J. KSIAM Vol.4, No. 2, 143-152, 2000

FATIGUE ANALYSIS OF ELECTROMYOGRAPHIC SIGNAL BASED ON STATIONARY WAVELET TRANSFORM

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Abstract

As muscular contraction is sustained, the Fourier spectrum of the myoelectric signal is shifted toward the lower frequency. This spectral density is associated with muscle fatigue. This paper describes a quantitative measurement method that performs the measurement of localized muscle fatigue by tracking changes of median frequency based on stationary wavelet transform. Applying to the human masseter muscle, the proposed method offers the much information for muscle fatigue, comparing with the conventional FFT-based method for muscle fatigue measurement.

I. Muscle fatigue analysis

When a muscle contraction continuously at a high force, it is seen that the frequency content of its electromyographic(EMG) signal gradually shifts to lower frequencies in the course of several minutes. This effect is commonly associated with the fatigue that manifests at same time[1]. It is generally accepted that the mean or median frequency of the power spectral density function effectively track the spectral scaling due to fatigue. The fatigue analysis of EMG signal offers much information about human muscle mechanics such as the firing rate of the motor unit, inter-pulse interval of impulse function which represents the time events of motor unit action potentials(MUAPs), and the frequency contents of time-dependent MUAPs and fiber conduction velocity(FCV). Especially significant parameter linked to FCV is the median frequency of the EMG spectrum f_m , which is defined as the frequency that divides the spectrum into equal areas as

$$\frac{\int_0^{f_m} G_e(f)\,df}{\int_0^{\infty} G_e(f)\,df}=\frac{1}{2} \tag{1}$$

Keywords : Electromyographic signal, Stationary wavelet transform, Muscle fatigue, Median frequency

This research was supported by the Chungwoon university research fund in 1998.

and it can be computed directly by fast Fourier transform(FFT)[2]. In fact, traditional spectral fatigue estimation requires the signal to be wide sense stationary within observation window. When muscle contractions depart from this constraint, as during dynamic contraction, the stationarity of the EMG signals can no longer be assumed.

Although there are numerous situations in which isometric and constant force contraction paradigm is rather uncommon in most daily muscle activities[3]. In this paper, we propose a different possible approach to spectral analysis of nonstationary EMG signal using stationary wavelet transform which is not the decimation of coefficient sequences at each stage and its property offers the much finer time resolution comparing with standard wavelet transform.

II. Stationary wavelet transform procedure

Discrete wavelet transform

Suppose we are given a sequence $\{c_i\}=c_0, c_1, \cdots, c_{N-1}$ where $N=2^J$ for some integer J. The standard discrete wavelet transform(DWT) is based on filters H and G and on binary decimation operator D_0. The filter H is a low pass filter, defined by a sequence conventionally denoted $\{h_n\}$ which is the discrete version of continuous mother wavelet $\psi(t)$. Typically, only a small number of the $\{h_n\}$ are non-zero. The action of the low pass filter on a doubly finite sequence $\{\cdots, x_{-1}, x_0, x_1, x_2, \cdots\}$ is defined by

$$(Hx)_k = \sum_n h_{n-k} x_n \tag{2}$$

The definitions for sequences of finite length depend on a choice treatment at the boundaries. In this paper periodic boundary conditions will be used.

The filter assumed to satisfy the internal orthogonality relation

$$\sum_n h_n h_{n+2j} = 0 \tag{3}$$

for all integers $j \neq 0$, and to have sum of squares $\sum_n h_n^2 = 1$. The high pass filter G is defined by the sequence

$$G_n = (-1)^n h_{1-n} \tag{4}$$

for all integers n. The filter G satisfies the same internal orthogonality relations as H and in addition that the filters obey the mutual orthogonality relation

$$\sum_n h_n \, g_{n+2j} = 0 \tag{5}$$

for all integers j. Filters constructed in this way are called quadrature mirror filters[4].

The binary decimation operator D_0 simply chooses every even number of a sequence, so that

$$(D_0x)_j = x_{2j} \tag{6}$$

for all integers j. It follows the internal and mutual orthogonality properties of the quadrature mirror filters that the mapping of a sequence x to the pair of sequences (D_0Gx, D_0Hx) is an orthogonal transformation. If x is a finite sequence of length 2^m with periodic boundary conditions applied, then each of D_0Gx and D_0Hx will be sequences of length 2^{m-1}. The DWT is derived from a multiresolution analysis, performed as follows

$$c^j = D_0Hc^{j+1} \text{ and } d^j = D_0Gc^{j+1} \tag{7}$$

for the smooth at level J, written c^J to be the original data $c_n^J = c_n$, $n=0,1,\cdots,2^{J-1}$ and for $j=J-1,J-2,\cdots,0$, recursively define the smooth c^j at level j and detail d^j at level j. Because the mapping (D_0Gx, D_0Hx) is an orthogonal transform it is inverted to find c^{j+1} in terms c^j and d^j by describing the transform as matrix and taking its transpose

$$c^{j+1} = R_0(c^j, d^j) \text{ for all each } j \tag{8}$$

where R_0 denotes the inverse transform to recover c^{j+1} from c^j and d^j.

