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Noise Reduction Methods for the EMG Median Frequency Data in Fatiguing Isotonic Exercise

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국문요약

등장성 운동 시 근전도 중앙주파수 데이터의 잡음 제거 방법

조상현
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19명의 건강한 성인 남자의 우세팔쪽 위팔두갈래근에서 피로가 생길 때까지 2.4초를 하나의 주기로 팔꿉을 반복적 등장성으로 굽히고 펴서 표면근전도 신호를 얻었다. 처리과정 A 중앙주파수(MDF)는 이 신호의 0.5초 구간을 power spectrum analysis (PSA)로 계산하였는데 상당량의 잡음이 있었다. 중앙주파수의 잡음 양을 비교하기 위해, 동일한 표면근전도에서 3번까지 신호를 받았다 (2.4초 구간을 PSA로 계산한 처리과정 B, 13 point로 moving averages한 처리과정 C, digital low pass filter한 처리과정 D). 그리고 나서 그 신호의 주요 주파수 성분을 뽑아내었다. 위의 중앙주파수 자료와 시간간의 회귀직선을 분석하면 초기 중앙주파수, 회귀기울기, 그리고 피로지수와 같은 모수를 얻을 수 있다. 비모수 검정의 하나인 Kendall 기법으로 네 개의 처리과정간의 모수를 비교하였다. 통계결과 잡음이 처리과정 A보다 B, C, D에서 적었고, D에서 가장 적게 나타났다. 중앙주파수를 digital low pass로 여과(filtering)함으로써 앞으로 있게 될 동적 운동 시 근피로 모니터기의 신뢰도를 높일 수 있다.

핵심단어: 중앙주파수; 피로; digital low pass filtering.

Introduction

Since the phenomenon was discovered that the frequency power spectrum of the electromyography (EMG) signal shifted toward the lower frequency band according to the local muscle fatigue developed due to sustained muscle contraction (Basmajian and DeLuca, 1985), it has been used in the muscle fatigue quantification through the inspection of its mechanism and validity. To represent such characteristics of power density spectrum from the fast Fourier transformation (FFT), the median frequency (MDF) of equation (1) has been preferred because it is known to be more resistant to noise than the mean frequency (MNF) (Basmajian and DeLuca, 1985; Hof, 1991),(1).

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$$\int_0^{f_{med}} S_m(f)df = \int_{f_{med}}^{\infty} S_m(f)df \qquad (1)$$

In addition, the MDF decrement pattern has revealed valid intra-subject reliability when the main muscles of the trunk, upper and lower limbs contracted isometrically in the state that other potentially disturbing factors were controlled (Daanen et al, 1990; Merletti et al, 1995; Merletti et al, 1998; Peach et al, 1998; Rainoldi et al, 1999). And there have been assumptions that local muscle fatigue monitor can be used in various fields involving muscle-strengthening programs if the monitor could provide us reliable and objective data about the development of muscle fatigue. Accordingly, it has induced many researchers to develop systems for muscle fatigue monitor by recording MDF change. Ever since Stulen and De Luca developed the analog hardware in 1982, researchers tried microprocessors, digital signal processors and software to realize these systems (Basano and Otello, 1986; Castaldo et al, 1991; Gilmore and DeLuca, 1985; Merletti et al, 1985; Seroussi et al, 1989; Stulen and DeLuca, 1982). However, these machines were not put to practical use because they considered only the cases of isometric contraction and were not portable.

Considering the usual muscle strengthening programs undertaken in physical therapy clinic and gymnasiums, people usually choose isotonic exercises, similar to the usual muscle activity, as the dynamic exercise for strengthening with some exceptions in special cases (De Lauter, 1996; Joynt et al, 1993). So, if such machines are to be practical tools in clinics, they should be geared towards dynamic or isotonic exercise. However, the EMG signals from dynamic exercise contain ample random noise which comes from the movement of muscles under the electrode, wavering of the electrode, periodic changes of muscle length, contraction mode, muscle torque and blood flow in muscles (Ament et al, 1993; Christensen et al, 1995; Conforto et al, 1999; De Lauter, 1996; Doud and Walsh, 1995; Gamet et al, 1993; Joynt et al, 1993; Masuda et al, 1999; Potvin, 1997) making it difficult to obtain reliable MDF data and fatigue determining variables.

