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New Automatic Measurement Method of the Motor Unit Action Potential Duration based on the Wavelet and Hilbert Transforms

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Abstract

A new automatic method based on the wavelet and Hilbert transforms for measuring the motor unit action potential (MUAP) duration is presented in this work. A total of 182 MUAPs from two different muscles were analysed. The average MUAP waveform was wavelet-transfomed, and a particular scale of the wavelet transform was selected to avoid baseline fluctuation and high frequency noise. Then, the Hilbert transform was applied to this wavelet scale to obtain its envelope. Amplitude and slope criteria in this envelope were used to obtain the MUAP start and end points. The results of the new method were compared to the gold standard of duration marker positions obtained by manual measurement. These new method was also compared to two another automatic duration methods: a recently method developed by the authors and a conventional automatic duration algorithm. The differences between the new algorithm's marker positions and the gold standard of duration marker positions were in some cases smaller than those observed with the recently published and the conventional method. Our new method for automatic measurement of MUAP duration is more accurate than other available conventional algorithms and performs better than the recent method in some cases.

Key words: Motor unit action potential, Duration, Quantitative electromyography, Wavelet transform, Hilbert transform

1 Introduction

Analysis of the motor unit action potential (MUAP) is an essential aspect of needle EMG studies. The MUAP waveform is quantitatively characterized by several parameters of which duration is indispendable, as the rest of parameters are measured within (Stalberg et al., 1986). MUAP duration is related to the number of muscle fibers in the motor unit and to the temporal dispersion of the activation times of the fibers and their conduction velocities (Stalberg et al., 1996). The MUAP onset is usually an abrupt takeoff due to the muscle fiber depolarization. However the offset is more difficult to determine as the final phase of the potential returns to the baseline very slowly and asymptotically without a distinct end point (Sonoo and Stalberg, 1993). This final slow afterwave has been related to the shape of the intracellular action potential (Lateva and McGill, 1998).

It has been demonstrated in real electromyographic (EMG) recordings and simulation studies that the extinction of the action potentials continues for over 20 miliseconds (ms) after the main spike of the MUAP (Lateva and McGill, 1998; Dumitru and King, 1999; Dumitru et al., 1999). In real routine EMG signals almost invariably show slow baseline fluctuations and other noise such that it is very difficult to distinguish the full extension of the final portion of the MUAP. Thus, this work is devoted to the "clinical MUAP duration", different from the "physiologic MUAP duration" (Dumitru and King, 1999; Dumitru et al., 1999).

On the other hand, the duration markers define the boundaries of the MUAP waveform and thereby separate the parts of the recorded signal that will be analyzed from what can be considered as baseline or background activity. Thus, duration is the MUAP parameter that must be determined first. The procedure of measuring MUAP duration presents hard intrinsic difficulties, and therefore manual duration measurement has been previously described as "an arbitrary task" (Sonoo, 2002). However, the manual placement of duration markers does not guarantee an accurate duration measurement and low degrees of reliability of manual duration markers have been reported (Stalberg et al., 1986; Nandedkar et al., 1988; Chu et al., 2003; Takehara et al., 2004b; Rodríguez et al., 2007a).

A number of automatic algorithms have been designed (Stalberg et al., 1986; Nandedkar et al. 1995) to try to overcome the limitations of subjective assessment of the MUAP duration. But, as reported by others (Bischoff et al., 1994; Stalberg et al., 1995; Takehara et al., 2004a), conventional automatic algorithms imply the necessity of continuous visual supervision and frequent manual readjustments of the duration markers. These methods fail the duration measurement due to the presence of fluctuations in the baseline and from noise of other potentials. Unfortunately, such baseline irregularities and noise are common in routine EMG signals.

A recently published algorithm was proposed by the authors (Rodríguez et

al., 2007b) based on the discrete wavelet transform (DWT), which is a processing technique that simultaneously obtain a time scale representation of the signal. In this transform, high frequency noise and baseline fluctuations can be put aside. This automatic method achieved excellent and accurate results significantly better than other available algorithms. Even though, this method had some limitations that the new presented method tries to outperform by applying the Hilbert transform.
The Hilbert transform is a useful mathematical tool used to detect the envelope of a real-valued carrier modulated signal in communications theory (Carlson , 1986). Applying this transform to an intermediate wavelet representation of a MUAP can approximate its envelope and then find the MUAP start and end points. This new algorithm is compared to the Aalborg method, the conventional algorithm that we found to be best in a previous comparative study (Rodríguez et al., 2007a), and also to the wavelet transform method already published (Rodríguez et al., 2007b). Part of the present study was presented at XVIth Congress of the International Society of Electromyography and Kinesiology (ISEK 2006) celebrated in Torino in June 2006.

2 Material

The continuous EMG signals of 2-second duration were recorded from the tibialis anterior (TA) and first dorsal interosseous (FDI) muscles of eight healthy voluntary subjects, five men and three women, mean age of 44 years with standard deviation of 11.2 and range of 27 to 61. Informed consent was obtained. The raw EMG signals were recorded during slight muscle contaction. From 1 up to 3 motor units were active and then from 1 to 3 MUAPs were manually extracted from each continuous signal.
Recording equipment comprised an electromyograph (Counterpoint, Dantec Co., Denmark) and disposable concentric needle electrodes (type DCN37; diameter = 0.46 mm, recording area = 0.07 mm^2; Dantec).
The acquisition bandpass filter had a bandwith from 2 Hz to 10 kHz, with a sampling rate of 25.6 kHz and 16-bit analog-to-digital conversion. Data were stored on a PC computer for off-line analysis using a home-made software tool in the $Matlab^{TM}$ 7 environment (The Mathworks, Natick, MA, USA).
We looked through each EMG recording for epochs of 50 miliseconds (ms) containing non-distorted discharges in the main spike of the MUAPs. These discharges were manually selected by using a software tool devised to visualize the set of the extracted discharges of the same MUAP. The selected epochs were firstly aligned with respect to the maximal negative peak of the discharge, which was positioned 15 ms after the start of the 50 ms analysis window. Next, a correlation maximization algorithm (Proakis and Manolakis, 1996; Campos et al., 2000) was used to match the discharges with visual supervision of the

waveform alignment, as MUAP discharges were shown in raster and superimposed modes. The MUAP waveform was finally obtained as the average of the samples of the aligned discharges. The mean of the number of discharges to obtain the MUAP waveform was 5.0 with standard deviation of 3.4 discharges per MUAP and range of 3 to 29. All of the MUAP waveforms accepted for subsequent studies were well-defined over baseline activity and had a rise-time < 1 ms (in most cases < 500 μs).
A total of 182 MUAPs, 115 from the TA and 67 from the FDI, were accepted to be analysed in this work.

3 Methods

3.1 Determination of the gold standard of the duration marker positions

The great variability in the manual process of duration markers causes the difficulty of determining the best manual position among a set of several placements. Hence, we designed a method to determine the "most likely" MUAP start and end points. Over the whole set of 182 MUAPs, LG and another experienced electromyographist made three independent measurements of the duration. To this aim they were provided with a software interactive tool (devised in $Matlab^{TM}$ 7) that allowed them to visualize the averaged MUAP and the set of the extracted discharges in raster and superimposed modes. The sensitivity used to place the duration markers was 100 μV/cm. From the six manually marked positions for the start or end markers, the "most likely" position was obtained as the mean point of the three closest ones using a probabilistic approach (Fig. 1). This was considered as our gold standard position (GSP). This process is described in more detail in Rodríguez et al. (2007a).

