Wavelet Analysis of Surface Electromyography to Determine Muscle Fatigue

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***Abstract*—Muscle fatigue is often a result of unhealthy work practice. It has been known for some time that there is a significant change in the spectrum of the electromyography (EMG) of the muscle when it is fatigued. Due to the very complex nature of this signal however, it has been difficult to use this information to reliably automate the process of fatigue onset determination. If such a process implementation were feasible, it could be used as an indicator to reduce the chances of work-place injury. This research report on the effectiveness of the wavelet transform applied to the EMG signal as a means of identifying muscle fatigue. We report that with the appropriate choice of wavelet functions and scaling factors, it is possible to achieve reliable discrimination of the fatigue phenomenon, appropriate to an automated fatigue identification system.**

***Index Terms*—Electromyography (EMG), muscle fatigue, wavelet transform.**

I. Introduction

MUSCLE FATIGUE is a condition when the ability of the muscle to contract and produce force is reduced. Localized muscle fatigue is the situation when a muscle or a group of muscles has a reduced ability to contract and produce force, generally as a result of prolonged, relatively strong muscle activity. Muscle fatigue threshold cannot be defined as a simple function of muscle load magnitude and timing because muscle characteristics and capabilities vary from person to person. Undetected fatigue can cause injury—often irreversible—to the subject and besides the pain and suffering, is a financial burden to industry and society.

There are number of techniques that can be used to objectively determine the level of fatigue in a subject. The most reliable of these is the direct measurement of chemical properties in the muscle of the subject. Since this is an invasive technique it is inappropriate for routine utilization, away from the clinical environment.

The electromyography (EMG) is a biosignal recording of the skeletal muscle activity of the body. It is routinely used by clinicians for analysis of the skeletal muscle activity. EMG may be recorded invasively by using needle electrodes inserted directly into the muscle through the skin or alternatively may be recorded from the surface of the skin without any invasion of the body. The former is generally referred to as needle EMG while the latter as surface EMG (SEMG).

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Needle EMG recording provides a more exact representation and finer resolution of the electrical activity of the muscle fibers than that possible with SEMG. This is because the SEMG signal is a result of the summation of nonsynchronous action potentials of a large number of muscle fibers that have been nonlinearly attenuated by body tissue due to the frequency dependent electrical properties of the tissues [3], [9], [14]. The SEMG signal is dependent on the number of muscle fibers and other tissue properties, masking the essential parametric data. Despite the complex nature of the signal, SEMG recording can still be used to extract a useable representation of muscle status. The SEMG can be used to analyze the strength of muscle contraction, to study muscle state and fatigue as well as possible muscle disorders. Research analysis to date aimed at extracting from the SEMG an indication of localized muscle fatigue has been frequently based on the observed shift of the power spectral density of the SEMG [9], [14], [15]. When the muscle is fatigued, a strengthening of low-frequency components and a reduction in intensity of high-frequency components modifies the spectrum of the SEMG signal.

Several parametric measures of SEMG signal have been used as a relative indicator of the muscle fatigue phenomenon for an individual subject. These include the root mean square (rms), instantaneous frequency, zero crossing rate, mean-frequency, and median-frequency. In general, there is a large variance in both the SEMG power spectrum itself and the nature of the power spectrum shift as a result of fatigue onset for different subjects. These generally unpredictable variations mean that the SEMG is difficult to model and the task of automating the process of signal classification as a generalized tool would be complex, as it would need to adapt to the SEMG power spectral density trends for each individual subject.

In addition to these difficulties, muscle properties associated with the production of force are time variant. Motor unit recruitment is dependent both on the load as well as the current fatigue status of the muscle itself, thus introducing a time dependency in the SEMG signal as muscle loading progresses. There is also a random variation in the effectiveness of the body tissues in conducting the signal from the muscle to the surface electrodes. In addition to a variance from subject to subject, the SEMG signal is, thus, also a nondeterministic, nonstationery signal.

