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5.7.4: EMG and ENG - Waveform Analysis

Wavelet Analysis of Motor Unit Action Potentials

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Abstract - In this study the usefulness of the wavelet transforms (WT) Daubechies with 4 and 20 coefficients, Chui, and Battle-Lemarie in analyzing MUAPs recorded from normal subjects and subjects suffering with motor neuron disease and myopathy was investigated. The results of this study are summarised as follows: (i) The orthogonal WT decomposes the MUAP signal into a set of orthogonal basis functions where each coefficient represents an entirely different signal feature descibing the energy content in the given time-frequency window. Most of the energy of the MUAP signal is distributed among a small number of well-localized (in time) WT coefficients in the region of the main spike. (ii) The WT uses long duration windows for low frequencies, and short duration windows for high frequencies. For MUAP signals, this means that we to look to the low frequency coefficients for capturing the average behaviour of the MUAP signal over long durations, and we look to the low frequency coefficients for locating MUAP spike changes. (iii) In the case of the Daubechies 4 wavelet an extremely high time-resolution of only four signal samples is provided tracking effectively the transient components of the MUAP signal. (iv) Finally, it is shown that the diagnostic performance of neural network models trained with the Battle-Lemarie wavelet feature set is similar to the empirically determined time domain feature set.

I. INTRODUCTION

Quantitative analysis in clinical electromyography (EMG) is very desirable because it allows a more standardised, sensitive and specific evaluation of the neurophysiological findings. With the development of computer aided EMG equipment different methodologies in the time domain and frequency domain have been followed for quantitative analysis. In this study the usefulness of the wavelet transform (WT), that provides a linear two dimensional time-frequency representation is investigated for describing motor unit action potential (MUAP) morphology. The WT is investigated because it has the ability to localize the changes in the statistics of nonstationary signals and it provides an alternative to the classical Short-Time Fourier Transform (STFT) which uses a single analysis window [1]. The WT uses short windows at high frequencies and long windows at low frequencies. It is shown that MUAP signals can be represented using a small number of significant WT coefficients that are located around the main spike. Also, due to the nature of the WT high frequency coefficients are highly localized in time and capture the location of MUAP spike changes whereas low frequency coefficients provide lower time localization describing the slow components of the signal.

II. THE FAST WAVELET TRANSFORM

The FWT algorithm consists of the decomposition and the reconstruction phases. For our purposes, we focus on describing the decomposition phase. In the decomposition phase, the original signal is decomposed into its high frequency and low frequency components. The original discrete signal $x_0, x_1, x_2, \ldots$ is low-pass filtered by $h_0, h_1, h_2, \ldots$ and down-sampled by two to produce the low-frequency content signal (smooth signal) $s_0^{-1}, s_1^{-1}, s_2^{-1}, \ldots$. Similarly, the original discrete signal is high-pass filtered by $g_0, g_1, g_2, \ldots$ and down-sampled by two to produce the high-frequency content signal (detail signal) $d_0^{-1}, d_1^{-1}, d_2^{-1}, \ldots$. In our notation, the superscript -1 of s^{-1}, d^{-1} denotes the first decompotision stage. The algorithm is repeated recursively for j stages where for the jth stage, the outpt signals are denoted by s^{-j} and d^{-j}. It is important to note that different wavelet transofrms can be defined in terms of different sets of decomposition filters. In this study four different wavelets were investigated: Daubechies 4 (DAU4) and 20 (DAU20), Chui (CH) and Battle-Lemarie (BL). For the Daubechies family of wavelets [2], the DAU4 is defined in terms of only four coefficients, while the DAU20 is defined in terms of twenty coefficients. Since the DAU4 is affected by much less signal samples than the DAU20, it is clear that the DAU4 has a better time-resolution than the DAU20. On the other hand, by design, the DAU20 provides for a much better approximation to the ideal low-pass/high-pass decomposition filters. This tradeoff between the time and scale resolutions obeys the uncertainty principle. For rapidly-changing signals (like MUAPs), we prefer time-resolution to scale-resolution. From the multi-resolution analysis perspective, the Chui and Battle-Lemarie wavelet transforms provide the familiar piecewise-polynomial approximateion to the signal [3]. Thus, for these spline-based wavelets, the scalograms measure how much the signal, and its increments jump from point to point [4].