3.2 Automatic methods for the measurement of MUAP duration

Three automatic mehotds for the measurement of MUAP duration were used: a well-known conventional algorithm, a recent method based on wavelet transforms and the new method presented here.

3.2.1 Description of the conventional automatic method

The conventional automatic method used in this work is the Aalborg method (AM) algorithm which was developed by Stalberg and co-workers (Stalberg et al., 1986) at the Institute of Electronic Systems, at Aalborg University Center

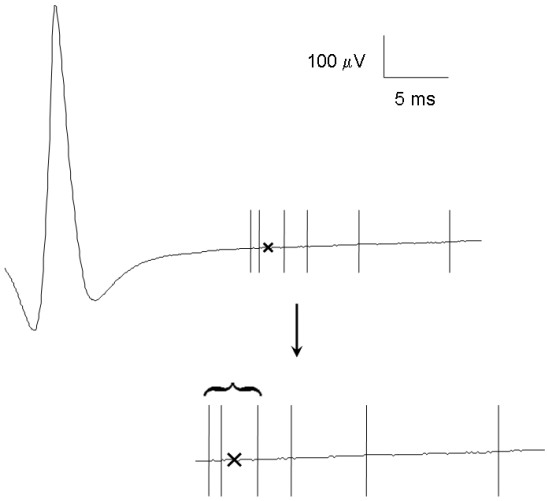

Fig. 1. Example of determination of the gold standard of the duration markers positions (GSP) from six manual marker positions for the end point (continuous vertical lines). The GSP (x) is calculated as the mean position of the three closest manual marker positions.

(Denmark). The authors selected this method as it gave the best results in a previous comparative study against other conventional methods (Rodríguez et al., 2007a). This algorithm could be implemented as it was sufficiently described in Stalberg et al. (1986).
In this method, MUAPs are automatically isolated with a software trigger level and classified by a template-matching method using the main spike of the potential. From each set of MUAPs, the 3 most similar discharges are selected to form the average MUAP waveform. The MUAP start and end points are found as the first point from the triggering point that has less than ± 5 μV signal fluctuation within the following (for the end) or previous (for the start) 5 ms window, and an absolute amplitude value less than 20 μV from the baseline. The baseline is considered to be the electrical zero of the amplifier.
In the present work, the MUAP waveform extraction process has been made manually, that ensures the picking up of undistorted waveforms of the MUAP even with relative low number of discharges but it does not overcome the presence of secondary MUAPs out of the analyzed one. Therefore, although the equipment and the MUAP extraction process was different than the original one, the performance of the AM should not have been modified significantly.

3.2.2 Wavelet based method for measurement of MUAP duration

On visual inspection of an EMG signal, MUAPs are distinguishable because they consist of a set of peaks (Fig. 2.a). The recent wavelet based method

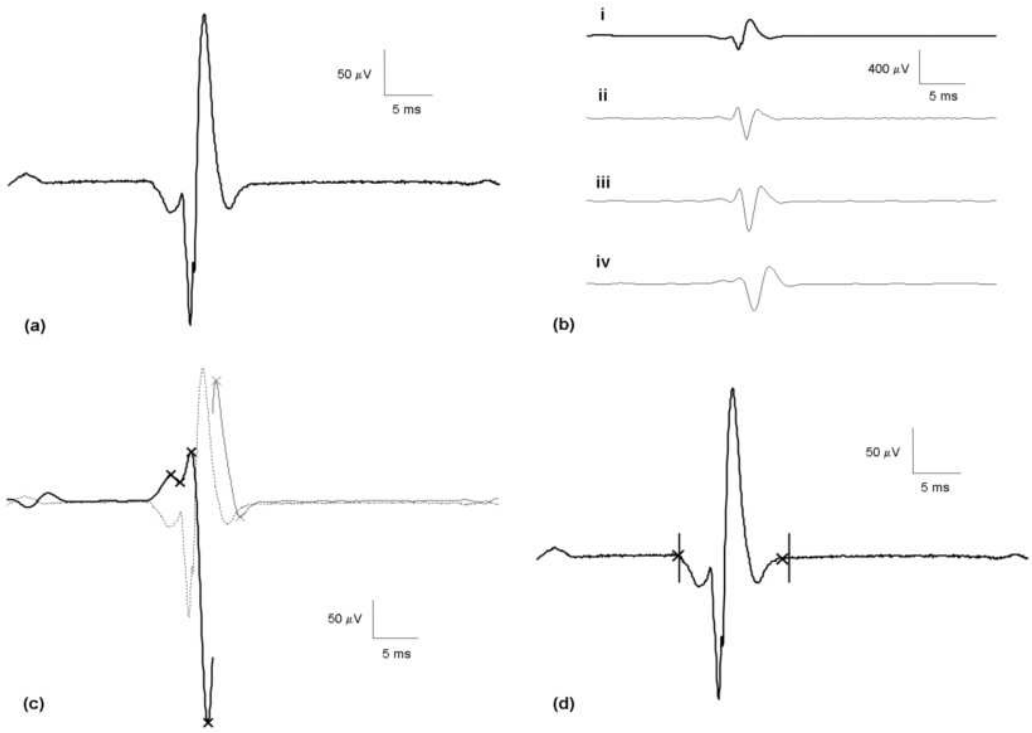

Fig. 2. (a) MUAP in a 50 ms long epoch. (b) The MUAP (i) and the DWT at scales 4 (ii), 5 (iii) and 6 (iv). (c) MUAP time course (dashed black points) and selected wavelet scales for finding start (thick continuous line) and end (thin continuous line) points. Maxima and minima related to the MUAP for the start (thick crosses) and the end (thin crosses). (d) MUAP duration calculated. Onset and offset (vertical lines) are shown and also the GSP markers (crosses) for this MUAP.

(WBM) makes use of the discrete wavelet transform (DWT) with the non orthogonal quadratic spline wavelet (Fig. 2.b) to detect not only the MUAPs but also the start and end points of these peaks. The method selects two intermediate scales (one to find the start and another to find the end marker) that represents the MUAP signal in terms of energy and evades noise and baseline fluctuation. In these scales the peaks related to MUAP peaks are identified (Fig. 2.c) and amplitude and slope thresholds are used to determine MUAP start and end points (Fig. 2.d). For finding MUAP start and end markers, the WBM makes use of 10 parameters including amplitude and slope thresholds. The values of these parameters were fixed by applying genetic algorithms with other 64 MUAPs from TA and FDI muscles recorded from the same electromyograph described in section 2. The WBM is described in detail in Rodríguez et al. (2007b).