So far, there have been a few attempts to overcome this problem. Some have tried moving average or other similar filters on EMG signals just prior to FFT process to get MDF data, successively overlapped FFT epochs on EMG data, and RMS (root mean square) process on the MDF data once it was obtained (Conforto et al, 1999; Daud and Walsh, 1995; Gamet et al, 1993). Others selected the stationary sections of EMG signal to make irregular EMG bursts more uniform and suitable for FFT process (Ament et al, 1993; Arendt-Nielsen and Sinkjaer, 1991; Potvin, 1997). Unfortunately, however, none of the above methods removed the noise from active motion sufficiently, and their MDF time-plots always showed saw-tooth patterns.

The purpose of this study is to compare three methods including digital low pass filter in their noise reduction effect for MDF data of fatiguing isotonic exercise. If one of the methods comes out to be satisfactory, it will enable the portable muscle fatigue monitor to provide reliable MDF data and fatigue determining variables, making the machine useful in various situations of strengthening exercises.

Methods

Subjects

Nineteen healthy college men volunteered for this study. None of them were athletes, had history of pathology in musculoskeletal or nervous system of the upper extremities and did regular muscle strengthening exercises. Their average age was 22.9±2.0 years, weight was 66.4±8.8㎏ and height was 172.2±6.2㎝. The dominant arms used for all the subjects were the right side. They agreed to participate in this experiment after listening to the details of this research.

Determining the load for isotonic exercise

Standing to the side of the chest pulley weight, the subjects maintained the posture fixed to the posterior surface of the upper arm and the back against the wall. The leather cuff, with the metal pulley connector attached, was fastened firm on the towel cuff which was put on the wrist of the dominant arm, and the length of rope was fixed so that the flexion of the elbow joint was no more than 90 degrees.

The maximal isometric contraction (MVC) tension of elbow flexor was measured by a digital tensiometer, TSD121C[1], which was installed between the leather cuff and the fixed pulley rope. During the measurement, caution was taken to keep the forearm maximally supinated in order to prevent supination effect by the contraction of the biceps brachii. The mean MVC was 40.7±6.1 ㎏, and the load for isotonic exercise was set to approximately 25% of the MVC for each subject with 1㎏ and 2㎏ units of the chest pulley weight[2] .

Measurement of EMG

The AE-131 circular surface EMG disposable electrode patch[3] was used for picking up EMG signals. It had three circular metal disk electrodes with a diameter of 12㎜, which were fixed in the form of an equilateral triangle with the center-to-center distance of 20㎜. Among these, the active and reference electrodes were laid in the direction of muscle fiber, and the ground electrode was laid lateral or medial to those two. The surrounding patch, which was not only self-adhesive but also made of flexible and compressible sponge, maintained the maximal contact with the curved surface of the muscles during dynamic exercise. Considering the change of muscle belly position under the skin during dynamic contraction of the biceps brachii muscle, the electrode patch was placed at the lower 1/3 of the muscle belly when it was palpated in 90 degrees elbow flexion (Basmajian and DeLuca, 1985). The chosen site for the electrode patch was cleaned with isopropyl alcohol and dried just prior to patch attachment.

The surface EMG signal was collected through EMG100B amplifier module and MP100WSW[4], a physiologic data acquisition

1. Biopac Systems Inc. CA. USA

2. Preston. MI. USA
3. NeuroDyne Medical Corp. MA. USA
4. Biopac Systems Inc. CA. USA

system, which was connected to it. This hardware provided a single channel EMG with the amplifier settings of sampling rate 1024 ㎐, low pass filter 500 ㎐, and high pass filter 30 ㎐. The Acqknowledge 3.53[5] program was employed to set up the required parameters and to store the EMG signal as computer files.

