do not have other high-amplitude muscular contractions to confound the observers. This explanation is reinforced by the improvement in both AUC and accuracy for detection of one contraction during supervised practice. For comparison, the double-threshold method (Bonato, et al., 1998) exhibited high accuracy (>95%) for detection of erroneous transitions in on-off timing for SNR only above 10 dB for one contraction. Moreover, automated methods for on-off timing in general showed systematic degradation of accuracy with acceptable results at 6 dB (De Marchis, et al., 2012; Staude, Flachenecker, Daumer, & Wolf, 2001). Therefore, the accuracy of manual segmentation obtained in this study is considered comparable to those exhibited by automated methods using simulated or real SEMG signals. This SNR could be the major confounder to the lack of improvement with supervised practice because some signals may simply be too poor for interpretation. Future studies need to investigate the effect of SNR, as there may be a threshold below which visual detection is not sufficiently accurate, consequently rendering the EMG signal of little value in clinical practice.

Some limitations of this study are worth noticing. The generalizability of the observed results to clinical practice might be limited by the lack of a consistent, statistically significant effect of supervised training. Also, this study has a small sample size of observers and results could be different or less variable with a larger sample size drawn from a wider pool of possible inexperienced observers. Nevertheless, the results of this study have important implications. Firstly, the lack of practice in manual segmentation may affect the accuracy of observers, particularly for shape-varying signals with one muscular contraction. Most importantly, this study recommends that inexperienced observers train manual segmentation with the same software for at least 300 signals under supervised practice before they are able to do this with the highest level of accuracy.

This project will be continued to phase-III study to compare the accuracy of inexperienced observers and computational methods for automated segmentation of SEMG. In this phase, the experimental procedure will include the implementation of most-commonly used algorithms for SEMG preprocessing (e.g. linear envelope, windowed RMS) and segmentation (e.g. single- and double-threshold detectors) to segment the SEMG for comparison with the manual method. In contrast to the phase-I and phase-II studies, not only the number of contractions will be analyzed, but also the on-off timing of each contraction, as well as its dependency on the SNR.

Supervised practice using visual feedback improves the accuracy of inexperienced observers to segment one contraction in shape-varying simulated surface electromyograms without the influence on the accuracy for detection of two contractions.

References

Abbink, J.H., van der Bilt, A., & van der Glas, H.W. (1998). Detection of onset and termination of muscle activity in surface electromyograms. *Journal of Oral Rehabilitation*, *25*(5), 365-369.

Anzanello, M.J., & Fogliatto, F.S. (2007). Curvas de aprendizado: estado da arte e perspectivas de pesquisa. [Learning curves: State-of-the art and perspectives for research. In Portuguese.] *Gest*ão e *Produção*, *14*(1), 109-123.

Bonato, P., D'Alessio, T., & Knaflitz, M. (1998). A statistical method for the measurement of muscle activation intervals from surface myoelectric signal during gait. *IEEE Transactions in Biomedical Engineering*, *45*(3), 287-299.

De Luca, C.J., Gilmore, L.D., Kuznetsov, M., & Roy, S.H. (2010). Filtering the surface EMG signal: Movement artifact and baseline noise contamination. *Journal of Biomechanics*, *43*(8), 1573-1579.

De Marchis, C., Schmid, M., & Conforto, S. (2012). An optimized method for tremor detection and temporal tracking through repeated second order moment calculations on the surface EMG signal. *Medical Engineering & Physics*, *34*(9), 1268-1277.

Di Fabio, R.P. (1987). Reliability of computerized surface electromyography for determining the onset of muscle activity. *Physical Therapy, 67*(1), 43-48.

Farina, D., Merletti, R., & Enoka, R.M. (2004). The extraction of neural strategies from the surface EMG. *Journal of Applied Physiology*, *96*(4), 1486-1495.

Ferreira, A.S., Guimarães, F.S., Magalhães, M.A.R., & Silva, R.C.S. (2013). Accuracy and learning curves of inexperienced observers for segmentation of electromyograms. *Fisioterapia em Movimento*, *26*(3), 559-567.

