Original Articles

Motor Unit Action Potential Duration, II: A New Automatic Measurement Method Based on the Wavelet Transform

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Summary: To present and evaluate a new algorithm, based on the wavelet transform, for the automatic measurement of motor unit action potential (MUAP) duration. A total of 240 MUAPs were studied. The waveform of each MUAP was wavelet-transformed, and the start and end points were estimated by regarding the maxima and minima points in a particular scale of the wavelet transform. The results of the new method were compared with the gold standard of duration marker positions obtained by manual measurement. The new method was also compared with a conventional algorithm, which we had found to be best in a previous comparative study. To evaluate the new method against manual measurements, the dispersion of automatic and manual duration markers were analyzed in a set of 19 repeatedly recorded MUAPs. The differences between the new algorithm's marker positions and the gold standard of duration marker positions were smaller than those observed with the conventional method. The dispersion of the new algorithm's marker positions was slightly less than that of the manual one. Our new method for automatic measurement of MUAP duration is more accurate than other available algorithms and more consistent than manual measurements.

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

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The definition of the motor unit action potential (MUAP) duration, as well as its measurement procedure, presents hard intrinsic difficulties, and therefore manual duration measurement has been described as "an arbitrary task" (Sonoo, 2002). However, delimitation of the length of the MUAP waveform, that is, the measurement of duration, is the first step in the quantitative analysis of the MUAP and thus estimation of this parameter is indispensable in quantitative electromyography.

A number of automatic algorithms have been designed (Stalberg et al., 1986) to try to overcome the limitations of subjective assessment of the MUAP duration. These algorithms use criteria of amplitude and slope to reproduce the process of visual inspection, avoiding subjective biases. In Part I of the present work, we demonstrated the big variability in manual measurements and the limitations of the currently available automatic methods. As reported by others (Bischoff et al., 1994; Stalberg et al., 1995; Takehara et al., 2004), these limitations imply the necessity of continuous visual supervision and frequent manual readjustments of the duration markers. Most of the errors of automatic methods derive from the presence of fluctuations in the baseline (BL) and from other noise of other sources. Unfortunately, such BL irregularities and noise are common in real recordings.

The discrete wavelet transform (DWT) is a technique that simultaneously obtains a time and a scale representation of signals and has been successfully applied for detecting biologic events (Akay, 1996). This technique has provided promising results in the analysis of various electrophysiological signals such as blink reflex (Kumaran et al., 2000), electromyographic (EMG) and electrocardiographic (ECG) recordings (al–Fahoum and Howitt, 1999; Cuiwei et al., 1995; Fang et al., 1999), electroencephalographic signals for analysis of epileptic activity (Geva and Kerem, 1998), or event-related potentials (Gurtubay et al., 2001). For EMG signals in the DWT domain, by regarding the transformed signal at a suitable scale, it is possible to evade the high-frequency noise and low-frequency fluctuation of the BL. Thus, the DWT is a useful way of detecting the boundaries between the MUAP waveform and the BL, that is, of measuring MUAP duration.

In this report, we present a new algorithm, based on the DWT, for automatic measurement of MUAP duration in clinical recordings. The algorithm is compared with the Aalborg method (AM), the conventional algorithm that we found to be best in the comparative study reported in Part I. We analyze the behavior of the above two methods with signals with different levels of noise. In addition, the variability of the new method is compared with that of manual measurements.

Part of the present study was presented at XVth Congress of the International Society of Electrophysiology and Kinesiology (ISEK 2004) and at the 42nd Annual Meeting of

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the Spanish Society of Clinical Neurophysiology (Rodríguez et al., 2004a, Rodríguez et al., 2004b).

METHODS

Subjects, MUAPs, and Manual Measurement of Duration

A total of 240 MUAPs, 152 from 8 tibialis anterior (TA) muscles and 88 from 8 first dorsal interosseous (FDI) muscles, were analyzed. The subjects, the procedures for recording and extraction of MUAPs, and the displays and user interface for manual duration measurement are described in Part I of this work. To establish a gold standard of the duration markers positions (GSP), each MUAP was measured six times (i.e., by two electromyographists, each on three occasions), and the GSP was established as the mean position of the three manual marker positions which were closest together (see Part I for further detail).

Description of the New Algorithm for MUAP Duration Measurement

On visual inspection of an EMG signal, MUAPs are distinguishable because they consist of a set of peaks. With the discrete wavelet transform (DWT), not only can we detect MUAP peaks but also the start and end points of these peaks (Cuiwei et al., 1995). The method we devised for finding the start and end points in MUAPs comprises several stages (Fig. 1).

1. First, we apply the DWT with a specific mother wavelet that has suitable properties for the task required and is similar to the MUAP waveform.

FIGURE 1. Method of finding the start and end points in MUAPs comprises several stages.

2. Scale selection. We select a scale that represents the MUAP signal in terms of energy but excludes high-frequency noise and low-frequency interferences such as BL fluctuation. Different scales for determining the start and end points of MUAPs are selected in accordance with experimental results.
3. Determination of MUAP peaks in the selected DWT scale. We use criteria of threshold and slope and an analysis of the specific properties of the selected wavelet to find the maxima and minima related to the MUAP in the time domain.
4. Determination of MUAP start and end points. From the DWT peaks found in the previous step, a simple slope-based algorithm is applied to find the MUAP duration.

Discrete Wavelet Transform

The DWT was applied to the averaged MUAPs (see Part I). As with other wavelet transforms, the DWT decomposes a signal into a rough approximation signal and a detail signal. The approximation signal is subsequently divided into new approximation and detail signals (Fig. 2). This process is carried out iteratively producing a set of approximation signals at different detail levels (scales) and a final gross approximation of the signal. The different scales contain different spectral components: Lower scales occupy higher frequency bands (although not strictly separated). In the case of an MUAP detection algorithm, it is the detail signals rather than the approximation signals that are of interest.