Fatiguing isotonic exercise

The metronome was set to 50 beats per minute, and the subject was instructed to flex his elbow joint at the first beat and extend it at the next beat satisfying 25 repetitions per minute or 2.4 seconds per repetition. After four or five times of practice exercise at the rhythm of the metronome, the pulley weight was attached to the wrist. Then, the cyclic isotonic exercise and EMG recording started simultaneously with attention to maintain the forearm fully supinated in order to avoid supination affected by the biceps brachii. As muscle fatigue developed, the subject verbally reported that he could not maintain the given exercise rhythm any more, both the exercise and EMG recording were terminated, and the endurance time was measured.

Signal processing

From the surface EMG signal stored during the endurance time, four sets of MDF data were obtained through the following signal processing methods. Process A was to derive the MDF data at the FFT epoch of 0.5 second (512 points, Hanning windows processing) using “Romeo” which was an automatic successive FFT program developed by dept. of Biomedical Engineering, Yonsei university. Process B was to obtain the MDF data at the FFT epoch of 2.4 seconds, which was identical with the cycle of isotonic exercise. Process C was to get a new MDF data by applying a 13 point moving average process of equation (2) on the MDF data from process A. This equation, x [ ] for input signal and y [ ] for output signal respectively, were incorporated into Microsoft Excel® spreadsheet to get process C MDF data (2).

$$y[i] = \frac{\begin{array}{c} x[i-6]+x[i-5]+x[i-4] \\ +x[i-3]+x[i-2] \\ +x[i-1]+x[i]+x[i+1]+ \\ x[i+2]+x[i+3]+x[i+4] \\ +x[i+5]+x[i+6] \end{array}}{13} \qquad (2)$$

Finally, process D was to derive another MDF data by filtering off the non-main frequency component of process A data. To do this, FFT for the MDF data of process A identified its main frequency bandwidth, and a finite impulse response (FIR) digital filter removed the non-main frequency band from it. The Acqknowledge 3.53 program was used for these processes and the required coefficient for digital filter was calculated by the equation (3).

$$\frac{\text{sampling rate}}{\text{cut off frequency}} \qquad (3)$$

Statistical analysis

Linear regression analysis was done between each set of the four MDF data and time. Then, Kendall’s non-parametric test calculated the mean ranks of parameters

5. Biopac Systems Inc. CA. USA

of the regression analysis, such as correlation coefficient and coefficient of determination, among the four kinds of processes. This test could tell which process removed the noise most from process A MDF data or distorted its regression line most. In addition, Kendall's W (coefficient of concordance) tested how consistent such effects in each of the 19 subjects.

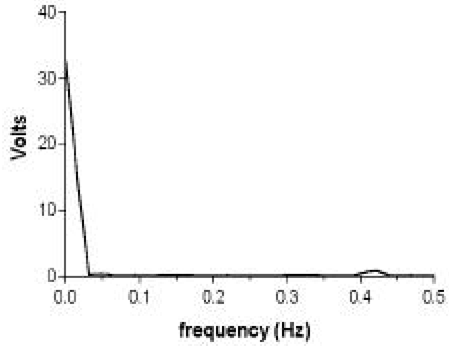

Fig 1. Power spectrum of process A MDF data from subject S.C.C. The main peak arises acutely below .023 Hz.

Results

FIR digital low pass filter

PSA on process A data showed that its main frequency component was in the bandwidth below .023 or .031 Hz (average .027 Hz),(Fig 1). Therefore, FIR digital low pass filter with a cut off frequency of .023 Hz or .031 Hz was adopted for process D. Because the sampling rate of process A data was 2 Hz and, the coefficient for this filter, as shown in the equation (3), was 2/.023=87 for 12 subjects and 2/.031=65 for the rest.