For automatic classification of the SEMG data as a function of muscle force and muscle fatigue in a generalized sense it is important first to reduce the complexity of the signal data, to extract only those features that correlate best with the force of contraction of the muscle and muscle fatigue and at the same time adaptively track the time variation of the properties of the muscle as well as the rate of stimulation.

Both time and frequency domain approaches (and a combination of the two) have been attempted in the past. Tools including rectification of the signal, "integration" of the signal, zero crossing count, fast Fourier transform (FFT), and short time Fourier transform (STFT) can provide a basis. Rectification of the signal is a convenient tool to measure the "relative strength" of the signal and "relative strength of contraction" of the muscle. RMS correlates well with the strength of total muscle contraction [15]. FFT and STFT provide the SEMG spectrum and information related to muscle fatigue status, size of motor units, synchronous activity between motor units, and rate of stimulation of the muscle.

The nondeterministic, nonstationary nature of the SEMG signal provides a challenge to the consideration of optimized transform domain signal processing. The STFT with relatively short time windows can attempt to track spectral variation with time but does not adopt an optimal time or frequency resolution for the nonstationary signal. In addition, the time frequency domain resolution tradeoff of a window are constrained by the Heisenberg uncertainty principle.

In the case of the SEMG signal, the constraint is a major drawback as both slow and fast changing properties of the SEMG signal are relevant to the analysis task. The slow variations provide information related to the body movements and tissue properties. The fast variations of the signal are useful for understanding the muscle activity and motor recruitment itself.

None of the previously mentioned techniques offer analysis that will take both time and frequency variation into account in an optimal sense. To date, practical analysis of the signal requires an experienced observer to provide subjective input in order to deal with time variance of the spectral properties of the signal and to interpret the simultaneous macroscopic and microscopic views of the signal. The salient features of the SEMG signal are apparent to the trained eye of the specialist but are not apparent to an untrained human eye or a computer [9]. Thus, there is the scope for developing new signal processing tools that can highlight the features of the signal and facilitate the extraction of the key parametric information.

In the recent past, time-scale methods (wavelet transform) have been used for the analysis of nonstationary signals. The wavelet transform (WT) decomposes a signal into several multiresolution components according to a basis function called the *"wavelet function"*. The "wavelet function" is both dilated and translated in time undertaking a two-dimensional cross correlation with the time domain SEMG signal. This method can be seen as a mathematical microscope that provides a tool to detect and characterize a short time component within a nonstationary signal. It is a technique that provides information related to the time-frequency variation of the signal. It has found numerous applications in data compression and feature enhancement for images, speech, and biosignals [2], [7], [8], [10], [16], [18]. In the past, the authors have successfully used WTs and neural networks to classify the SEMG for fatigue [13]. However, the system was not optimized nor was the results modeled. To achieve this, there is a need to be able to analyze the decomposed data resulting from different wavelet functions and at different scales to determine the most suitable technique.

In this experiment, the nonfatigue and fatigue SEMG are decomposed using WT with various *wavelet functions*. The output power of the transform domain is calculated and used as the deciding parameter in choosing the wavelet function that provides the best contrast in general between nonfatigue and fatigue SEMG cases.

The results suggest a specific wavelet function and a certain scale as providing the best contrast. Though the exact scale for which the difference is the largest is different for different subjects, at scale 8, the difference for all the subjects was significant. The results also suggest that the properties of the wavelet function (i.e., regularity, vanishing moment, and symmetricity) affect the result of the analysis, with the difference being the most significant for sym4 and sym5 wavelet functions.

II. Wavelet Decomposition

The WT is an extremely flexible approach to signal decomposition. While the basis functions of Fourier techniques are time invariant, the basis functions for WTs are time variant and localized in time with the location and scale adjustable by the user. The WT offers a wide choice of standardized basis functions *("mother wavelet functions")*. The user also has the option to custom design an optimized wavelet function if required.