DWT by even and odd number decimation

To define stationary wavelet transform(SWT), The modified version of the standard DWT is required. In this paragraph, we describe the modified procedure of the standard DWT. Since the DWT is an orthogonal transform it corresponds to particular choice of basis for the space R^N in which the original sequence lies and the decomposition could equally be carried out by selecting every odd number of each sequence rather than every even number, i.e., for sequence x, the operator D_1 is defined by

$$(D_1x)_j = x_{2j+1} \tag{9}$$

for all integers j. The mapping (D_1Gx, D_1Hx) is still an orthogonal transform, and the multiresolution analysis can be carried out by successively applying this operation in (7) instead of (D_0Gx, D_0Hx). The results will not be same, but the overall transformation will still be an orthogonal transformation. The reconstruction can be obtained by successive application of the corresponding inverse operator, denoted R_1.

Suppose that $\varepsilon_{J-1}, \varepsilon_{J-2}, \cdots, \varepsilon_0$ is a sequence of $0's$ and $1's$. We can then use the operator D_{ε_j} at level j. and perform the reconstruction by using the corresponding sequence of operator R_{ε_j}. called the ε-decimated DWT. This procedure can be obtained by considering shift operators. Let S be the shift operator defined by

$$(Sx)_j = x_{j+1} \tag{10}$$

It is from the definitions that $D_1 = D_0S$ and that $R_1 = S^{-1}R_0$. And also it is that $SD_0 = D_0S^2$ and that the operator S commutes with H and G. Now define p to be the integer whose binary representation is $\varepsilon_0, \varepsilon_1, \cdots, \varepsilon_{J-1}$.
It can be shown that the coefficient sequences c^j and d^j yielded by the standard DWT applied to the shifted sequence S^px. To see this, consider any fixed j and let p_1 and p_2 be the integers with binary representations $\varepsilon_0\varepsilon_1\cdots\varepsilon_{j-1}$ and $\varepsilon_j\varepsilon_{j+1}\cdots\varepsilon_{J-1}$. In standard DWT, the sequence $d^j = D_0G(D_0H)^{J-j-1}c^J$. In the ε-decimated case, the sequence is

$$\begin{aligned} d^j &= D_{\varepsilon_j}GD_{\varepsilon_{j+1}}HD_{\varepsilon_{j+2}}H\cdots D_{\varepsilon_{J-1}}Hc^J \\ &= D_0S^{\varepsilon_j}GD_0S^{\varepsilon_{j+1}}HD_0S^{\varepsilon_{j+2}}H\cdots D_0S^{\varepsilon_{J-1}}Hc^J \end{aligned} \tag{11}$$

By repeatedly commuting the shift operators with G and H and applying the property $SD_0 = D_0S^2$, equation (11) is

$$d^j = D_0G(D_0H)^{J-j-1}S^{p_2}c^J \tag{12}$$

and applying the operator S^{p_1}

$$S^{p_1} = D_0G(D_{0H)}^{J-j-1}S^Pc^J \tag{13}$$

since $P = 2^{J-j}p_1 + p_2$. Thus d_j shifted by an amount p_1 is the jth detail sequence of the standard DWT applied to the original data sequence by an amount P.
It follows that the basis vectors of the ε-decimated DWT can be obtained from those of the standard DWT by applying the shift operator S^P, and the choice of ε thus corresponds to a choice of origin with respect to which the basis function defined.

Properties of SWT

Unlikely standard or ε-decimated DWT, the SWT do not decimate at each level and the two new sequences have the same length as the original sequence. Instead the filters at each level are modified by padding them with zeros.