Time plot of the four MDF data sets

Figures 2, 3, and 4 show the time plot

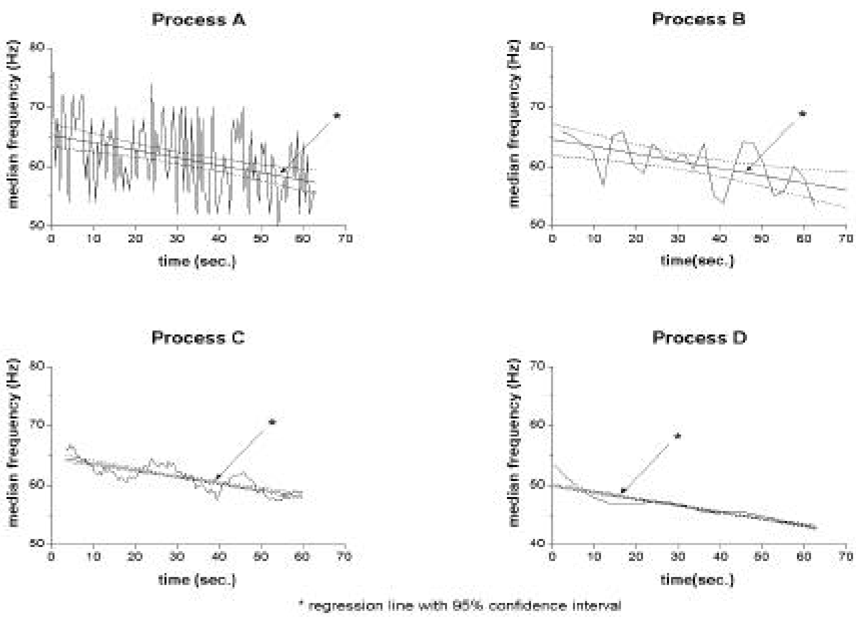

Fig 2. Time-plot of the MDF data sets from the four processes in subject S.C.Cheon. Regression line (* arrow) with 95% confidence interval is overlaid.

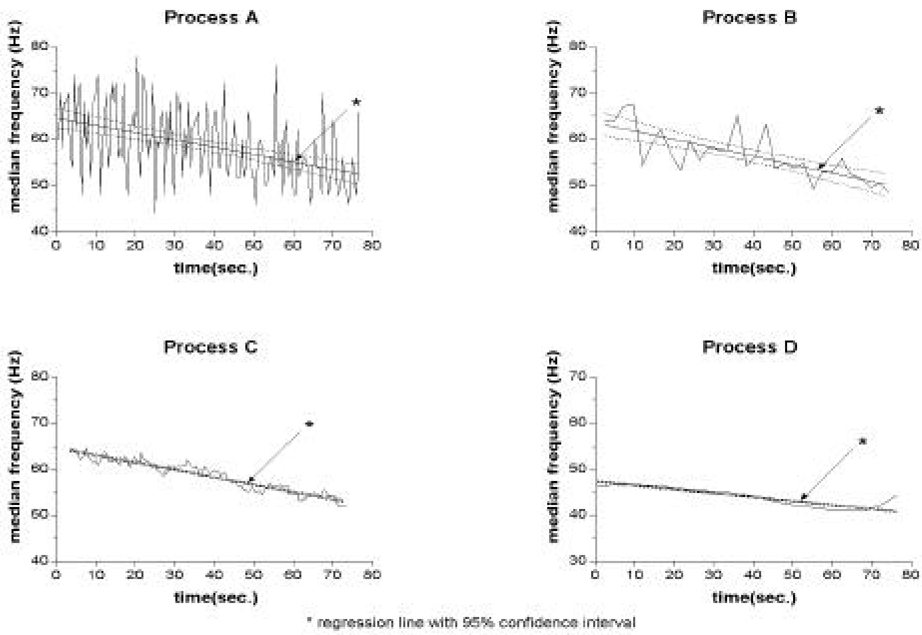

Fig 3. Time-plot of the MDF data sets from the four processes in subject Y.N.Cho. Regression line (* arrow) with 95% confidence interval is overlaid.