III. RESULTS

A total of 800 MUAPs were recorded from 40 subjects (12 normal (NOR), 15 subjects suffering with motor neuron disease (MND), and 13 subjects suffering with myopathy (MYO)). Each MUAP was represented with 512 points, sampled at 20 kHz with 12 bits resolution, making the total analysis epoch 25.6 ms. The MUAP mean was subtracted and each MUAP was normalized to its own power before analysis. MUAP position was adjusted so that the maximum positive peak to occur in the region of 200 points (10ms). Analysis was carried out for six wavelet bands. Scale d^1 represents the highest frequency bandwidth 5000-10000 Hz, and the lowest time bandwidth 0.1 ms with 256 points. The next scale, d^2, represents the next lower frequency bandwidth, 2500-5000 Hz, with the time bandwidth doubled, 0.2 ms, and with half the number of data points, and so on. Note that the wavelet band d^6 represents the lower bandwidth for the detail coefficients, 156.25-312.5 Hz with 3.2 ms time bandwidth and 8 points, whereas s^{-6} represents the coarse coefficients, covering the frequencies 0-156.25 Hz, with the same time bandwidth and number of points.

Figure 1 illustrates the decomposition of a MUAP into its coarse, s^{j}, and detail components, d^{j}, using the Battle Lemarie wavelet. It is shown that at each successive scale, $j=-1, \ldots, -6$, the coarse components, maintain only the larger features of the temporal signal. At each scale some signal information is extracted, and the extracted information is retained as the detail coefficients. This is very vividly shown from the s^{-3} to s^{-4} and d^{-4} projections in Fig. 1. The high frequencies in the MUAP main spike are seen removed from the s^{-3} coefficients and appear in the d^{-4} projection. This is demonstrated by the fivefold increase in the d^{-4} wavelet coefficients present in the region within the MUAP main spike.

Figure 2 shows typical recorded MUAPs, and the averaged time-frequency plots for the DAU4 and Battle-Lemarie wavelets for typical MND, and MYO subjects. As shown in Fig. 2 DAU4 captures the rising edge of the potential at 10 ms at scales d^{-1}, and d^{-2}. Its obvious that DAU4 provides the best time localization at high frequencies, whereas at the lower frequencies it has a smaller time spread. Thus the DAU4 has a large frequency-spread and a small time-spread. On the other hand the Battle-Lemarie and Chui provide a low time frequency localization. They are characterised by a smaller frequency-spread and a larger time-spread. In all of the plots, most of the power was concentrated in the lower three detail bands d^{-4}, and d^{-5}, d^{-6}, and coarse band s^{-6}. Comparing the time domain waveforms and the wavelet transform plots, long duration MUAPs produce longer spread in the lower detail bands (e.g. MND subject) whereas short duration MUAPs produce shorter spread in the lower detail bands (e.g. MYO subjects). Also the complexity of the MUAP time domain waveform is captured, localised in both the time and frequency domains by the time-frequency plot.

Table I tabulates the normalised MUAP wavelet power distribution per band per group for DAU4 and BL. It is shown that more than 85% of the power is concentrated in d^{-4}, d^{-5}, d^{-6} and s^{-6}. The same finding was also obtained for CH and BL. Also, for all the wavelets, for the MND group there is a shift towards lower frequency bands, whereas for the MYO group there is a shift towards higher frequency bands when compared to the NOR group. These findings are in agreement with conventional frequency analysis [5].

The diagnositc performance of wavelet analysis and their comparison to time domain and frequency domain features was investigated using artificial neural network (ANN) models. Twenty four subjects (eight from each group) were used to train the ANN models, and 16 subjects were used to evaluate the performance of the models. A total of sixteen coefficients were extracted, four from each of the following bands around the main spike at 10 ms: s^{-6}, d^{-6}, d^{-5} and d^{-4}. These coefficients were extracted for DAU4 and BL wavelets covering approximately 86 and 82% of the total energy. Table II tabulates the evaluation set performance (EV) for (i) DAU4 and BL, (ii) their log transforms, (iii) the time domain features: duration, spike duration, amplitude, area spike area, phases and turns [6], and (iv) the frequency domain features: spectral moments of order 0, 1 and 2, median frequency, maximum frequency, bandwidth, and quality factor [7]. The highest diagnostic performance was obtained for the BL wavelet and the time domain feature set, whereas the worst performance was obtained for the frequency domain feature set.

IV. CONCLUDING REMARKS

In conclusion, wavelet analysis provides a new way in describing MUAP morphology in the time-frequency plane. This method allows for the fast extraction of localized frequency components of MUAPs that may prove to be valuable in the early and accurate diagnosis of neuromuscular disorders.