The previous properties of wavelet transform can help track the time-frequency variation information within the SEMG signal. The WT also allows for multiresolution analysis of the signal allowing one to focus on different signal components. Because of these properties, the WT has found numerous applications in signal processing including data compression of related images and speech. Success has also been achieved in the extraction of the waveform of a single motor unit action potential (MUAP) from SEMG (at a very low level of voluntary contraction) [12].

WT of a time domain signal $\boldsymbol{x(t)}$ is defined as

$$W(s,\tau) = \int x(t)\psi^*_{s.\tau}(t)\,dt. \tag{1}$$

The fundamental or mother wavelet ψ is scaled by parameter $\boldsymbol{s}$ and translated by τ. This provides the information of the signal at different time and scales (the information of the signal localized in time and frequency).

The scaled mother wavelet is called *baby wavelet* and defined as [11]

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right). \tag{2}$$

By combining (1) and (2), the wavelet transform of the signal $x(t)$ can be written as

$$W(s,\tau) = \frac{1}{\sqrt{s}}\int x(t)\psi\left(\frac{t-\tau}{s}\right)dt. \tag{3}$$

Large $\boldsymbol{s}$ correlates with the low-frequency components of the signal, while small $\boldsymbol{s}$ correlates with the high-frequency components. The factor $(1/\sqrt{s})$ is used to preserve the energy. This wavelet transform is called *continuous wavelet transform* (CWT).

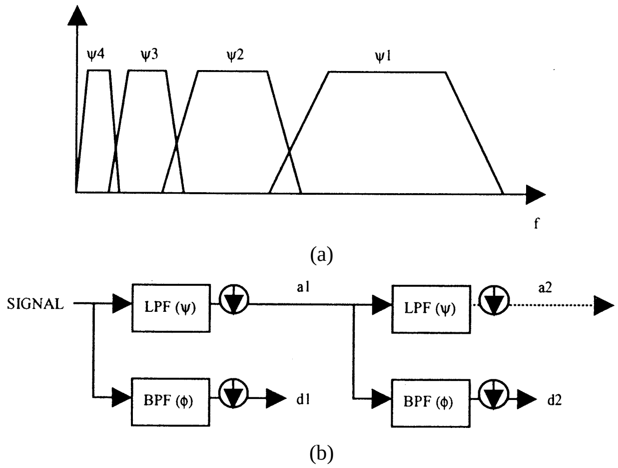

Fig. 1. (a) With increase in scale, the frequency band shifted to the lower frequency. (b) Mallat's algorithm uses pyramid filter bank.

If both the input signal and the parameters are discrete, the transform is called *discrete wavelet transform* (DWT). The discrete values of s and τ are commonly on a dyadic grid. Thus

$$\{(s_j, \tau_k)\} = \{(2^j, k2^j) \colon j, k \in Z\}. \tag{4}$$

The DWT is applied to discrete sequence of input $x[n]$. The wavelet function used in this transform is the discrete version of the continuous wavelet.

The DWT can be calculated using matrix multiplication, but an efficient way to implement DWT is by using digital filter bank, i.e., *Mallat's algorithm* [17]. This technique uses filter bank pairs which involve lowpass and bandpass filters and *down-sampling* (decimation) as shown in Fig. 1.

The lowpass filter uses "scaling function" ϕ (derived from wavelet function) as its impulse response while bandpass filter uses "wavelet function" ψ as its impulse response. The scaling is achieved by down-sampling. The result of such decomposition is a series of "*detail*" coefficients d_j and approximation coefficients a_j. The index j represents the decomposition level which equal to 2^j scale.

The ability of DWT to extract features from the signal is dependent on the appropriate choice of the mother wavelet function. Some of the popular standard families of wavelet basis functions are *Haar, Daubechies, Coiflet, Symmlet, Morlet, and Mexican Hat*. Even though there is no well-defined rule for selecting a wavelet basis function in a particular application or analysis, some properties of wavelets make a specific mother wavelet more suitable for a given application and signal type. There are some general guidelines for the choice of wavelets such as *Db4* is more suitable for signals that have "linear approximation" over the support of four samples, while *Db6* is better suited for a signal approximated by a quadratic function over the support of six, *coiflet6* provides better data compression results while *Db4* is more suitable for feature extraction [21]. However, for a more precise choice of a wavelet function, the properties of the wavelet function and the characteristic of signal to be analyzed need to be more carefully matched.