3.3 The new method based on the wavelet and the Hilbert transforms

MUAPs can be viewed as stretched electrical impulses with a certain duration in time. Comparing MUAPs to a double side band modulated signal, the MUAP waveform fluctuation (with a decaying frequency) can be consider as the carrier signal and the message waveform can be the MUAP envelope. Then, the duration of its envelope can estimate the MUAP duration. And the envelope can be calculated using the Hilbert transform (HT). Besides, we know that the non-orthogonal quadratic spline wavelet used in this method is shift-invariant with regard to local peaks and zero crossings of the signals. Moreover, using the DWT we can choose a representation of the signal without high frequency noise and low frequency components or baseline fluctuation. That is the reason why a new method based on both transforms, the DWT and the Hilbert transform was designed. This wavelet and Hilbert transforms based method (WHM) comprises several phases (Fig. 3):

- Discrete Wavelet Transform. We apply the DWT using the nonorthogonal quadratic spline wavelet transform.

- Scale selection. The scale containing most energy is selected, avoiding the high frequency noise and the baseline fluctuation.

- Hilbert transform. Then, we apply the HT to this wavelet scale to obtain its envelope. We assume that this scale is the one that best characterizes the MUAP in terms of energy and frequency. Thus, the envelope of the MUAP is inherently related to MUAP duration.

- Determination of the difference signal. We calculate a difference signal between the HT and the first approximation of the DWT signal to obtain more accurate start and end markers.

- Determination of MUAP start and end points. We apply thresholding and slope criteria on the HT and the difference signal to look for the MUAP onset and offset.

3.3.1 Discrete Wavelet Transform

The DWT is applied to the averaged MUAPs (Fig. 4.a). The signal is fully decomposed in $J \leq log_2(L)$ levels (Fig. 4.b), where L is the length of the signal. The non-orthogonal quadratic spline wavelet with one vanishing moment was used. It has been shown that this wavelet (Mallat and Zhong, 1992) has the property that every uniphasic wave in a signal leads to a pair of peaks at every scale of the DWT. The DWT was implemented using Mallat's algorithm

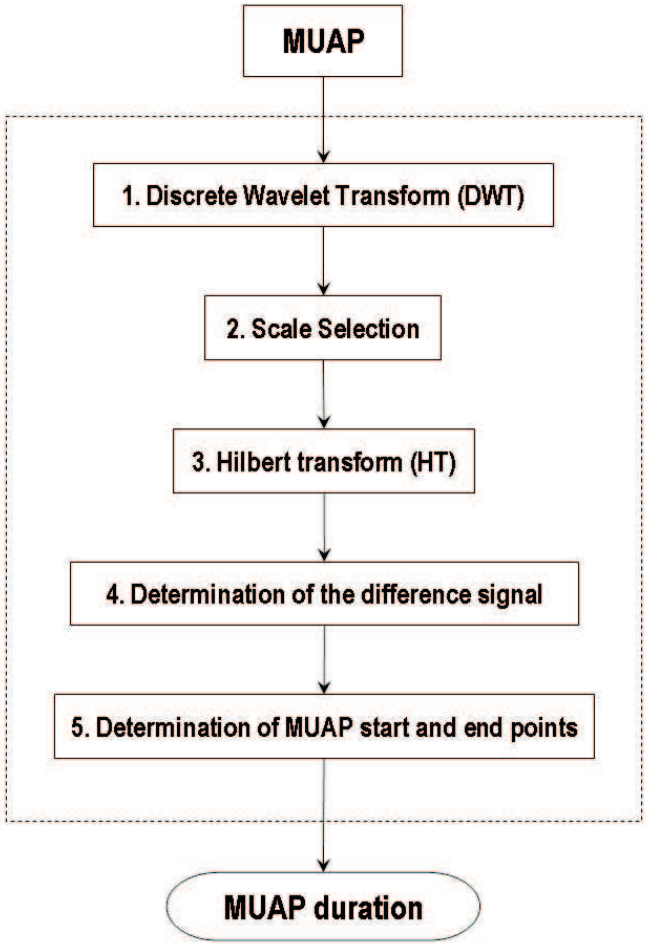

Fig. 3. Block diagram of the devised automatic duration method based on the DWT and the HT.

(Mallat, 1992b).

3.3.2 Scale selection

To find the MUAP start and end points, we select the highest energy scale of the first five, $d_e(n)$ (Fig 4.c). In this new method we do not select different detail signals as in the WBM for the MUAP onset and offset. A process of scale selection is needed because MUAP waveforms vary and energy is not always concentrated within the same wavelet scale or frequency band.

3.3.3 Hilbert transform

The HT is then applied for finding the envelope of this DWT scale (Fig. 4.d). Firstly, we find the maximum HT peak occurring within the 30-60% (usually