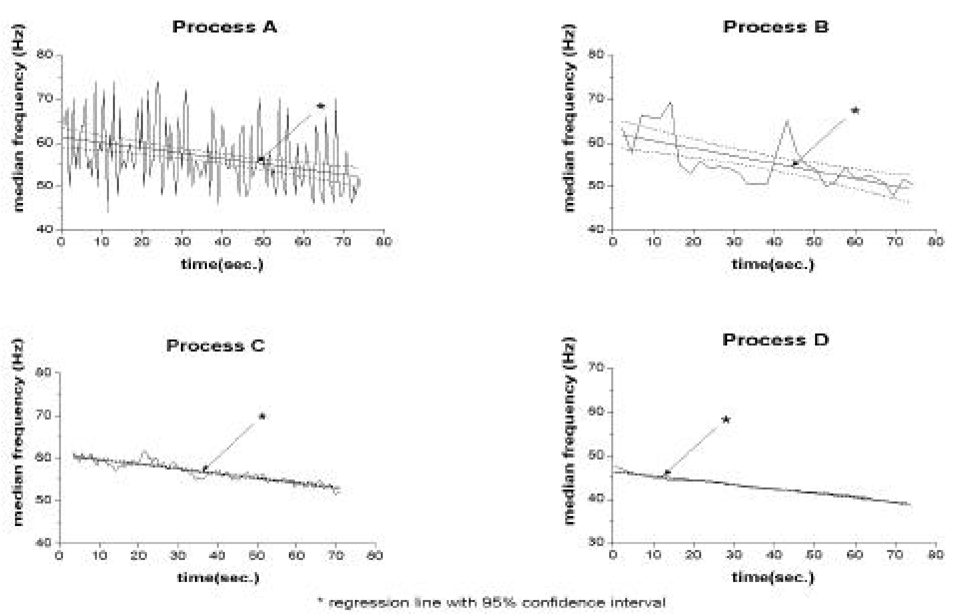

Fig 4. Time-plot of the MDF data sets from the four processes in subject K.W.Kim. Regression line (* arrow) with 95% confidence interval is overlaid.

of the four MDF data sets from three of the subjects with overlay of their linear regression lines and 95% confidence intervals.

Arbitrary signals deviating the regression line were most extreme in process A but they progressively reduced in the order of process B, C and D. The time plot shapes of process D MDF data from the three subjects were similar in their mid range, but had some variations in their first and last ranges.

In process B data, as the first MDF value appeared 2.4 seconds after the beginning of measurement, the initial data gap for 2.4 seconds existed accordingly. And as seen in equation (2), the moving average values of process C lay at the 7th point of 13 data points, leaving blank periods at both the first and the last 6 data points which equaled 3 seconds, respectively. On the contrary, process D MDF data had no blank at all.

Statistics

The F-test p value of the linear regression equations and slope of the regression lines were less than .05 in all the cases except process B data of two subjects. Kendall's non-parametric test showed that the mean ranks of the p values decreased in the sequence of process A>B>C=D (p=.000),(Table 1). The coefficient of concordance, Kendall's W, of these order pattern among the 19 subjects was .46, which meant that such patterns had some individual variations.

The mean ranks of correlation coefficients and the coefficients of determination (r^2) from the linear regression analysis increased in the order of process A<B<C<D (p=.000), (Table 2),(Table 3).

The average correlation coefficient of process D was .91, which was 2.5 times larger than that of process A, and the average coefficient of determination of the same process was .83, which was 5.5 times bigger than that of process A. Kendall's W for the order pattern was .86,

Table 1. Mean and standard deviation of significance of F-tests(p-value) from regression analysis between MDF (median frequency) data and time (n=19). Kendalls non-parametric test calculated mean ranks of each data set among the four

MDF data set	p	Mean Rank
Process A	.005±.01	3.21
Process B	.017±.04	2.79
Process C	.000	2.00
Process D	.000	2.00
Friedman significance		.00*
Kendall' W		.46

*p<.05

Table 2. Mean and standard deviation of correlation coefficients(c.c) from regression analysis between MDF (median frequency) data and time (n=19). Kendalls non-parametric test calculated mean ranks of each data set among the four