The specific mother wavelet that we used was the nonorthogonal quadratic spline wavelet with one vanishing moment, which has previously been successfully used for the detection of characteristic points (QRS complex and P and T waves) in ECG signals (Cuiwei et al., 1995). An important feature of this wavelet is its shift invariance with regard to local extremes and zero crossings; the locations of local
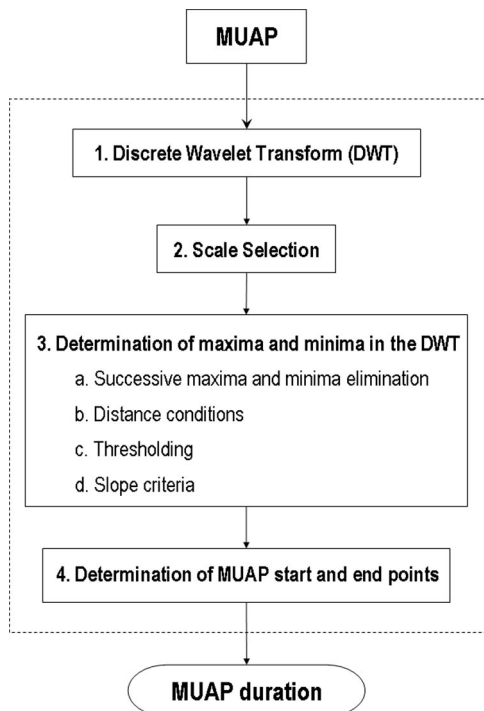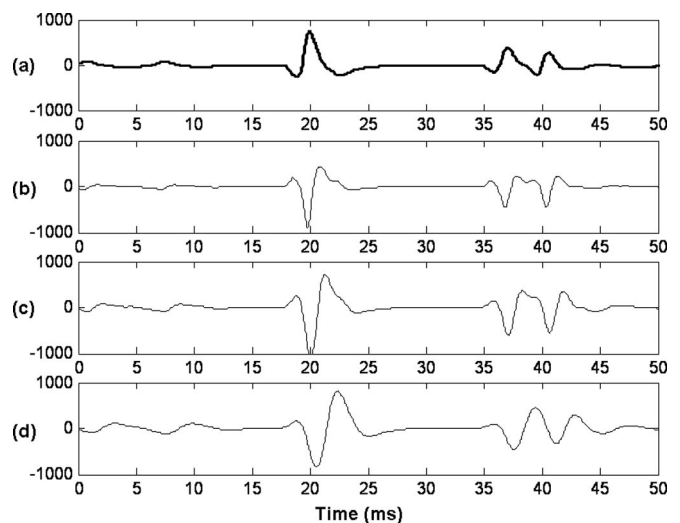

FIGURE 2. DWT decomposes a signal into a rough approximation signal and a detail signal; approximation signal is subsequently divided into new approximation and detail signals.
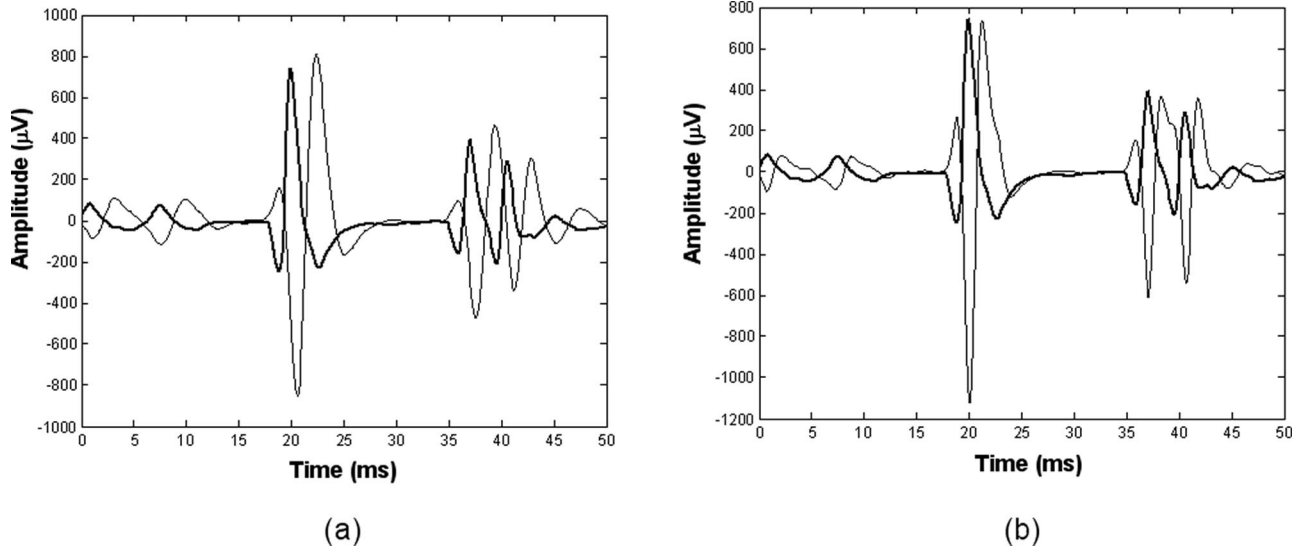
FIGURE 3. To find the MUAP start, we select the scale containing most energy, ds(n) (a). To find the MUAP end, we select the highest energy scale of the first five, de(n) (b).

extremes and zero crossings in the EMG record correspond with those in the wavelet domain. It has been shown (Mallat, 1992a) that using this wavelet every uniphasic wave in the original signal leads to a pair of peaks (a negative followed by a positive one) at every scale of the DWT. We implemented the DWT with the Mallat algorithm (Mallat, 1992b).

Scale Selection

The signal is fully decomposed in $J \leq \log_2 L$ levels, where L is the length of the signal. To find the MUAP start, we select the scale containing most energy, ds(n) (Fig. 3a). To find the MUAP end, we select the highest energy scale of the first five, de(n) (Fig. 3b). These scales may or not may coincide. As the MUAP start is usually abrupt and sharp, it can be recognized in all scales. On the other hand, the end of an MUAP is often long and of low amplitude and is thus more difficult to discriminate; a smaller scale may give better temporal resolution and facilitate visual assessment. The above scale selection rules are empirical.

Typically, the most energetic scale is considered to be the most informative and usually corresponds to an intermediate scale, little affected by either high-frequency noise or low-frequency BL fluctuation. Working in this scale simplifies detection of start and end points in the DWT domain. We use the detail signal corresponding to this scale for subsequent processing of the signal. 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. The higher the scale, the higher the frequency resolution but the lower the temporal resolution. In this application, temporal resolution is more important than frequency resolution.

Determination of Maxima and Minima of the DWT

In this stage, we detect the N relevant maxima and minima related to the MUAP. While aware of BL fluctu-

ation and other noise, we find the set of local extremes in the wavelet domain. We will call a_k and l_k the amplitude and position of the k-th maximum or minimum in ds(n) or de(n), respectively.

First, we find the maximum DWT peak occurring within the 15- to 30-ms interval of the whole 50-ms window. The use of this time interval helps to limit the search to those DWT peaks that correspond to the MUAP under analysis as opposed to those of other MUAPs caught on the record. The maximum DWT peak corresponds to the maximum MUAP peak near the triggering point (Fig. 4). We refer to this peak as [amax, lmax].

Next, we obtain two different sets of DWT maxima and minima points: the set to the right (RMM) of the maximum peak position (max) over de(n), $RMM = \{[a_k, l_k] \in de(n); k = max + 1, \ldots, N\}$ (Fig. 5a); and the one to the left (LMM) over ds(n), $LMM = \{[a_k, l_k] \in ds(n); k = max - 1, max - 2, \ldots, 1\}$ (Fig. 5b).