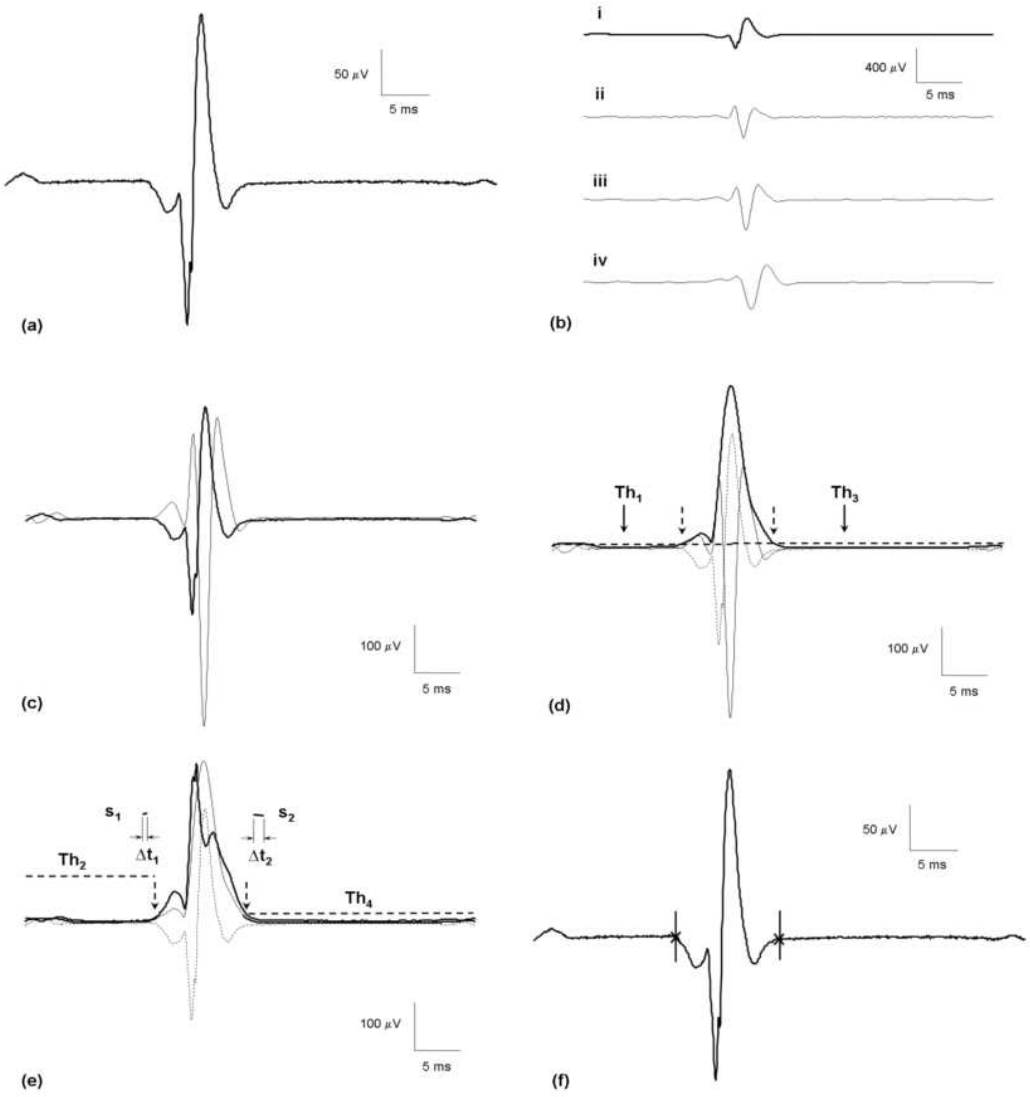

Fig. 4. HT (blue) of the selected DWT scale (dashed red) of a MUAP (dashed black). The thresholds Th_1 and Th_3 for the determination of MUAP onset and offset are shown too. Difference thresholds $Th2$ and Th_4 over the difference signal (green) between the first approximation of the DWT (dashed black) and the HT (dashed blue). Slope criteria s_1 and s_2 for the determination of MUAP start and end points. MUAP duration calculated. MUAP onset and offset (vertical continuous lines) are shown. GSP markers (x) are also shown.

15-30 ms) interval of the whole window (50 ms). For the MUAP start point, we select the HT from the beginning of the analysis window to the maximum peak. Then we subtract the minimum value of this first part of the HT. Similarly, for the MUAP end point, we select the HT from the maximum peak to the end of the analysis window. The minimum of the final part is subtracted too. These subtractions are performed to assure the existence of samples below any small amplitude threshold to look for MUAP onset and offset.

3.3.4 Determination of the difference signal

The absolute difference signal (ADS) is calculated between the first DWT approximation signal and the HT (Fig. 4.e). Thresholding over the difference between this signal and the HT will help to find out if the MUAP is beginning or finishing. Notice that the original MUAP can be obtained as the sum of the first DWT scale (detail) and the first DWT approximation. For the ADS we use the first approximation instead of the MUAP to avoid the high frequency noise, which is usually present in the first DWT detail signal.

3.3.5 Determination of MUAP start and end points

For the MUAP start point we considered the maximum in the HT and then, towards the beginning of the analysis window, we looked for a sample in the HT with amplitude within Th_1 (Fig. 4.d). If there is no sample below Th_1, the MUAP onset is the start of the analysis window. From this point and over the ADS, the MUAP start point is the sample with amplitude less than $Th2$ and slope less than s_1 (Fig. 4.e) over a window of Δt_1 ms. If there is not a sample fulfilling the difference threshold $Th2$, the MUAP onset is the sample that accomplishes the slope criterion given by s_1. Again, if there is not a point fulfilling both the $Th2$ and s_1 criteria, the MUAP onset is the point fulfilling the Th_1 criterion.
The MUAP end point is obtained in a similar way towards the end of the analysis window with parameters Th_3, Th_4, and s_2 over a window of Δt_2 ms (Figs. 4.d and 4.e). Duration is then measured as the time interval between the initial and final points (Fig. 4.f).
All the parameters involved in the calculation of MUAP start and end points were experimentally obtained using genetic algorithms. We applied the same genetic algorithm applied to the WBM parameters with the WHM parameters (Th_1, $Th2$, s_1, Δt_1, Th_3, Th_4, s_2 and Δt_2) to the same training set of other 64 MUAPs from TA and FDI muscles to fix the WBM parameter values recorded from the same equipment described in section 2. The parameters values for the WHM were:

$$Th_1 = 6.40\ \mu V,\ Th2 = 96.19\ \mu V,\ \Delta t_1 = 0.58\ ms,\ s_1 = 1.17\ \mu V/s \quad (1)$$

$$Th_3 = 9.19\ \mu V,\ Th_4 = 18.47\ \mu V,\ \Delta t_2 = 0.50\ ms,\ s_2 = 1.16\ \mu V/s \quad (2)$$

Notice that $Th_4 < Th2$ and $s_2 < s_1$ what is reasonable with the nature of MUAP onset and offset.

3.4 Assessment of the accuracy of the automatic measurements

To compare the three automatic duration methods, we calculated the differences between the automatic marker position and the GSP for the MUAPs start and end markers from both TA and FDI muscles. Then several statistical procedures were applied:

- To assess the accuracy of the automatic methods the relative mean differences between the automatic marker position and the GSP were compared using a one-factor ANOVA test.

- We calculated the mean of the differences between the automatic marker position (considering both start and end markers for both TA and FDI muscles) and the GSP (i.e., the bias of each method) and the standard deviation (SD) of such differences (the precision) for each automatic method. We used the estimated mean squared error (EMSE) of the differences as criterion for choosing the most efficient method. It was calculated as follows:

$$\mathrm{EMSE} = \frac{\underset{ta}{\mathrm{EMSE}} \cdot 115 + \underset{fdi}{\mathrm{EMSE}} \cdot 67}{182} \tag{3}$$

  where 115 and 67 are the number of TA and FDI MUAPs, respectively, and

$$\underset{ta/fdi}{\mathrm{EMSE}} = \mathrm{mean}^2_{\substack{d,start \\ ta/fdi}} + \mathrm{var}_{\substack{d,start \\ ta/fdi}} + \mathrm{mean}^2_{\substack{d,end \\ ta/fdi}} + \mathrm{var}_{\substack{d,end \\ ta/fdi}} \tag{4}$$

  with $\mathrm{mean}_{\substack{d,start \\ ta/fdi}}$ and $\mathrm{var}_{\substack{d,start \\ ta/fdi}}$ being the mean difference or the variance, respectively, between the start marker position of the method and the start GSP for the TA or FDI muscle, and $\mathrm{mean}_{\substack{d,end \\ ta/fdi}}$ and $\mathrm{var}_{\substack{d,end \\ ta/fdi}}$ being equivalent figures for the end marker.

- The number of cases in which the absolute difference between the GSP and the automatic marker position was greater than 5 ms was counted for each method. Such cases can be generally considered as gross errors. The proportions of gross errors corresponding to each method were compared using the χ^2 (Chi-square) test.

3.5 Behaviour of the automatic methods with noise

To assess the robustness of the automatic methods in the presence of noise, we added zero-mean white gaussian noise to all the 182 accepted MUAP signals and ran the AM, the WBM and WHM algorithms for different signal to noise

ratios (SNR). The differences between the GSP and the automatic placements of the duration markers for the three methods were obtained.