Let Z be the operator that alternates a given sequence with zeros, so that, for all integers j, $(Zx)_{2j} = x_j$ and $(Zx)_{2j+1} = 0$.. Define filters $H^{[r]}$ and $G^{[r]}$ to have weights $Z^r h$ and $Z^r g$ respectively. Thus the filter $H^{[r]}$ is obtained by inserting a zero between every adjacent pair of elements of the filter $H^{[r-1]}$, and similarly for $G^{[r]}$. It is that $H^{[r]}$ and $G^{[r]}$ commute with S and that

$$D_0 H^{[r]} = H D_0^r \text{ and } D_0 G^{[r]} = G D_0^r \tag{14}$$

For the original data sequence a^J, the SWT is recursively defined

$$a^{j-1} = H^{[J-j]} a^j \text{ and } b^{j-1} = G^{[J-j]} a^j \tag{15}$$

and for any given ε and corresponding origin S in the ε-decimated DWT, the detail at level j are shifted version of $D_0^{J-j} S^P b_j$ and the data at level j the same shifted version of $D_0^{J-j} S^P a_j$ by

$$\begin{aligned} S^{-p_1} D_0^{J-j} S^P b_j &= D_0^{J-j} S^{p_2} G^{[J-j-1]} H^{[J-j-2]} \cdots H^{[0]} c^J \\ &= D_0 G D_0 H D_0^{J-j-2} \cdots H S^{p_2} c^J \\ &= D_0 G (D_0 H)^{J-j-1} S^{p_2} C^J = d^j \end{aligned} \tag{16}$$

Equation (16) implies that the SWT contains the coefficients of the ε-decimated DWT for every choice of ε. And it means that the SWT fills in the gaps between the coefficients in any particular ε-decimated DWT.

For each fixed j, the sequence b_k^j provides information about the original data at scale 2^{J-j} and position k because that the mother wavelet $\psi(t)$ is band-limited in the frequency domain, so we can see that b_k^j is a band-limited filtering of the original sequence. As j varies, the frequency response function of the filter is dilated by a factor of 2^j. And it implies that the frequencies allow through by the band-limited filter are in interval whose endpoints are proportional to 2^j.

III. Experimental results

The conventional methods for the muscle fatigue analysis are mostly FFT-based spectral frequency estimations[5][6]. The typical procedure of the conventional method is following steps. The 1st step is the EMG signal acquisition under isometric contraction and constant

force conditions at applicable frequency band. The 2nd step divides the acquisited EMG signal to the some data block and performs the FFT at each data block.
The last step calculates the median frequency from the calculated FFT data of each data block and performs the linear regression of the calculated median frequencies at each data block. The problem of the FFT-based conventional method is that the frequency resolution of EMG data at each data block is decreasing, increasing the number of data block.
It means that the decreased number of data block improves the frequency resolution at each data block, but diminishes the time resolution of the calculated median frequencies. Finally, the slope of linear regression curve of median frequencies is used for the muscle fatigue analysis.

To overcome these disadvantages of conventional methods, we proposed the stationary wavelet transform-based muscle fatigue analysis method. The procedure the proposed method is the same as the conventional method except that the stationary wavelet transform is applied between the 1st and the 2nd step. The stationary wavelet transform offers the same time resolution as the original data by its property, not decreasing of the corresponding frequency resolution.
So the *N* level stationary wavelet transform of *M*-points EMG data produces the *M*-points data at each level and the FFT-based median frequencies can be calculated from the data blocks of each level.