From these DWT local extremes, we now need to ascertain which are related to MUAP maxima and minima. The algorithm uses the following approaches to achieve this.

Elimination of Successive Maxima or Minima

As is evident by visual inspection, MUAP waveforms are composed of successive maxima and minima. The wavelet applied will not alter this morphology, and so DWT maxima and minima should alternate. Peaks that do not conform to this disposition must be from other sources, such as high-frequency noise, and are removed. If the peak being analyzed is of opposite morphology to the one before it, the next condition is checked, as described below.

Checking the Distance Between Peaks

The difference in time interval between successive pairs of maxima and minima, Δl_k, must be in accordance with
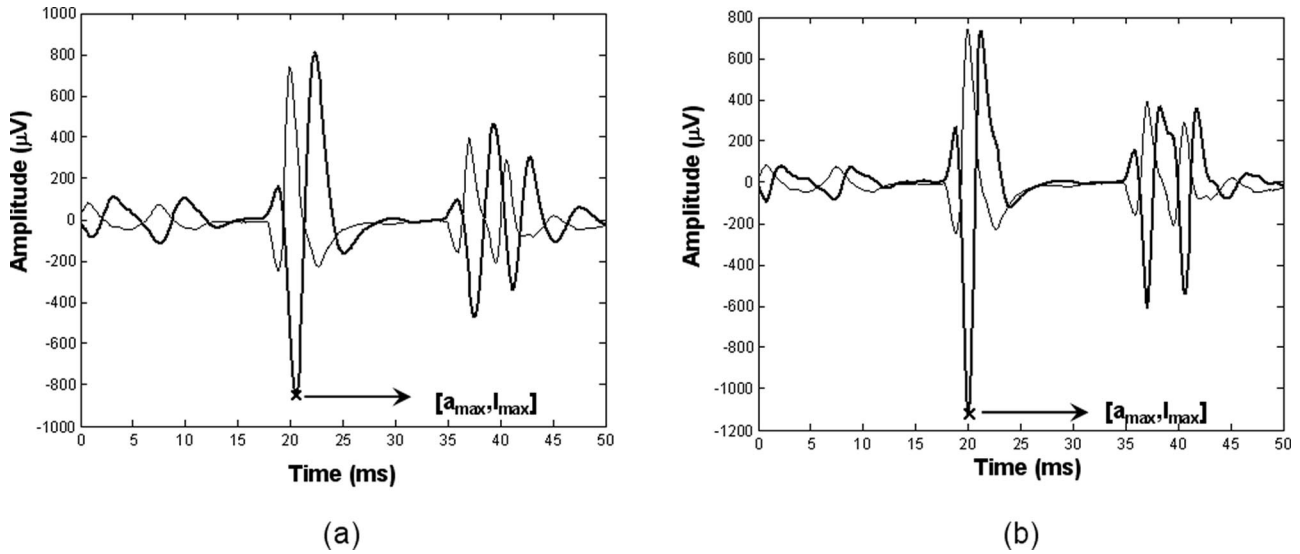
FIGURE 4. Maximum DWT peak corresponds to maximum MUAP peak near the triggering point.
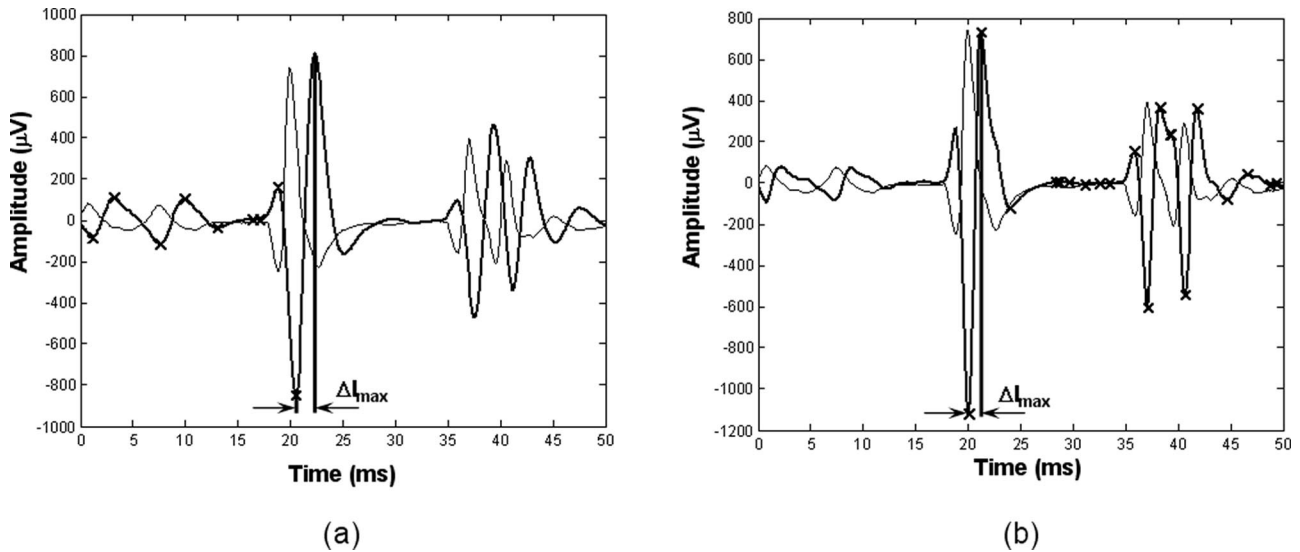

FIGURE 5. Two different sets of DWT maxima and minima points.

the following equations with regard to the start and final MUAP points, respectively:

$$195 \ \mu s \leq \Delta l_k \leq k_1 * \Delta l_{max}$$

$$0 \leq \Delta l_k \leq k_2 * \Delta l_{max}$$

where Δl_{max} is the measured time interval between the maximum peak and the next peak (whether maximum or minimum) to the right. The factors k_1 or k_2 are for start and end point calculations, respectively.

This temporal separation criterion is applied to separate maxima and minima related to the peaks of the object MUAP from those related to secondary MUAPs or noise (Fig. 5). We use the distance from the maximum DWT peak to the next local extreme to the right, Δl_{max}, as a time interval related to the features of the analyzed MUAP. We can assume that there will

always be an extreme to the right of the maximum DWT peak because the tail of an MUAP is longer than the initial part.

Thresholding

To find the start point we look, in the scale ds(n), for maxima and minima above a symmetric threshold ($\pm Th_1$) (Fig. 6). Likewise, for calculating the end point, maxima and minima above a different symmetric threshold ($\pm Th_2$) are looked for in the scale de(n). The thresholds serve to differentiate between MUAP samples and noise samples or low-frequency fluctuation samples. Threshold values were obtained experimentally, as explained below.