3.6 Study of sensibility of the parameters of the WHM

The genetic algorithm provides different sets of parameters for the WHM when several independent runs are performed. Every set of parameters is valid, and may be quite different from each other. Notice that for the WHM we need to fix the values of 8 parameters (4 for the start, and 4 for the end). We studied the sensibility of all the parameters for the WHM. To measure the sensibility of a parameter, we fixed the values of the rest of the parameters and varied its value in an interval in which the original value of this parameter is included. For each value, we calculated the bias (mean) and the precision (SD) of the differences between the method marker and the corresponding GSP marker (start or end marker) for the whole evaluation set of 182 MUAPs.

3.7 Computational cost

The computational cost of the three automatic mehods were measured too. For each method and for each MUAP the CPU time when measuring duration was calculated. The mean and SD of these times were then obtained.

4 Results

4.1 Comparison of the automatic methods

The mean differences between AM, WBM and WHM marker positions and GSPs for the TA and FDI MUAPs are respectively given in Table 1. For both start and end markers, the WBM and WHM have lower mean differences with lower SD. The lower SD of our methods means that they are more accurate and consistent. Besides, our methods are less unbiased, as their mean values are closer to zero. Significant differences were found for the start and end markers between the conventional AM and the new methods ($p<0.05$, one-factor ANOVA). However, for the FDI muscle, significant differences were found for the start marker between AM and WBM and for the end marker between AM and WHM. No significant differences were found between the WBM and WHM. The behaviour of the WHM seems quite better than WBM in the TA muscle, with higher precision for the start marker and lower mean for the end

marker. In the FDI muscle the WHM presents lower mean for the end marker. It seems that the WHM outperforms the WBM when placing the end marker. On the other hand, the WBM and the WHM gave less gross errors than the AM (Table 2). There were significant differences ($p<0.05$, Chi-square test) for the start markers. The lowest rate was 1.6% for the WHM start marker. However, significant differences were not found for the end markers but also the WHM had the lowest rate, 10.4%. Hence, the WHM was the method with less number of gross aberrant errors. This result confirm the better performance of the WHM compared to the WBM. These results are in accordance with the ones shown in Table 1. In Fig. 5 the mean and the SD of the differences between the automatic positions and the GSP estimates (considering start and end markers conjointly) for the three automatic methods are graphically represented. The EMSE value calculated as (4) of each method is in brackets. In fact, the EMSE value in the figure is correlated to the distance to the origin. The lower the mean and the lower the SD, that is the lower EMSE, the more precise the method, with resulting positions more closer and centered around the GSP. As it can be seen, the WHM shows the lowest EMSE, which means that its duration markers are slightly closer to the GSP and they are slightly

Table 1
Differences between GSP and the positions assigned by the automatic methods for the TA muscle. Mean/standard deviation (ms). $*$ = $p<0.05$ (one-way ANOVA). Two vertical lines joined together with an horizontal line and an asterisk above or below the horizontal line in the mid point between two methods indicate significant differences between them.

Muscle	Marker	AM	WBM	WHM
TA (n=115)				
			*	
			*	
	start	2.8/6.0	-0.2/2.3	0.2/1.6
			*	
			*	
	end	-2.1/6.5	1.7/3.4	0.7/3.6
FDI (n=67)				
			*	
	start	2.7/6.7	0.4/2.3	1.0/1.2
			*	
	end	-1.8/5.7	-0.3/1.8	0.0/2.6

Table 2
Rate of automatic marker placements with differences to the GSP greater than 5 ms. n = 182. * = p<0.01 (Chi-square test).Two vertical lines joined together with an horizontal line and an asterisk above or below the horizontal line in the mid point between two methods indicate significant differences between them.

Marker	AM	WBM	WHM
		*	
		*	
start	20.3	3.3	1.6
end	16.5	13.2	10.4

more precise than the WBM. As it can be appreciated from Fig. 5, the results are in accordance with the results in Table 1.

As illustrated in Figs. 6.a and 6.b, the WBM and WHM overcome the problem of discharges of other MUAPs present in the record before and after the MUAP under analysis. However, the AM sometimes fails in positioning markers when the amplitude samples of the following (or previous) 5-ms window from the trigger point fluctuate more than $\pm 5\mu V$, as in the end marker in Fig. 6.b or in the start in Fig. 6.c. Besides, the AM also fails as a consequence of the selection of the baseline level as the electrical zero. In many cases, a large and slow fluctuation of the baseline results in a considerable shift of the MUAP up or down with respect to the electrical zero, in spite of the fact that

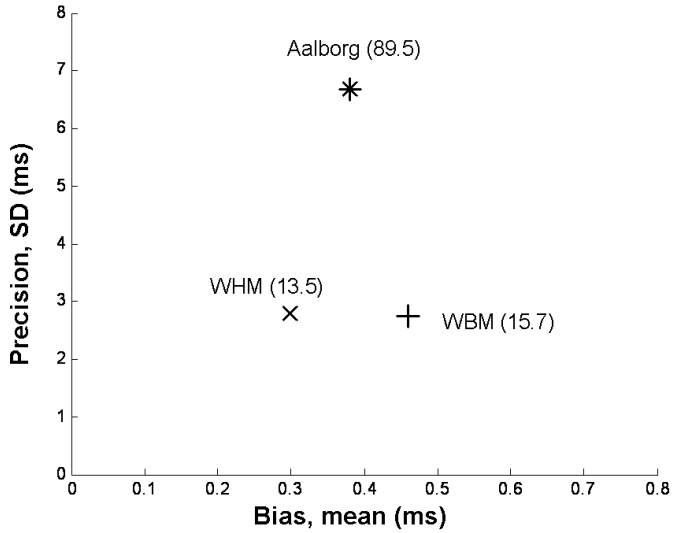

Fig. 5. Bias and precision of the differences between the GSP and the duration marker positions of the automatic methods (considering start and end markers for both TA and FDI muscles). The estimated mean square error (EMSE) of such differences for each method is in brackets.