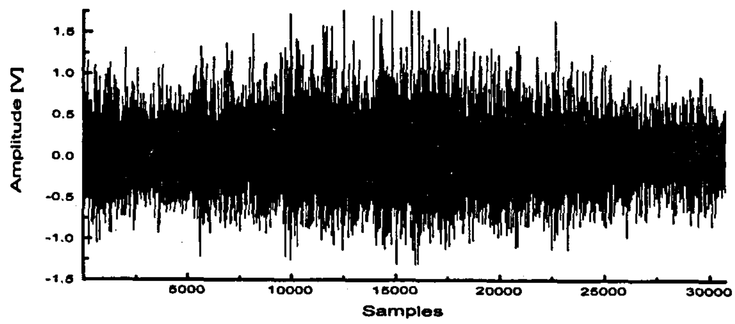
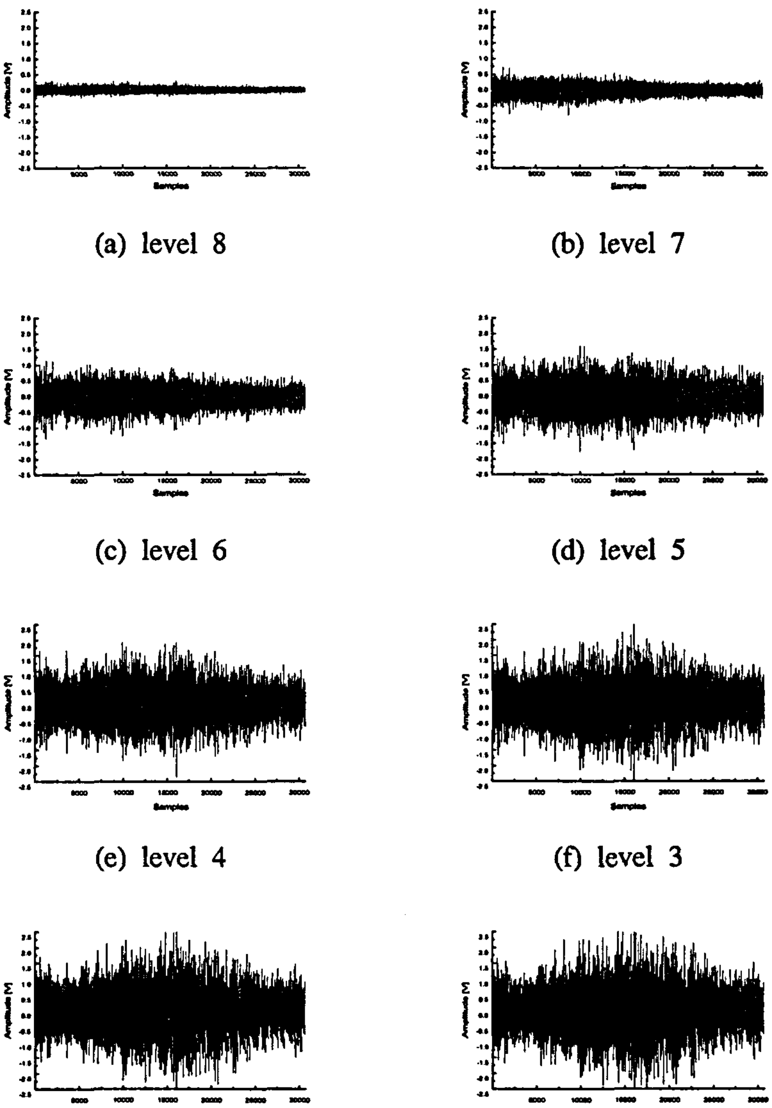


Fig.1. The acquired EMG data from the masseter muscle of human subject

This implies that the proposed method can perform the muscle fatigue analysis which is not the loss of the time and corresponding frequency resolutions.