For the start point, if the amplitude of the peak being analyzed is higher than the threshold, the next condition can be checked.
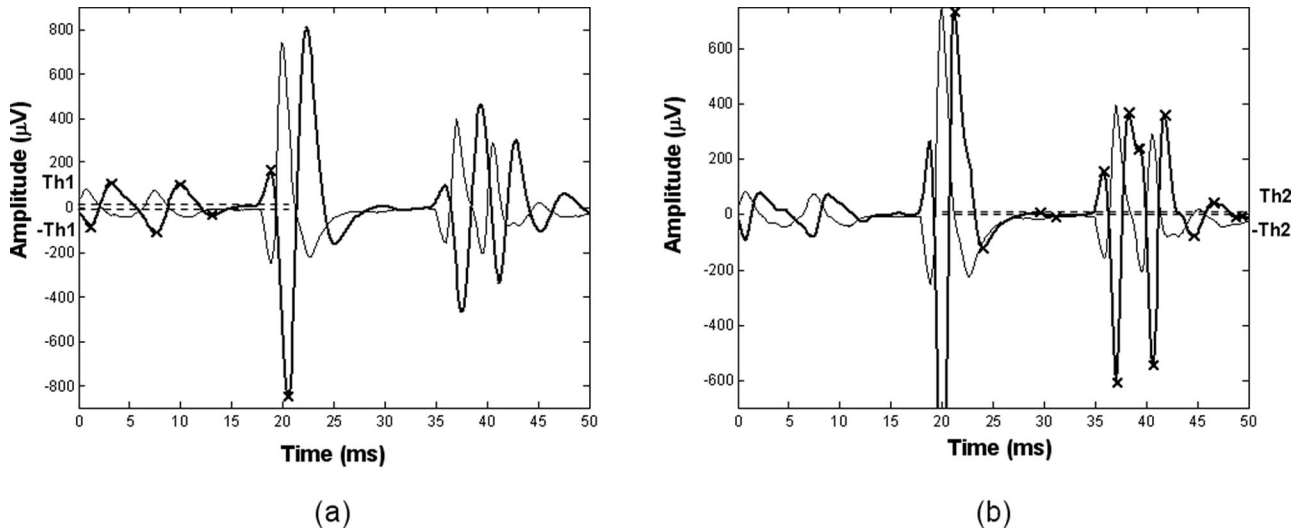
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FIGURE 6. To find the start point we look, in the scale ds(n), for maxima and minima above a symmetric threshold ($\pm Th_1$).
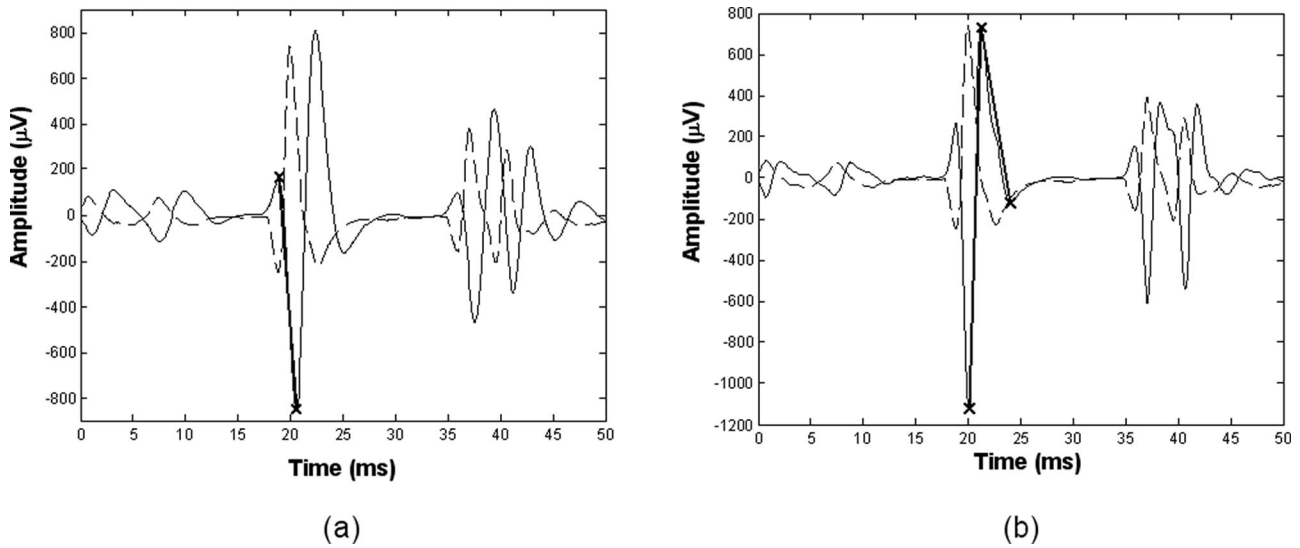

FIGURE 7. Start and end points. Peak is related to the MUAP.

A different approach is applied for the end point. As mentioned above, the MUAP end point is indistinct and difficult to determine because the final phase of the potential returns to the BL very slowly and asymptotically. However, very low-amplitude MUAP turns do exist, and their corresponding low-amplitude DWT maxima or minima may escape detection by the previous processes when their amplitude is below the threshold Th_2. Thus, for such DWT extremes, conditions a, b, and d are rechecked, and if the extreme passes these criteria, it is not excluded, that is, it is considered to be related to the MUAP.

Applying Slope Criteria

If the absolute value of the slope between the last accepted local maximum or minimum and the peak that is being analyzed is greater than s_1 or s_2 (for start and end

points, respectively), then that peak is considered to be related to the MUAP (Fig. 7). The values for s_1 and s_2 were obtained experimentally.

After consecutively subjecting each of the peaks of the LMM and RMM sets to these conditional tests and excluding those peaks that do not meet the criteria, we assume we have identified the maxima and minima in the DWT related to the MUAP peaks (Fig. 7).

Determination of the Start and End Points of the MUAP Waveform

To find the MUAP start point, we identify the left-most DWT maximum or minimum that has passed the four conditions described above and proceed to search toward the beginning of the analysis window; the MUAP is considered
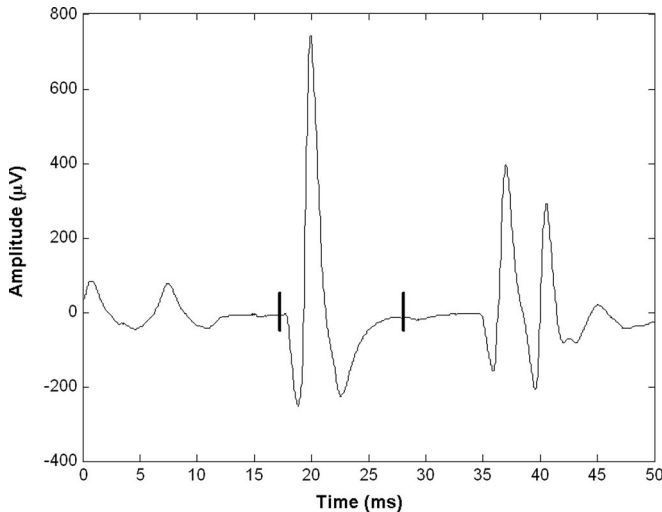
FIGURE 8. MUAP duration is calculated as the time interval between start and end points.