The following are some of the important properties of wavelet functions.

TABLE I
PROPERTIES OF WAVELET FUNCTIONS

	Haar	DbN	SymN
Orthogonal	Yes	Yes	Yes
Time Support	[0,1]	[0,2N-1]	[0,2N-1]
Frequency Support	$1/\omega$	$1/\omega^{0.2N}$	$1/\omega^{0.2N}$
Regularity	0	0.2N	0.2N
Symmetry	Yes	No	Yes
Zero Moment	1	N	N

TABLE II
FREQUENCY BAND OF WAVELET FUNCTIONS FOR SAMPLING RATE 5 kHz

Wavelet Function	Decomposition Level (j)	Time frame size (ms)	Frequency Band (Hz)
Haar	4	3.4	208 – 417
	5	6.6	104 – 208
	6	13	52 – 104
	7	25.8	26 – 52
	8	51.4	13 – 26
	9	102.6	6.5 – 13
Db2	4	9.6	198 – 395
	5	19.2	99 – 198
	6	38.4	50 – 99
	7	76.8	24 – 50
	8	153.6	12 – 24
	9	307.2	6 – 12
Db3	4	16	191 – 380
	5	32	96 – 191
	6	64	48 – 96
	7	128	24 – 48
	8	256	12 – 24
	9	512	6 – 12
Db4	4	22.4	186 – 375
	5	44.8	93 – 186
	6	89.6	47 – 93
	7	179.2	24 – 47
	8	358.4	12 – 24
	9	716.8	6 – 12
Sym4	4	22.4	186 – 375
	5	44.8	93 – 186
	6	89.6	47 – 93
	7	179.2	24 – 47
	8	358.4	12 – 24
	9	716.8	6 – 12

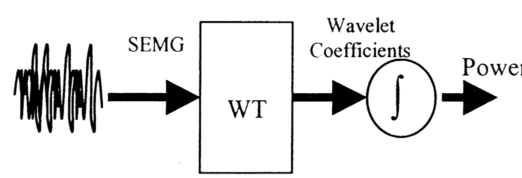

Fig. 2. Block diagram of the experiment procedure. Fatigue and normal SEMG signals are decomposed using six different wavelet functions at decomposition level 1–10. The power of the reconstructed wavelet coefficient are calculated and being used to classify SEMG signals.

1) *The Smoothness* is indicated by the regularity of the function. Regularity of r means that the rth derivative exists almost everywhere in the function. The *Haar* wavelet has regularity of zero since it is a discontinuous function.
2) *Time and frequency localization* is defined as the ability of wavelet function to localize in time and frequency. This is generally inversely related to the smoothness of the wavelet function.

TABLE III
PERCENTAGE DIFFERENCE BETWEEN THE AVERAGE POWER OF NORMAL AND FATIGUE SEMG OF SUBJECT 1. THE PEAK DIFFERENCES ARE HIGHLIGHTED

Wavelet Function	Decomposition Level									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Haar	5%	4%	0%	2%	20%	55%	41%	46%	**191%**	190%
Db2	23%	23%	14%	3%	7%	48%	57%	55%	**196%**	192%
Db3	26%	24%	21%	8%	12%	39%	62%	81%	115%	**132%**
Db4	27%	26%	23%	11%	15%	45%	47%	75%	**231%**	117%
Db5	23%	29%	22%	6%	4%	56%	54%	55%	286%	**456%**
Sym4	20%	26%	23%	11%	14%	39%	56%	82%	160%	**167%**
Sym5	15%	27%	21%	6%	3%	50%	63%	59%	188%	**613%**