MDF data set	C.C	Mean Rank
Process A	.36±.14	1.05
Process B	.66±.19	2.11
Process C	.83±.11	3.00
Process D	.91±.07	3.84
Friedman significance		.00*
Kendall' W		.86

*$p<.05$

Table 3. Mean and standard deviation of coeffients of determination (r^2) from regression analysis between MDF (median frequency) data and time (n=19). Kendalls non-parametric test calculated mean ranks of each data set among the four

MDF data set	r^2	Mean Rank
Process A	.15±.11	1.05
Process B	.47±.23	2.11
Process C	.70±.18	3.00
Process D	.83±.12	3.84
Friedman significance		.00*
Kendall' W		.86

*$p<.05$

which meant that these processes had similar effects in most of the subjects. Consequently, even though MDF data of process B, C, D contained less noise than process A data, process D which used a digital low pass filter had the least noise in most of the subjects.

The mean ranks of slope of the regression line increased in the sequence of process B<A<C<D (p=.000),(Table 4). Considering that these slopes had minus values, process D showed the bluntest average slope, -.10 ㎐/sec, which was 15% less than the slope of process A. Kendall's W for this order pattern was .74 meaning that these processes had similar effects in many of the subjects.

The initial MDF, Y-axis intercept of the regression line, had F-test p-value of .000 in every subject for all four processes. Its mean rank decreased in the sequence of process A>B>C>D (p=.000) and process D reduced the initial MDF of process A by 23% (Table 5).

Table 4. Mean and standard deviation of slopes of the regression line from regression analysis between MDF (median frequency) data and time (n=19). Kendalls non-parametric test calculated mean ranks of each data set among the four

MDF data set	Slope(㎐/sec)	Mean Rank
Process A	-.13±.07	2.26
Process B	-.17±.08	1.26
Process C	-.13±.06	2.53
Process D	-.10±.05	3.95
Friedman significance		.00*
Kendall' W		.74

*p<.05

Table 5. Mean and standard deviation of initial MDF (median frequency) from regression analysis between MDF data and time (n=19). Kendalls non-parametric test calculated mean ranks of each data set among the four

MDF data set	Initial MDF(㎐)	Mean Rank
Process A	65.65±3.30	2.84
Process B	66.91±3.51	3.63
Process C	65.63±3.26	2.53
Process D	49.15±2.49	1.00
Friedman significance		.00*
Kendall' W		.73

*p<.05

Kendall's W was .73, which meant a similar effect of the processes in many of the subjects.

The endurance time, average 74.8±12.8 seconds, was substituted for t in the regression equations to get the last MDF. Together with the initial MDF, the Fatigue Index of equation (4) was calculated.

$$FI = \frac{\text{initial MDF - last MDF}}{\text{initial MDF}} \quad (4)$$

The average fatigue index of the four processes had small differences, and the mean ranks of the index decreased in the order of process B>A>D>C (p=.000),(Table 6).

However, Kendall's W was .35 showing that the four processes' effects were rather variable among the subjects. The above results revealed that the digital low pass filter had some effect of lowering the entire regression line of process A data,

Table 6. Mean and standard deviation of fatigue index (n=19). Kendalls non-parametric test calculated mean ranks of each data set among the four

MDF data set	Fatigue Index**	Mean Rank
Process A	.15±.06	2.32
Process B	.19±.07	3.63
Process C	.15±.06	2.00
Process D	.14±.05	2.05
Friedman significance		.00*
Kendall' W		.35

*$p < .05$

$$^{**}F = \frac{\text{initial MDF - last MDF}}{\text{initial MDF - last MDF}}$$

and blunting the slope of the same regression line.

Discussion

Load for isotonic exercise

According to the length-tension relationship of the elbow flexor, the elbow joint position for its maximum voluntary contraction (MVC) tension is 90 degrees flexion. And at 0 degree flexion or full extension, the contraction tension is only 50% of the MVC (Smith et al, 1996). Therefore, 25% of such elbow flexor MVC tension was used as the load for flexion-extension isotonic exercise, to prevent the endurance time from being extremely shortened due to difficulties in the initial flexion range.