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to start in the sample whose absolute slope is greater than the slope threshold, s_3.

Similarly, to find the MUAP end point, we take the right-most DWT peak that has passed the four conditions and proceed to search toward the end of the analysis window; the sample whose absolute slope is greater than the slope threshold, s_4, is considered to contain the MUAP end point.

The values for s_3 and s_4 were obtained experimentally. MUAP duration is calculated as the time interval between start and end points (Fig. 8).

We used a genetic algorithm to determine the values of all the parameters (Th_1, Th_2, k_1, k_2, s_1, s_2, s_3, and s_4) involved in the calculation of MUAP start and end points. Genetic algorithms are general optimization procedures, the inspiration for which is based on the mechanisms such as natural selection genetic coding and gene combination and mutation, which underlie natural evolution (Goldberg, 1989).

We applied genetic algorithms to a "training set" of 64 randomly selected MUAPs to optimize parameter values such that the automatic algorithm's MUAP start and end points were as close as possible to the corresponding GSP positions.

The parameters values for the initial points were

$$Th_1 = 8.74 \ \mu V, \ \ k_1 = 3.2, \ \ s_1 = 0.67 \ \mu V/s, s_3 = 0.19 \ \mu V/s$$

The parameter values for the final points were

$$Th_2 = 3.67 \ \mu V, k_2 = 3.91, s_2 = 2.79 \ \mu V/s, s_4 = 0.18 \ \mu V/s$$

Note that the amplitude threshold, Th_1, used to identify DWT maxima and minima for the start point, is higher than that, Th_2 for the end point. The explanation can be found in the MUAP waveform, in which the peak after the start point is usually "sharp" and of high amplitude, whereas the peak before the end point is "blunt" and of low amplitude, with a slow return to the BL. This is also the reason why the constant time interval for MUAP end (k_2) is larger than that for the start (k_1).

Description of the Aalborg Method

The AM algorithm was developed by Stalberg and coworkers (Stalberg et al., 1986) at the Institute of Electronic Systems at Aalborg University Center (Denmark). The MUAP start and end points are found as the first point from the triggering point that has less than $\pm 5 \ \mu V$ 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 BL. The BL is the electrical zero of the amplifier. Of published automatic duration algorithms, the AM gave the best results in our previous comparative study (see Part I of this work).

Comparative Study of the Conventional and New Methods for Automatic Duration Measurement

We applied the AM and our wavelet-based method (WBM) to our set of 240 MUAPs. The results were compared with the GSP and the relative mean differences evaluated with Student *t*-test. For each method, we counted the number of "gross errors," which we defined as an absolute difference between automatic marker position and GSP of greater than 5 ms. The proportions of gross errors under the AM and the WBM were compared with the χ^2 test.

Behavior of the Automatic Methods With Noise

To assess the robustness of both automatic methods in the presence of noise, we added zero-mean white gaussian noise to all the 240 accepted MUAP signals and ran both AM and WBM algorithms for different signal-to-noise ratios (SNR). The differences between the GSP and the automatic placements of the duration markers for both methods were obtained. The mean and SD of such differences were plotted against SNR.

Comparative Study of Manual and Automatic Duration Measurements

To analyze the consistency of the manual and the WBM duration measurements, we recorded 19 MUAPs between 3 and 7 times. Then, six manual duration measurements (by two electromyographists on three occasions) and one automatic duration measurement were available for each recorded MUAP. Thus, for each of the 19 MUAPs, we had between 18 and 42 manual marker placements and between 3 and 7 automatic placements. We compared the dispersion of these placements. We used the standard deviation (SD) to estimate the dispersion of manual measurements. However, because of the small sample size, to estimate the dispersion of the automatic placements we used a method based on the range, according to the following estimator:

$$\sigma = \frac{R}{d_2}$$

where R is the range of the start or end marker positions for the same MUAP and d_2 is a parameter dependent on the number of automatic positions for the same MUAP (Mont-

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TABLE 1. Differences Between the Gold Standard of the Duration Marker Positions and Marker Positions Obtained by Aalborg Method and by Our New Wavelet Based Method for Automatic Duration MUAP Measurement

Muscle/Method	AM	WBM
TA (n = 152)		
Start	2,4/5,6/1,5–3,3	−0,1/2,2/−0,5–0,2
End	−1,7/5,9/−2.6––0,7	−0,4/3,2/−0,1–0,9
FDI (n = 88)		
Start	2,6/6,7/1,2–4,0	0,1/1,0/−0,1–0,3
End	−1,9/5,8/−3,1––0,61	−0,9/2,3/−1,3–0,4

GSP, Gold standard of the duration marker positions; AM, Aalborg method; WBM, wavelet-based method; TA, tibialis anterior muscle; FDI, first dorsal interoseous muscle.

Mean/SD/95% confidence interval (ms). All mean differences between the two methods are significant ($P < 0.001$; t-test).

gomery, 2001). For start and end markers respectively, we used the t-test to compare the dispersions of manual (SD) and automatic (σ) placements.

RESULTS

Comparison of the Automatic Methods

The mean differences between AM and WBM marker positions and GSPs are given in Table 1. For both start and end markers in both TA and FDI muscles, our new method has lower mean differences, with lower SDs. The lower SD means that our method is more accurate and consistent. The confidence intervals illustrate that our method is unbiased (i.e., centered on the GSP), as zero is included in all cases.

The WBM gave fewer gross errors than did the AM: 2.9% versus 17.9% for MUAP start points and 8.8% versus 15.0% for end points ($P < 0.05$; χ^2 test).

As illustrated in Fig. 9a, the WBM overcomes the problem of discharges of other MUAPs present in the record before and after the MUAP under analysis.

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. 9b. Besides, the AM also fails as a consequence of the selection of the BL level as the electrical zero. In many cases, large, slow fluctuation of the BL results in a considerable shift of the MUAP up or down with respect to the electrical zero, despite the fact that several discharges are averaged. This error will affect the thresholds of this algorithm referred to the BL, and it may obtain inaccurate start and end MUAP points (Fig. 9, c and d).