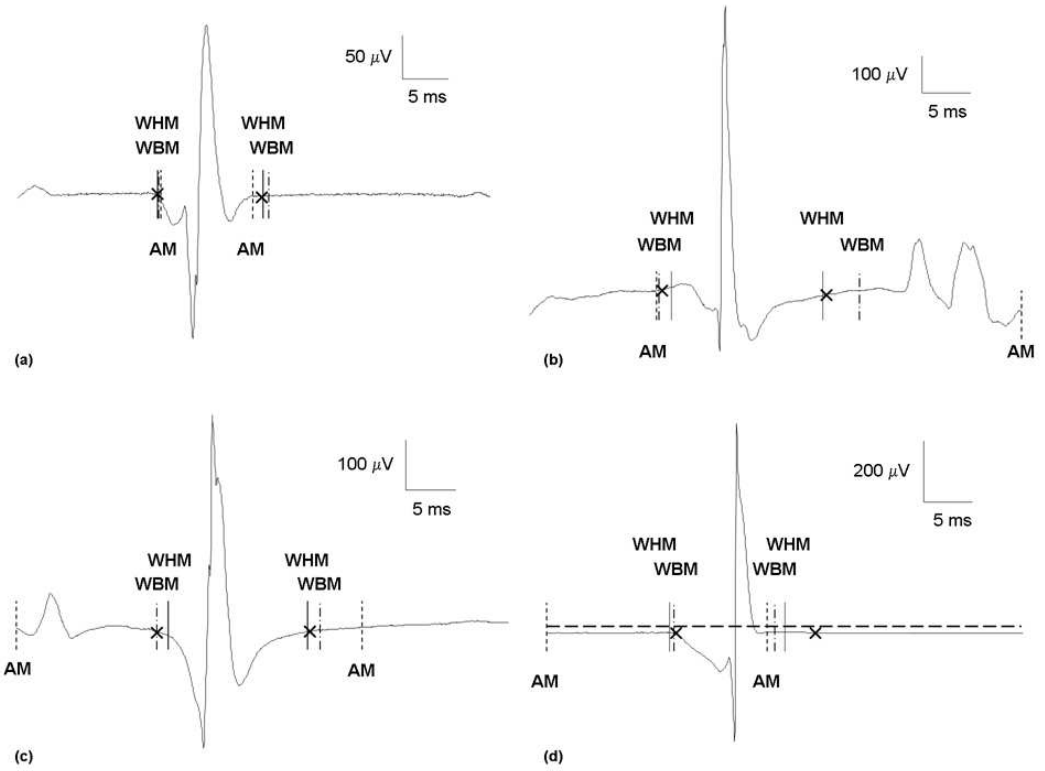

Fig. 6. WBM (dashed dot markers), AM (dashed markers) and WHM (continuous markers). GSP(crosses). Electrical zero (horizontal dashed line) is shown in (d). In (a) the methods overcome the presence of secondary MUAPs before and after the analyzed MUAP. In (b) and (c), the end and start marker obtained by the AM does not meet the criterion of an amplitude fluctuation of more than $\pm 5\mu V$ in the samples of the following or previous 5-ms window, so they are misplaced. In (d), the WBM and WHM overcome the fails of the AM start marker due to shifts of the MUAP down or up with respect to the electrical zero, taken as baseline in the AM

several discharges are averaged. This error will affect the thresholds of this algorithm referred to the baseline, and it may obtain inaccurate start and/or end MUAP points (Fig. 6.d). Although the WHM and WBM performs better than the AM, they still produce gross errors in a small number of cases. The WBM sometimes fails to position the start or end markers correctly when a MUAP waveform has low amplitude peaks or long and low-sloped tails (Rodríguez et al., 2007b). Nevertheless it can be observed that the WHM is able to overcome these errors or at least to obtain better results than the WBM in most of the cases (7.a and 7.b). The WHM also produces some gross errors. The thresholds Th_2 and Th_4 considered for the difference signal between the first approximation of the DWT and the HT were designed to improve the measurement of long and low-sloped tails that the WBM did not deal with correctly. When the MUAP has a DC offset, these difference thresholds may be reached far from the MUAP onset or offset. Fig. 8 shows this effect over the MUAP end marker. The WHM algorithm begins from the point where the HT amplitude

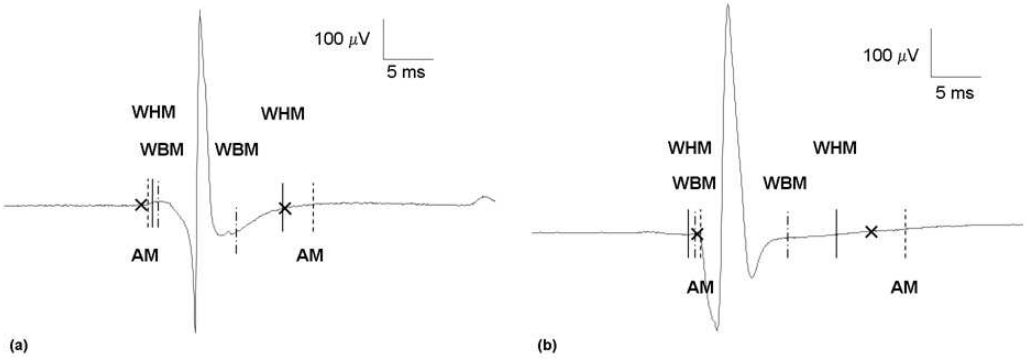

Fig. 7. Errors of the WBM when positioning the end marker due to low amplitude peaks in the MUAP waveform (a) and to long and low-sloped tails (b). WBM (dashed dot markers), AM (dashed markers) and WHM (continuous markers). GSP(crosses)

is smaller than Th_1 or Th_3. Then, it looks for a point in the difference signal smaller than Th_2 or Th_4, and finally applies the slope criteria. Besides, if the MUAP has a long and low tail and also a small amplitude, the parameter Th_2 in this case is not adequate to look for the MUAP onset (Fig. 9).

4.2 Behaviour of the automatic methods with noise

The mean and SD of the differences between the GSP and the markers of the three automatic methods for the start and end for both muscles conjointly were plotted against SNR (Fig. 10). Across the SNR range and for both start

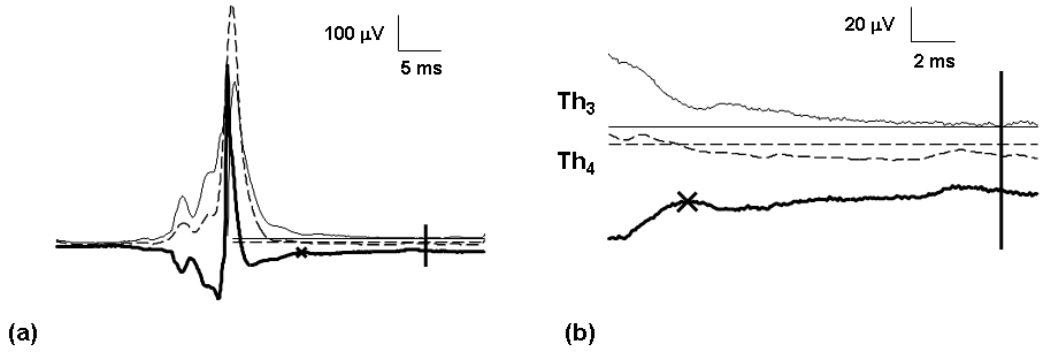

Fig. 8. Errors of the WHM when positioning the end marker (a) and zoom for the same case (b). The MUAP (thick line), the HT (dashed line), the difference signal (thin line) and GSP (x) are shown. End point placed by WHM (vertical line). From the point below Th_3 (dashed horizontal line), a point in the difference signal below Th_4 (horizontal line) is erroneously found due to a certain offset in the final part of the MUAP.