TABLE IV
PERCENTAGE DIFFERENCE BETWEEN THE AVERAGE POWER OF NORMAL AND FATIGUE SEMG OF SUBJECT 2. THE PEAK DIFFERENCES ARE HIGHLIGHTED

Wavelet Function	Decomposition Level									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Haar	8%	8%	4%	2%	12%	37%	84%	171%	**313%**	106%
Db2	1%	22%	26%	14%	13%	28%	78%	172%	212%	**368%**
Db3	55%	16%	25%	26%	2%	20%	93%	210%	296%	**419%**
Db4	81%	23%	31%	23%	3%	19%	90%	237%	**435%**	273%
Db5	61%	21%	25%	31%	9%	22%	75%	211%	301%	**453%**
Sym4	16%	19%	24%	29%	2%	17%	97%	230%	365%	**607%**
Sym5	87%	19%	29%	30%	9%	24%	73%	198%	250%	**317%**

TABLE V
PERCENTAGE DIFFERENCE BETWEEN THE AVERAGE POWER OF NORMAL AND FATIGUE SEMG OF SUBJECT 3. THE PEAK DIFFERENCES ARE HIGHLIGHTED

Wavelet Function	Decomposition Level									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Haar	323%	325%	352%	309%	329%	302%	360%	402%	301%	**739%**
Db2	252%	262%	280%	379%	388%	253%	322%	481%	**509%**	309%
Db3	205%	232%	305%	361%	404%	295%	275%	406%	**708%**	267%
Db4	159%	196%	236%	309%	383%	317%	294%	386%	575%	**695%**
Db5	134%	203%	266%	365%	405%	262%	323%	**464%**	332%	290%
Sym4	186%	199%	285%	351%	403%	309%	268%	401%	**800%**	300%
Sym5	266%	185%	226%	367%	415%	252%	316%	483%	**494%**	219%

3) *Zero moments*. A wavelet function with N zero moment satisfies

$$\int_{-\infty}^{\infty} t^n \psi(t)\, dt = 0 \quad n = 0, 1, 2, \ldots, (N-1). \tag{5}$$

The zero moment represents the polynomial degree of the wavelet function. In the frequency domain, this may be seen as related to the slope of the bandpass filter characteristics—the higher the "*zero moment*," the sharper the cutoff of the filter is.

4) *Symmetry*. A function is defined as a symmetric function about τ if

$$f(t+\tau) = f(-t+\tau). \tag{6}$$

A symmetric wavelet function introduces linear phase when used as impulse response in Mallat's algorithm [17]. The symmetry property of the wavelet function is required when the shape of the signal is to be maintained.

The properties of the wavelet functions used in this paper are shown in Table I [12]. Table II shows the characteristics of the different wavelets at different scales.

III. METHODOLOGY

For this experiment, 240 separate SEMG data files were recorded from the surface of the right arm biceps-bracii muscle of three healthy males volunteer. The signals were recorded while a load of 50% MVC was held on the right arm with elbow flexion of 90°. The SEMG signal files were recorded using Amlab biosignal equipment with sampling rate of 5 kHz. The duration of each recording was 2 s. The surface electrodes were placed along the longitudinal midline of the muscle, between

TABLE VI
AVERAGE OF TABLES III–V

Wavelet Function	Decomposition Level									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Haar	51%	51%	58%	58%	72%	91%	135%	205%	**297%**	212%
Db2	40%	24%	30%	60%	78%	75%	128%	216%	286%	**330%**
Db3	59%	23%	28%	46%	68%	74%	132%	238%	**387%**	314%
Db4	61%	13%	15%	42%	65%	77%	129%	253%	**445%**	388%
Db5	50%	13%	21%	46%	75%	73%	123%	247%	306%	**386%**
Sym4	41%	15%	24%	42%	66%	73%	132%	252%	**461%**	382%
Sym5	102%	13%	15%	47%	76%	72%	123%	239%	296%	**321%**

the end-plate region and both tendons. The distance between the centre of electrodes was kept at 5 cm and the reference electrode (ground electrode) placed under the elbow of the subject.