Although the WBM performs better than the AM, it still produces gross errors in a small number of cases. The WBM fails to position the start marker correctly when a MUAP waveform has turns with a low level of amplitude variation. This failure is a consequence of the wavelet transformation because with quadratic spline wavelet DWT, such peaks yield a low-amplitude maximum-minimum pair that may not exceed the threshold, Th_1, and so they are excluded from the MUAP and halt progression of the algorithm. An example is given in Fig. 10, in which the start marker is located after the GSP.

Also, the WBM sometimes fails when positioning the end marker. The DWT cannot fully cope with the problematic long, low-sloped tails of some MUAPs (Fig. 11). The algorithm searches for peaks with amplitude values below Th_2 and sometimes finds a noise peak or a BL fluctuation peak
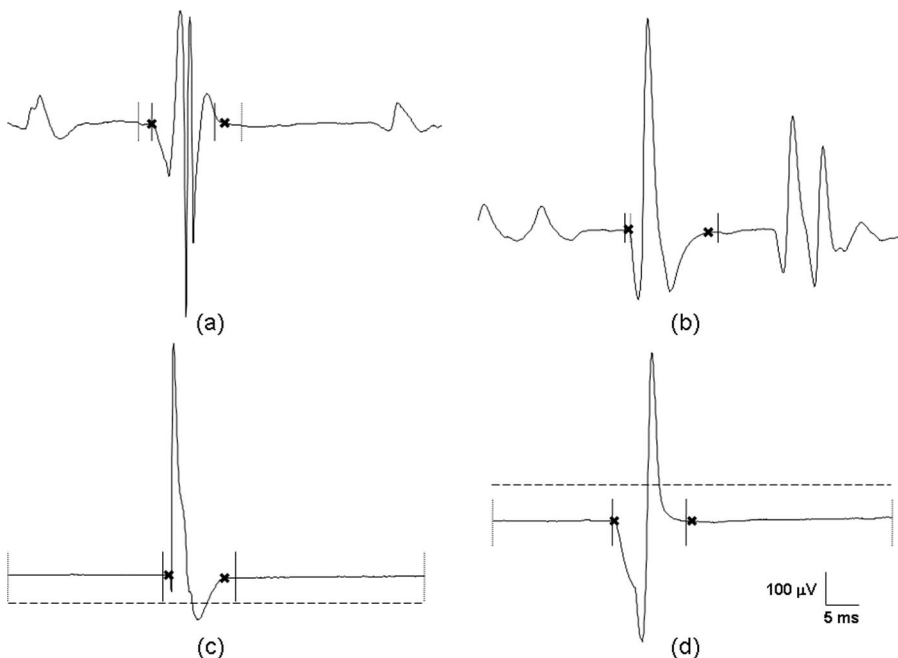

FIGURE 9. WBM overcomes the problem of discharges of other MUAPs present in the record before and after the MUAP under analysis (a). AM sometimes fails in positioning markers when the amplitude samples of the following (or previous) 5-ms window from the trigger point fluctuate more than $\pm 5\ \mu$V, as in the end marker in b.
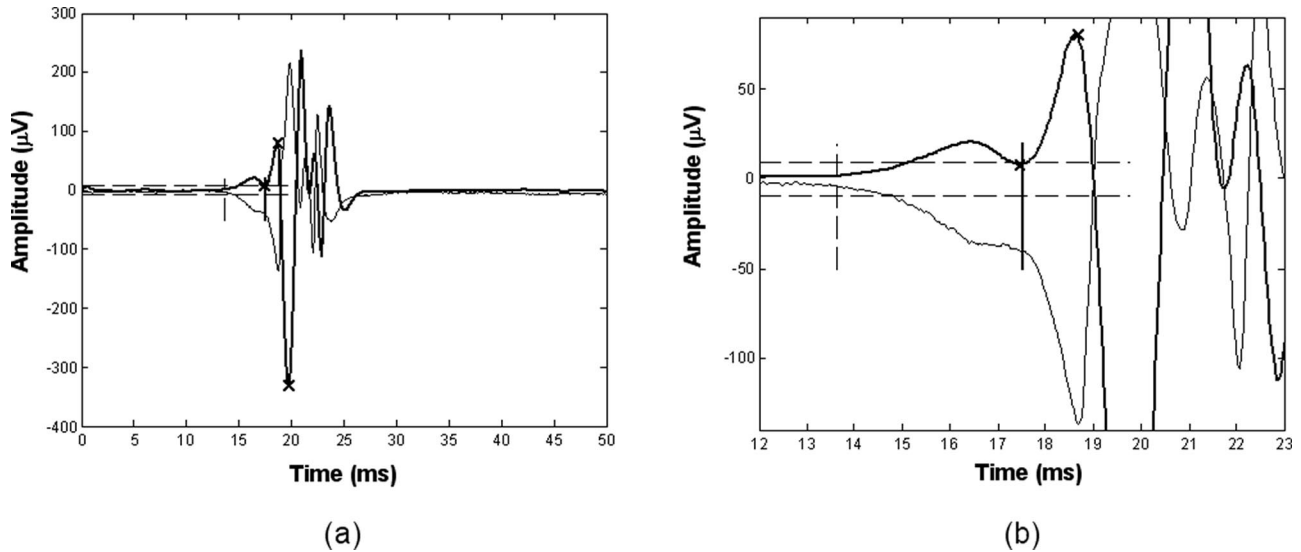
FIGURE 10. With quadratic spline wavelet DWT, peaks yield a low-amplitude maximum-minimum pair, which may not exceed the threshold, so they are excluded from the MUAP and halt progression of the algorithm. Start marker is located after the GSP.
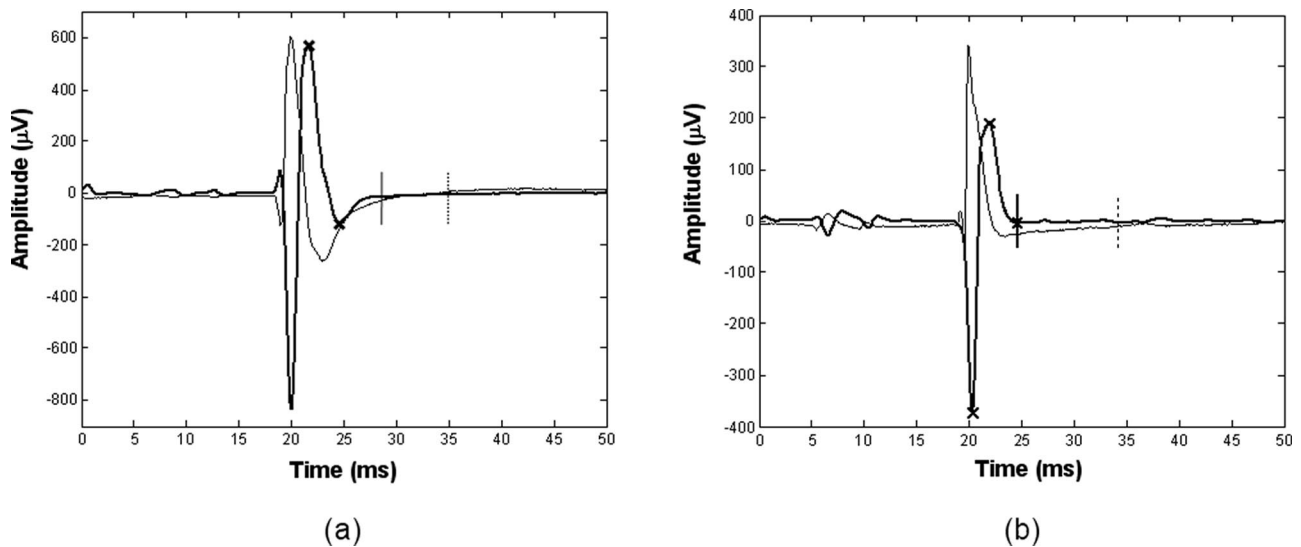