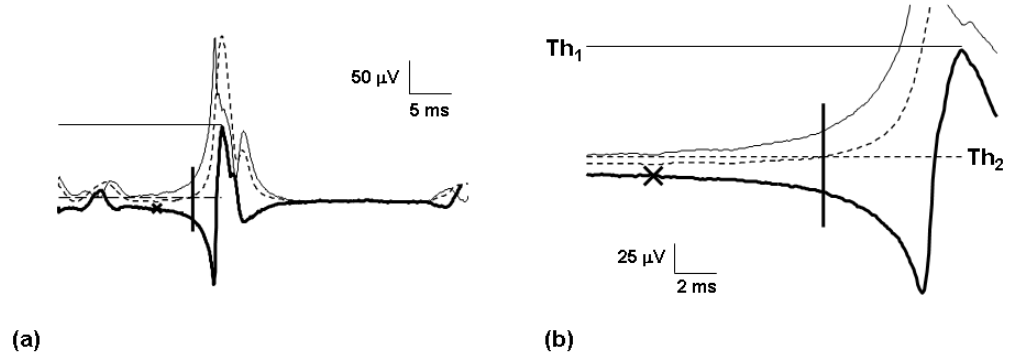

Fig. 9. Errors of the WHM when positioning the start marker (a) and zoom for the same case (b). The MUAP (thick line), the HT (dashed line), the difference signal (thin line) and GSP (x) are shown. Start point placed by WHM (vertical line). From the point below Th_1 (horizontal line), a point in the difference signal below Th_2 (dashed line) is erroneously found due to its great value for a small MUAP.

and end marker positions, the WHM gave lower mean differences and SD values than the WBM and the AM, which indicate that WHM is the most precise method. The WHM attained stable performance at higher levels of noise than the other methods did which indicates that WHM is more robust to white gaussian noise than the other methods. Only at low SNR, when the AM presented very high mean differences, SD was lower for AM.

4.3 Study of sensibility of the parameters of the WHM

Figures 11 and 12 show the results of the study of sensibility for the parameters related to the new automatic duration algorithm WHM. The mean (bias) and the SD (precision) of the differences of the WHM markers and the GSP

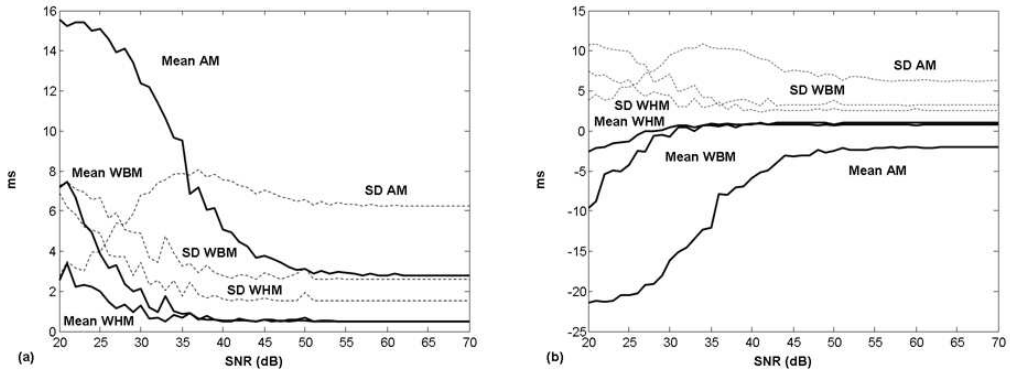

Fig. 10. Mean (continuous lines) and SD (dashed lines) of the differences between the GSP and the WHM, WBM and AM against different levels of signal to noise ratio (SNR) for start (a) and end (b) points.

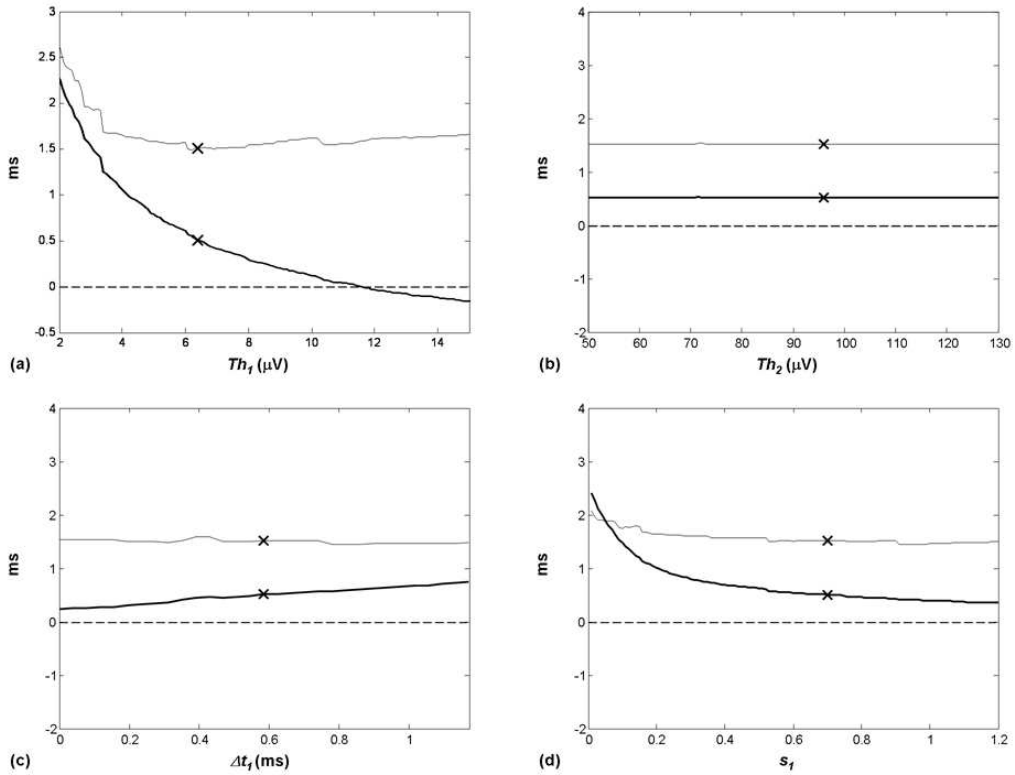

Fig. 11. Study of variability for the parameters $Th1$, $Th2$, Δt_1, and s_1 of the WHM used for determining the start marker. Mean/bias (black thick lines) and SD/precision (black thin lines) of differences to the GSP markers. Values obtained by the genetic algorithm (x).

markers for all the 182 MUAPs are shown in the figures. We varied the value of each analyzed parameter while keeping the rest to the fixed values previously shown at equations (1) and (2).

As it can be appreciated, the genetic algorithm achieved a very good value for Th_1 (Fig. 11.a) with the best precision of the WHM in its interval. Increasing Th_1 could improve the bias performance with a small lost in SD. From (Fig. 11.b) it can be stated that the bias and precision of the WHM do not seem to be affected by changes in the amplitude threshold Th_2. The values for the parameters Th_3 (Fig. 12.a), Δt_2 (Fig. 12.c) and s_2 (Fig. 12.d) yield the closest bias to zero, with very good precision, as well. For Th_4 (Fig. 12.b), the genetic algorithm reached the value with closer bias to zero, with anot so good precision value. Finally, a decrease in the parameter Δt_1 (Fig. 11.c) and an increase in s_1(Fig. 11.d) could improve the bias of the WHM.