The recorded SEMG signals were grouped into two groups: *nonfatigue* and *fatigue signals*. The initial SEMG recording when the subject was feeling “fresh” was the nonfatigue recording while the recording after the subject complained of fatigue and had lifted the load for a long duration of time was declared as the fatigue signal case. Muscle fatigue was confirmed by observing that there was an increase in the ripple in the force recording.

These SEMG signals were decomposed using discrete wavelet transform (DWT) with five different wavelet functions (*Haar, db2, db3, db4*, and *Sym4*). The DWT was implemented using MATLAB Wavelet Toolbox.

The power of the DWT coefficients at various levels was calculated. This power was then compared for the SEMG before and after the onset of muscle fatigue. Fig. 2 shows the block diagram of the experiment process.

IV. RESULTS

The Tables III–VI present the results of the experiment. The first three tables are for the each of the individual subjects and the last is for the average. For the ease of reading the results, the tables have been graphically presented in Figs. 3–6.

Tables III–VI give the power of the output of WT for five different wavelet functions at decomposition level 1 to 10. These also provide the difference as a percentage between the power of fatigue SEMG and nonfatigue SEMG. This is important because the difference of power of the signal can be easily used to automate the classification process.

It can be clearly observed that:

1) power of the SEMG is concentrated at level 5–8;
2) within this region, the power of fatigue SEMG is mostly higher than normal SEMG;
3) the level when the highest power occurs is different for different subjects and different wavelet functions;
4) the largest contrast between fatigue and nonfatigue SEMG cases occurs at decomposition levels 9 or 10;
5) though there is no single wavelet function that gives “the best contrast,” Sym4 and Sym5 provide contrast that is useable for all cases.

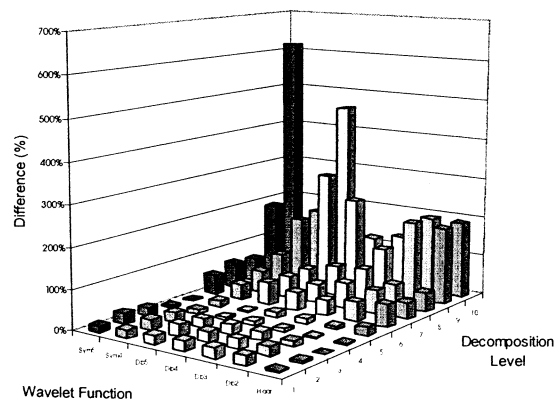

Fig. 3. Percentage difference between the average power of normal and fatigue SEMG for subject 1. The same data are presented on Table III.

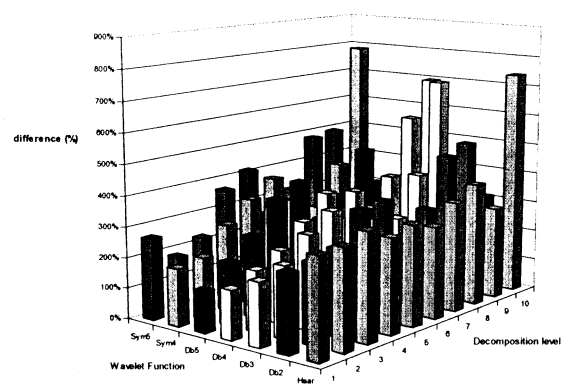

Fig. 4. Percentage difference between the average power of normal and fatigue SEMG for subject 2. The same data are presented on Table IV.

V. DISCUSSION AND CONCLUSION

The previously mentioned research activity demonstrates that there is a clear difference between the SEMG of the fatigue muscles compared with the SEMG of the muscles not fatigued. Though this has been known for over 30 years [3], the signal processing by the use of wavelets has enhanced the difference. This is evident from the Figs. 2–5.