FIGURE 11. DWT cannot fully cope with the problematic long, low-sloped tails of some MUAPs.

that meets the stipulated conditions but is not really a part of the MUAP under analysis (Fig. 12).

Comparison of the Automatic Methods With Different Levels of Noise

In Fig. 13, we plot the means and standard deviations of differences from differences between the GSP and the positions obtained by both automatic methods against SNR.

Across the SNR range and for both start and end marker positions, the WBM gave lower mean differences than the AM. The WBM attained stable performance at higher levels of noise than the AM did, which indicates that the WBM is more robust in this respect.

Standard deviation values indicate that the WBM was more precise than the AM; for most of the SNR range, SD values were lower with the WBM than with the AM. Only at low SNR, when AM presented very high mean differences, was SD lower with AM than with WBM.

Comparison of Manual and Automatic Duration Measurements

The means of SD values for the start and end manual positions were 0.5 and 1.1 ms, respectively. The mean of σ values was 0.6 ms for both start and end WBM markers. No significant differences were found between the respective dispersions of the start point. However, the difference be-
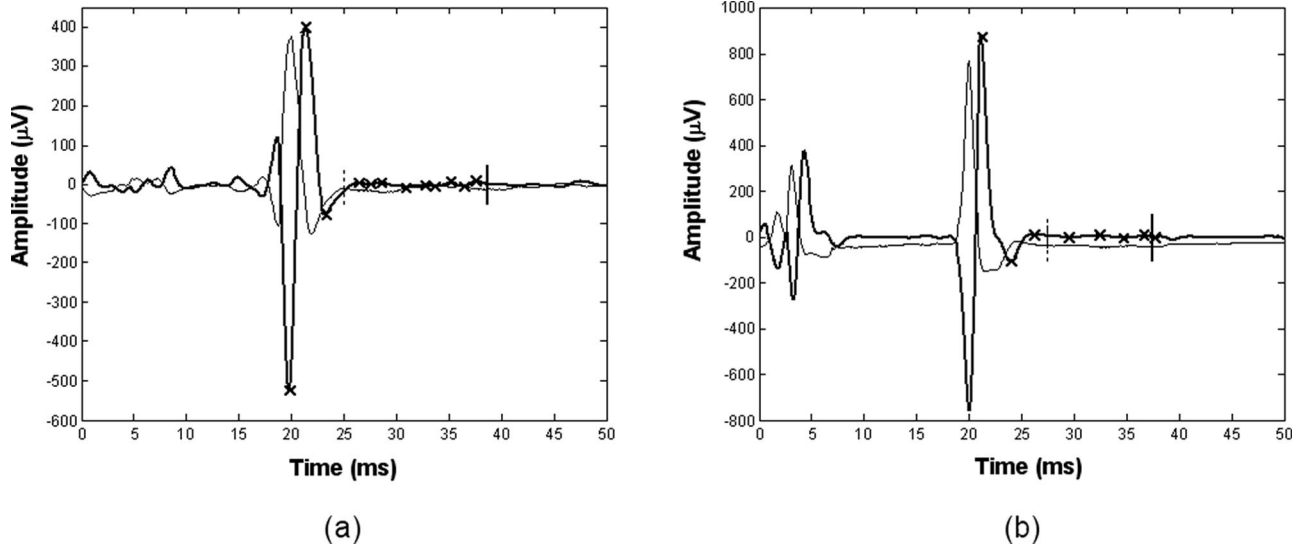
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FIGURE 12. Algorithm searches for peaks with amplitude values below Th_2 and sometimes finds a noise peak or a BL fluctuation peak that meets the stipulated conditions but is not really a part of the MUAP under analysis.
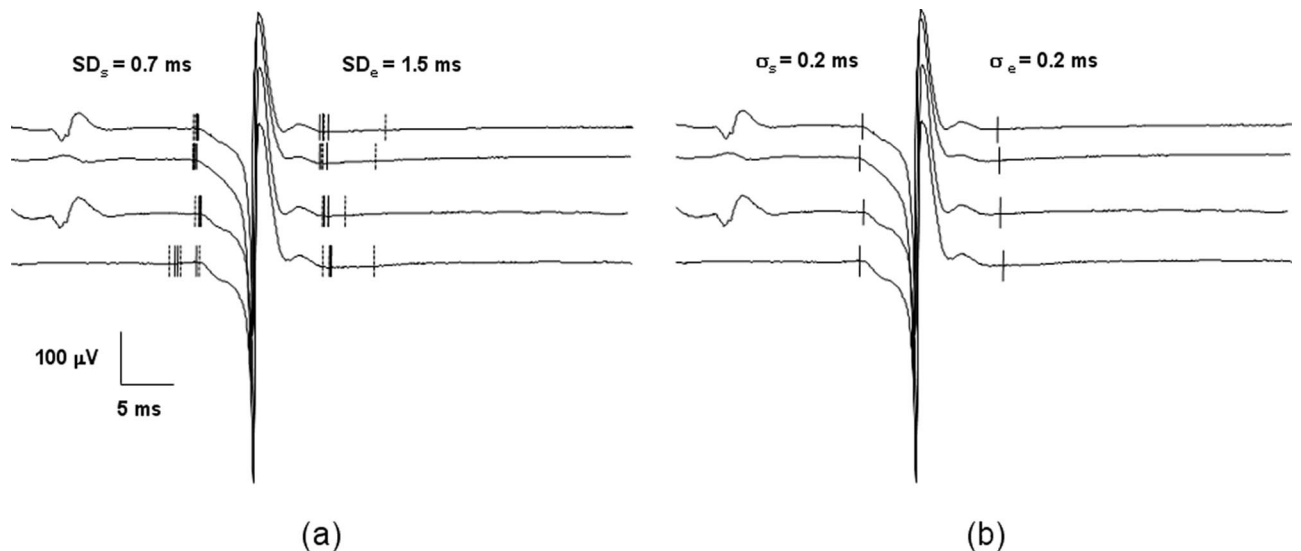

FIGURE 13. Mean and standard deviations of differences are plotted from differences between the GSP and positions obtained by both automatic methods against SNR.

tween the estimated dispersions of the end point placements was significant ($P < 0.05$; t-test), that of the WBM being lower (0.6 against 1.1 ms). An example of the different degree of dispersion in the placements of the duration markers obtained manually and with our new automatic method is given in Fig. 14.