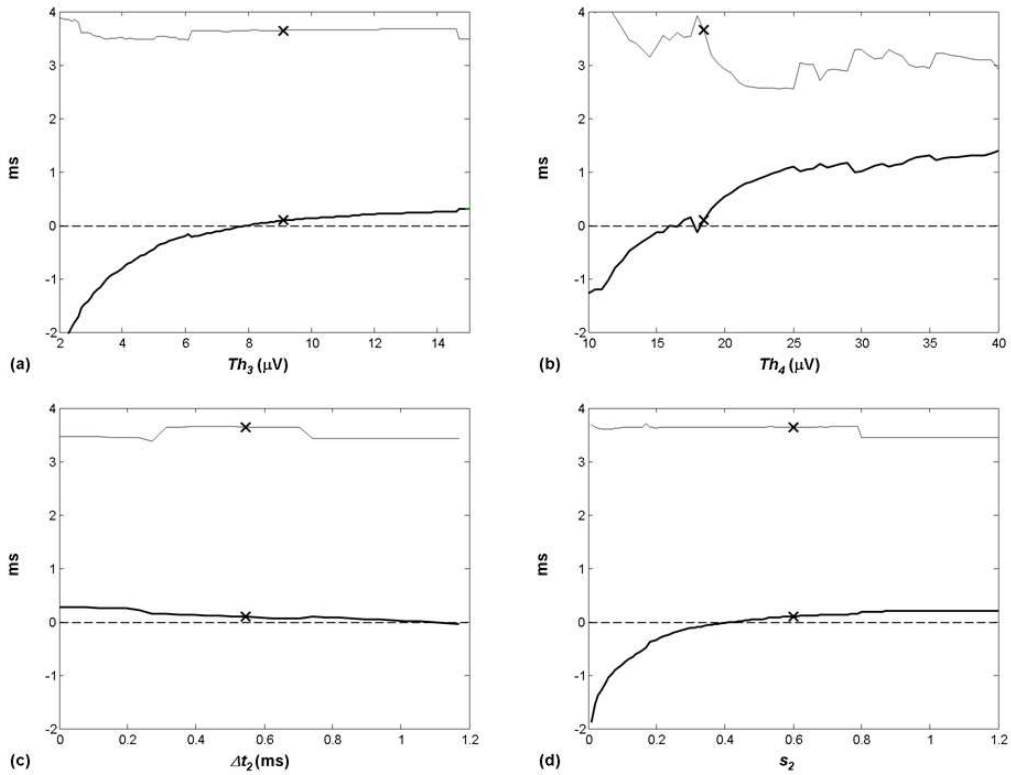

Fig. 12. Study of variability for the parameters $Th3$, $Th4$, Δt_2, and s_2 of the WHM used for determining the start marker. Mean/bias (black thick lines) and SD/precision (black thin lines) of differences to the GSP markers. Values obtained by by the genetic algorithm (x).

4.4 Computational cost

The CPU times in ms (mean/SD) for the WBM, the WHM and the AM were 20.4/12.6, 79.5/165.8 and 4.2/8.5, respectively.

5 Discussion

The new automatic method for measuring MUAP duration based on the wavelet and Hilbert transforms which we describe here deals with the presence of other MUAPs at both ends of the analysis window, high-frequency noise and baseline fluctuations, slightly better than the WBM and much better than the AM. It also provides accurate duration marker placements and fewer gross aberrant errors than the other methods. Besides, the WHM clearly seems to manage more robustly against high-frequency noise.
Errors in the AM when placing MUAP start and end markers are produced if the MUAP initial or end parts are shift up or down from the electrical zero,

which it is consider in this method as the baseline. This problem could be fixed by applying before baseline cancellation removal methods (Rodríguez et al., 2006). AM also fails in determining MUAP start or end markers when other MUAPs lie at the start or end of the analysis window, as the matching template method used only considers the spike of the triggered MUAP. In this case, a more robust procedure of MUAP extraction could increase the perfomance of this method. Another error in AM was due to the low amplitude threshold of the previous or following 5-ms window used. In noisy signals with an unstable baseline with amplitude variations of more than this amplitude threshold, MUAP start or end points cannot be found as there are no points fulfiling the criteria. This is the reason why it does not behave correctly when gaussian noise is added to MUAPs. However, it is reasonable to affirm that this duration method was created to run in a certain equipment that recorded EMG signals with different characteristics (signal to noise ratio, different types of acquisition filters and others) and therefore better results may reach using that equipment. On the other hand, current commercial equipments use multi-motor unit action potential analysis (Stalberg et al. 1995; Nandedkar et al. 1995) in which a much low number of discharges is extracted and in which more secondary potentials might be present at both ends of the analysis window, or even in which recorded signals have a lower signal to noise ratio, or even present a more unstable baseline.

With respect to these facts, the WHM largely precludes such errors and obtains accurate measurements of duration with a low number of MUAP dicharges. Besides this method achieved the lowest bias and highest precision when testing the robustness against white gaussian noise. Its good performance is due to the use of the intermediate scales of the wavelet transform, which filter out the noise and baseline fluctuations previous to the application of thresholding and slope criteria. Although the WBM is relatively robust against these artifacts, it does present certain limitations. As we have seen it fails to position the markers correctly when a MUAP waveform has low amplitude peaks and also when MUAPs have long and low-sloped initial or terminal portions.

The WHM is a new duration algorithm with even better results than the WBM. The WHM improves the performance of the WBM and makes fewer gross errors. Besides the WHM can deal with the MUAP long and sloped tails better than the WBM, which was the main reason that led the authors to devise it. However, this method also presents some errors as its markers may be misplaced when measuring low amplitude MUAPs.

The study of sensibility of the parameters used in the WHM have shown that the values obtained by the genetic algorithm are optimum and only a few parameters can be modified to improve even more the satisfactory results obtained.

In spite of making use of the DWT, the WHM also depends on thresholding and slope criteria. The values of the parameters found from the genetic algorithm try to best reproduce manual duration measurements, as it also have

been done previously by others (Stalberg et al. 1986; Stewart et al., 1989; Stalberg et al. 1996). To obtain these values for the parameters we used a carefully prepared set of gold standard manual duration measurements from two senior electromyographists. Since the main purpose of the algorithm is to measure MUAP duration in a clinical setting, we think it is a good way to optimize the parameter values. Nevertheless, duration measurements and corresponding gold standards will vary to some degree from electromyographist to electromyographist and so the resulting parameter values cannot be completely objective. Therefore, the errors of the algorithm are not fully dependent on its execution, as there are difficulties in the definition of clinical MUAP duration (Dumitru and King, 1999; Dumitru et al., 1999) and inherent limitations and randomness in its manual measurement (Sonoo, 2002) which are represented in the automatic methods. For all this, further refinements of the methods can still be made to achieve the best adaptation to the EMG signals and to the intrinsic difficulties of the MUAP duration measurement.

The WBM and the WHM have not been tested with signals from abnormal muscles. In respect to polyphasic MUAPs one would expect a similar performance than in normal ones, since with regard of the spike shape complexity the critical issues of the MUAP for duration measurement are the initial and terminal parts and they do not differ significantly between irregular and simple MUAPs. In any case, specific studies with pathological MUAPs are necessary to test both algorithms.

The WHM has shown good performance to be tested by practical application in a clinical setting. Although the WHM was more time consuming than the other automatic methods, its mean CPU time were about 80 ms which is short enough for real-time processing. In clinical practice, this algorithm could reduce the requirement for manual intervention in duration measurement thereby facilitating the electromyographist's work, reducing the exploration time and hence reducing patient discomfort.

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