Regression analysis on MDF data

In order to characterize the time-dependent change of MDF data, the regression analysis has been used, and its derivative parameters such as initial slope, initial value and fatigue index have been employed as the fatigue determining variables in many studies (Krivickas et al, 1998; Merletti et al, 1990; Merletti et al 1995; Merletti et al, 1996; Merletti et al, 1998; Standridge et al, 1988). All of these studies obtained EMG data from isometric exercises, and the time-plot of the MDF data were close to the decreasing quasi-linear regression model. Meanwhile, it has been known that the MDF decrease is rather small because both the local muscle blood supply and muscle temperature increase due to repetitive changes in muscle length during dynamic exercise (Arendt-Nielsen and Sinkjaer, 1991; Basmajian and DelLuca, 1985; Soderberg and Cook, 1984). Recent studies on the regression model of MDF data in fatiguing dynamic exercise, which has been scarce, revealed that it was close to linear regression model (Gamet et al, 1993; Potvin, 1997). Therefore, in this study, the linear regression model and its fatigue determining variables such as initial value, slope, and fatigue index were employed. The study on the intra-subject and inter-subject reliability of these variables in fatiguing isotonic exercise is under way in our laboratory.

Noise reduction methods

1. Exercise synchronized FFT epoch

It is very difficult for the EMG signal of dynamic exercise to satisfy the basic assumption for FFT that the subject signal repeats itself infinitely (Smith et al, 1996). To complement this problem, there have been a few studies that calculated a single MDF for each burst of EMG signal by choosing its relatively stationary signal section for FFT (Ament et al, 1993; Arendt-Nielsen and Sinkjaer, 1991; Potvin, 1997).

As another complement for the problem, this study tried to synchronize the epoch of FFT to the cycle of isotonic exercise, 2.4 seconds. It reduced the noise of MDF data more or less, but other preliminary trials using FFT epoch of 2.0 or 3.0 seconds showed a similar amount of noise. In addition, the reciprocal of the exercise cycle, 1/2.4 second or .42 ㎐, lay in the noise range of the frequency spectrum without building up its own peak. Accordingly, it was thought that the periodicity of repeated exercise can be a reason to cause noise in MDF data but it could not be the main component of it. From these findings, the focus of this study shifted from the periodicity of exercise to finding out proper methods for reducing noise in the MDF data, which was obtained with FFT epoch of .5 seconds.

2. Moving average

The moving average, which is well known for its capacity to reduce random noise [30], was applied to process A MDF data to show the better filtering effect than the exercise synchronized FFT epoch of process B. However, as shown in equation (1), the 13 points moving average left blank periods of 3 seconds at the initial and final part of the MDF. Also, in the preliminary study, as the data points for moving average increased the smoothening effect increased considerably but the blank periods increased, too, making it difficult to determine the optimal size of data points. So, the 13 data points for moving average in process B were chosen arbitrarily by the author.

3. FIR digital low pass filter

As shown in Figure 1, the frequency spectrum of process A MDF, its main frequency component appeared below on the average .027 ㎐, and left no other peak beyond it. Moreover, when the main frequency component was extracted through the FIR digital low pass filter, the saw tooth like signals in the time-plot of process A data disappeared making the time-plot of the new MDF data so smooth that it almost overlapped with it's regression line. Therefore, the saw tooth like signals in process A could be regarded as random noises.

In most subjects, the digital low pass filter removed more random noise of process A data than the other two methods and enhanced the reliability of the regression analysis tremendously. Even though the digital low pass filter had some effect of lowering the entire regression line of process A data and blunting the slope of the regression line, its usage in muscle fatigue monitor is still expected to be justified. As the definite method for realizing the real-time FFT and digital low pass filter in such fatigue monitor being developed, and the test for reliability of the fatigue determining variables gives us satisfactory results, the algorithm will be implanted into the portable muscle fatigue monitor which is presently being developed in our laboratory.

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