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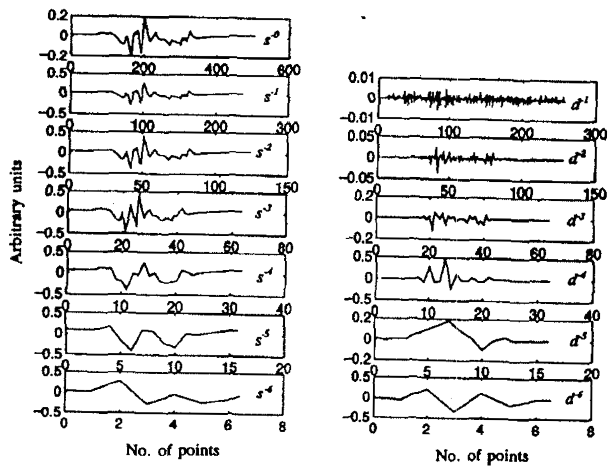

Fig. 1 Decomposition of a MUAP into coasre (s^{-1}, ..., s^{-6}) and detail waveforms (d^{-1}, ..., d^{-6}) using the Battle-Lemarie wavelet.

Table I Normalised percentage MUAP wavelet power distribution per band

	DAU4			BL		
	NOR	MND	MYO	NOR	MND	MYO
d^{-1}	0.56	0.39	0.76	0.14	0.07	0.19
d^{-2}	1.70	1.19	3.60	1.08	0.78	1.70
d^{-3}	5.16	3.22	8.72	8.12	4.39	14.56
d^{-4}	28.14	16.28	42.28	15.32	8.98	24.39
d^{-5}	17.63	17.31	20.45	28.29	25.86	30.77
d^{-6}	16.43	21.53	10.26	27.13	32.00	14.73
s^{-6}	30.33	38.71	15.38	20.27	25.41	12.48

Table II Diagnostic performance of neural network models

Feature set	EV
DAU4	69%
BL	81%
Log DAU4	51%
Log BL	69%
Time	81%
Frequency	51%

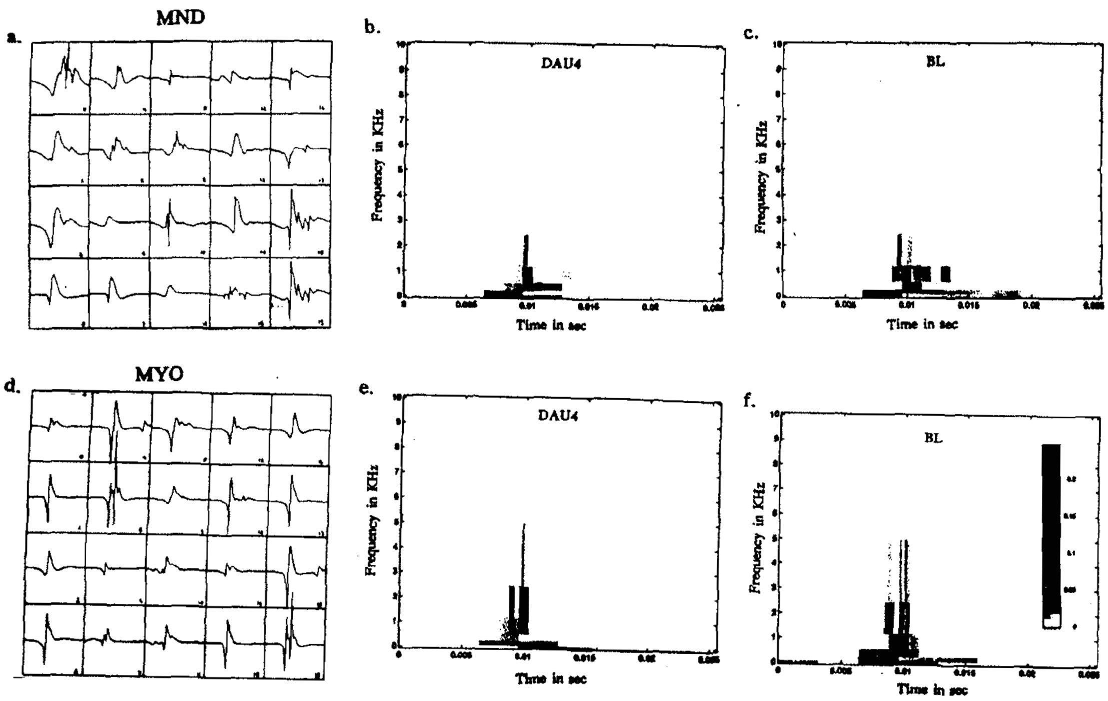

Fig. 2 Wavelet analysis for typical MND and MYO subjects: **a.** recorded MUAPs for MND, **b.** and **c.** DAU4 and BL averaged time-frequency plots; **d.** recorded MUAPs for MYO, **e.** and **f.** DAU4 and BL averaged time-frequency plots.