(a) level 8 (b) level 7

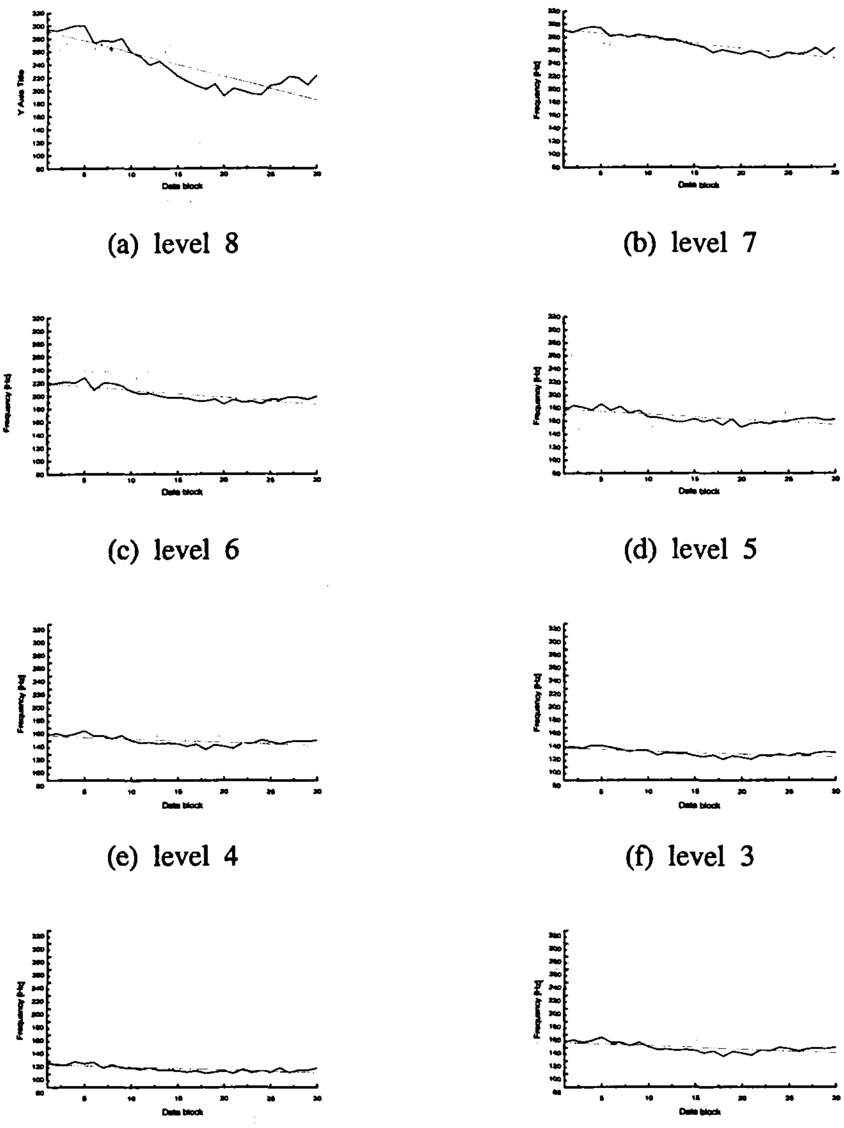
(c) level 6 (d) level 5

(e) level 4 (f) level 3

(g) level 2 (h) level 1

Fig. 2. The results of 8-level stationary wavelet transform of acquired EMG data

To experiment, we acquire the EMG data from the masseter muscle of human subject which is used for masticating operation of tooth in the conditions of isometric contraction and constant force of 100% MVC(maximum voluntary contraction) for 30 seconds. Then it is amplified 1000 times by the differential amplifier and digitalized by the sampling frequency of 1024Hz. Fig. 1 is shown the acquisited EMG data. Applying the 8-level stationary wavelet transform, the acquired EMG data is devided at each level as fig. 2.



(a) level 8 (b) level 7

(c) level 6 (d) level 5

(e) level 4 (f) level 3

(g) level 2 (h) level 1

Fig. 3. The curves of calculated median frequencies at each level

And also we calculate median frequency at each level, where the sample number of data block for calculating the median frequency is 1024 samples so that the number of block at each level is 30. The curves of calculated median frequencies are showing as Fig. 3. and Fig. 4 is the curve of median frequencies by the conventional method.

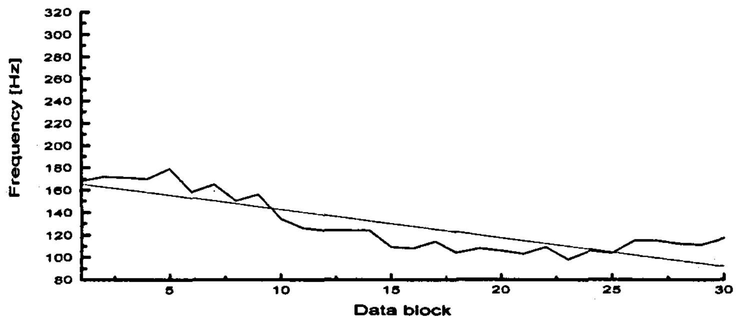


Fig. 4. The curve of median frequencies by the conventional method

The table 1. is the results of linear regression of median frequency curve by the proposed and the conventional method.

Table 1. The results of linear regression of median frequency curve by the proposed and the conventional method

Level	Proposed method	Conventional method
level 1	$y=-0.359x+102.475$	$y=-2.53x+167.956$
level 2	$y=-0.433x+114.813$	
level 3	$y=-0.467x+129.052$	
level 4	$y=-0.506x+148.018$	
level 5	$y=-0.806x+178.381$	
level 6	$y=-1.122x+220.036$	
level 7	$y=-1.545x+293.514$	
level 8	$y=-3.684x+295.110$	

The results of the proposed method show that the median frequencies of low frequency components of EMG signal which correspond to low level data of the stationary wavelet transform is slow changed. It means that the muscle fatigue is not affected by the low frequency components of EMG signal. But the median frequencies of high frequency components of EMG signal is fast changed and it is similar to the result by the conventional method. It means that muscle fatigue affected by high frequency components of the EMG signal.

The results of Fig.3 and Fig.4 may be interpreted in different manner as well. the conventional method can not represent the muscle fatigue in the total frequency band of EMG signal, which is only approximately represents muscle fatigue. But the proposed method offers the total muscle fatigue informations by median frequency curve at each level. So the proposed method can be used for accurate clinical diagnosis of muscular disorders related with muscle fatigue.

IV. Conclusions

In this paper, we propose the new method for muscle fatigue analysis based on stationary wavelet transform, which offers the various spectrum information related with muscle fatigue comparing with the conventional method. And also we confirm that the proposed method can be used for muscle fatigue analysis instead of the conventional method. The advantage of the proposed method can analyze the muscle fatigue for EMG signal of all possible frequency bands but the conventional method offers approximately muscle fatigue information. As a result., the proposed method can be used for accurate clinical diagnosis of muscle fatigue instead of the conventional method.

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