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Computational Cost

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

DISCUSSION

In terms of automatic measurement of MUAP duration, real EMG signals pose several problems, such as the presence of MUAPs other than the one being analyzed, high-frequency noise, and BL fluctuations. The new automatic method for measuring MUAP duration that we describe in this report deals with the aforementioned problems better than previously described algorithms, such as the AM, thereby providing more accurate duration marker placements and fewer gross aberrant errors.

The AM differentiates the MUAP waveform from the BL on the basis of the quantitative criteria of amplitude and slope. If, as in the AM, the BL is taken as electrical zero without consideration of possible DC offset in the MUAP, then application of the amplitude criteria can result in misplacement of markers (Rodríguez et al., 2006). The WBM largely precludes such errors because the intermediate scales of the wavelet
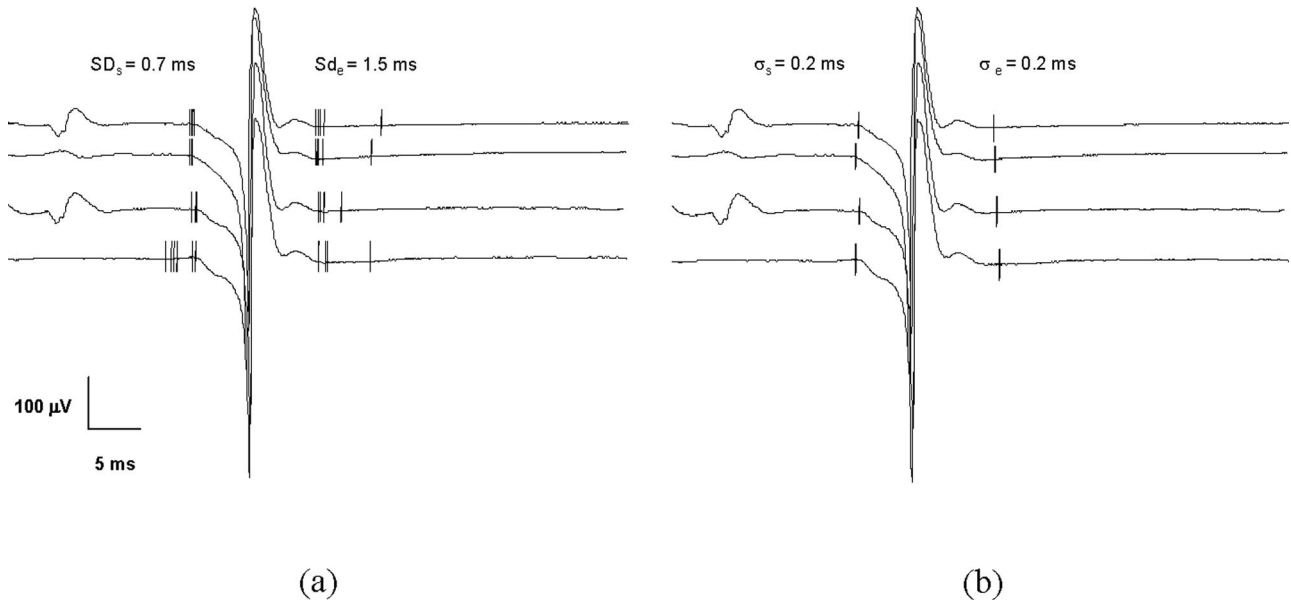
(a)   (b)

FIGURE 14. Example of the different degree of dispersion in the placements of the duration markers obtained manually and with our new automatic method.

transform separate out a lot of the noise and BL fluctuation before application of thresholding and slope criteria.

Although the WBM is relatively robust against BL fluctuation and other artifacts, it does present certain limitations. It fails to position the start marker correctly when a MUAP waveform has turns with a low level of amplitude variation. Also, the WBM sometimes fails when positioning the end marker of MUAPs with long, low-sloped tails.

Besides making use of the DWT, the WBM also depends on thresholding and slope criteria. As with previously reported automatic methods (Stalberg et al., 1986; Stalberg et al., 1996; Stewart et al., 1989), we established the values of the parameters used in these criteria by finding those values that enabled the algorithm to best reproduce manual duration measurements. To achieve this, we used genetic algorithms and a carefully prepared set of gold standard manual duration measurements from two senior electromyographists. Since our goal is the measurement of MUAP duration in a clinical setting, we believe this is a good way to optimize the parameter values. However, 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.

Thus, errors in positioning the end point are not fully dependent on the algorithm execution because 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 in some way represented in the automatic method. Nevertheless, further refinement of the method is necessary to obtain the best adaptation to the particular characteristics of the EMG signals and to the intrinsic difficulties of the MUAP duration measurement.

Setting aside the problems of the appropriate definition and criteria of MUAP clinical duration, an automatic method capable to fulfill any given criteria in any condition should present a high reliability. When analyzing several times the same MUAP, an automatic method always gives the same positions for start and end markers, showing maximum repeatability. With an efficient automatic method, if there were any bias in the marker positioning, it would be systematic and homogeneous in trend and magnitude, not arbitrary as subjective manual placements. Thus, the ideal method for reaching a satisfactory consistency in the MUAP duration measurement should be automatic, overcoming the inherent variability of human appreciation.

To assess the variability of an automatic method, it is necessary to present the same MUAP in different fashions, for example, by recording it several times, as it has been done in the present work. The dispersion of end markers positions obtained by the new automatic method was slightly but significantly lower than that of the corresponding manual measurements. This result tantalizingly points at the possibility of improving the consistency of duration measurements by means of an automatic method. To demonstrate this conclusively, a larger study, which will allow for the use of more powerful statistical methodologies such as, for example, the Gage R & R method, is required.

The WBM has sufficiently good performance to proceed to be tested by practical application in a clinical setting. Although the algorithm was more time-consuming than other automatic methods, its mean CPU time in the Matlab environment was about 20 ms, which is short enough for real-time processing. In clinical practice, the algorithm could reduce the requirement for manual intervention in duration marker placement, thereby facilitating the electromyographist's work. Together with multi-MUAP systems, the presented algorithm could also reduce patient discomfort by reducing the exploration time. Nevertheless, further research is necessary to assess the behavior

of the new algorithm under the different recording conditions of both normal and pathologic MUAPs.

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