From the results, it is also evident that the difference between the two types of SEMG is not consistent at different scales of decomposition. There is also a clear difference between the decomposition that is dependent on the wavelet function. Except

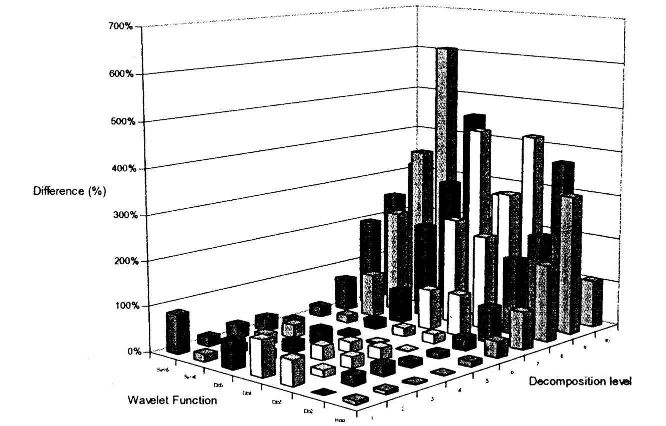

Fig. 5. Percentage difference between the average power of normal and fatigue SEMG for subject 3. The same data are presented on Table V.

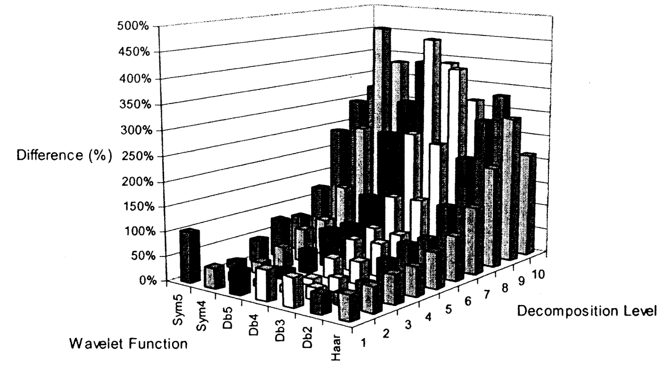

Fig. 6. Percentage difference between the average power of normal and fatigue SEMG for all subjects (average of those three subjects).

for case of subject two, the difference in the power at the lower levels is small and barely noticeable while at levels 8 and 9, the difference is highlighted—with the difference being of the level of 300%–400%.

In the past, spectral analysis of the SEMG has demonstrated a significant change of the spectrum of the signal due to muscle fatigue [3], [9], [13]. However, the change was small and because the shape of the spectrum of SEMG varied, it was difficult to provide an objective and numeric parameter to distinguish between the two SEMG's. However, with the difference between the SEMG from fatigue and nonfatigue muscles being so clearly highlighted by this technique and with the difference being uniform despite the differences between subjects, it is possible to identify a parameter that can be used to distinguish between the two SEMGs.

The results of this work clearly demonstrate that using wavelets, the differences between the SEMG corresponding to fatigue muscles and nonfatigue muscles is highlighted when using Sym4 and Sym5 wavelet functions. The study also demonstrates that the difference is dependent on the scale of decomposition, the difference being very significant at scales 8 and 9.

As a result of this research activity, it can be said that using SEMG and wavelet transforms, it may be possible to determine the muscle fatigue status simply by determining the Sym4 or Sym5 wavelet decomposition of the signal at level 8 or 9. The occurrence of fatigue will result in the power in this scale increasing by more than a factor of two. Based on this, it would be easy to automate the process of determining localized muscle fatigue which could have applications related to physiotherapy and also to determine the healthy working environment.

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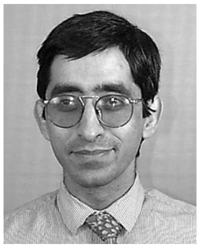

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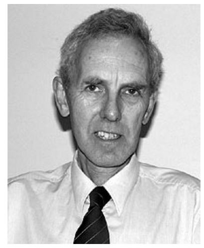

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