Ferreira, A.S., Guimarães, F.S., & Silva, J.G. (2010). Methodological aspects of surface electromyography: Signal composition and processing for neuromuscular function assessment. *Revista Brasileira de Ciência do Esporte, 31*(2), 11-30.

Hanley, J.A., & McNeil, B.J. (1982). The meaning and use of the area under a receiver operating characteristic (ROC) curve. *Radiology*, *143*(1), 29-36.

Jesunathadas, M., Aidoor, S.S., Keenan, K.G., Farina, D., & Enoka, R.M. (2012). Influence of amplitude cancellation on the accuracy of determining the onset of muscle activity from the surface electromyogram. *Journal of Electromyography and Kinesiology, 22*(3), 494-500.

Lu, G., Brittain, J.S., Holland, P., Yianni, J., Green, A.L., Stein, J.F., Aziz, T.Z., & Wang, S. (2009). Removing ECG noise from surface EMG signals using adaptative filtering. *Neuroscience Letters, 462*(1), 14-19.

Malone, A., Meldrum, D., Gleeson, J., & Bolger, C. (2011). Reliability of surface electromyography timing parameters in gait in cervical spondylotic myelopathy. *Journal of Electromyography and Kinesiology, 21*(6), 1004-1010.

Marques, C.K., Terrien, J., Rihana, S., & Germain, G. (2007). Preterm labour detection by use of a biophysical marker: the uterine electrical activity. *BMC Pregnancy and Childbirth, 7*(Suppl 1): S5.

Merletti, R., & Parker, P.A. (2004). *Electromyography: Physiology, engineering, and noninvasive applications.* New Jersey: IEEE Press.

Mewet, D.T., Reynolds, K.J., & Nazeran, H. (2004). Reducing power line interference in digitised electromyogram recordings by spectrum interpolation. *Medical & Biological Engineering & Computing, 42*(4), 524-531.

Micera, S., Vannozzi, G., Sabatini, A.M., & Dario, P. (2001). Improving detection of muscle activation intervals. *IEEE Engineering in Medicine and Biology Magazine, 20*(6), 38-46.

Moslem, B., Khalil, M., Marque, C., & Diab, M.O. (2010). A wavelet package-based energetic approach for the analysis of the uterine EMG. In *Proceedings of ISSNIP Biosignals and Biorobotics Conference*, Vitoria, Brazil (pp. 98-102).

Reaz, M.B.I., Hussain, M.S., & Mohd-Yasin, F. (2006). Techniques of EMG signal analysis: Detection, processing, classification and applications. *Biological Procedures Online*, *8*(1), 11-35.

Staude, G., Flachenecker, C., Daumer, M., & Wolf, W. (2001). Onset detection in surface electromyographic signals: A systematic comparison of methods. *EURASIP Journal of Advanced Signal Processing*, *2*, 67-81.

Staude, G., & Wolf, W. (1999). Objective motor response onset detection in surface myoelectric signals. *Medical Engineering & Physic*s, *21*(6-7), 449-467.

Wilen, J., Sisto, S.A., & Kirshblum, S. (2002). Algorithm for the detection of muscle activation in surface electromyograms during periodic activity. *Annals of Biomedical Engineering*, *30*(1), 97-106.

Submitted: March 13, 2014
Accepted: November 28, 2014

Correspondence to:
Adjunct Professor Arthur de Sá Ferreira, Ph.D.
Av. Paris 34, Bonsucesso, RJ – Brazil
CEP 21041-010
Phone: +55 (21) 3882-9797 (extension 1015)
E-mail: arthur_sf@ig.com.br; arthurde@unisuamdoc.com.br

Acknowledgement

This study was supported by the grant (nº E-26/103.066/2012) from the Fundação Carlos Chagas Filho de Amparo à Pesquisa no Estado do Rio de Janeiro (FAPERJ) and the undergraduate scholarship from the Institutional Scholarship Program for Scientific Initiation (PIBIC).