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슬관절의 등속성 최대 반복 신전시 Hilbert-Huang 변환과 AR 모델을 이용한 근피로 평가

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Muscle Fatigue Assessment using Hilbert-Huang Transform and an Autoregressive Model during Repetitive Maximum Isokinetic Knee Extensions

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Abstract

In the working population, muscle fatigue and musculoskeletal discomfort are common, which, in the case of insufficient recovery may lead to musculoskeletal pain. Workers suffering from musculoskeletal pains need to be rehabilitated for recovery. Isokinetic testing has been used in physical strengthening, rehabilitation and post-operative orthopedic surgery. Frequency analysis of electromyography (EMG) signals using the mean frequency (MNF) has been widely used to characterize muscle fatigue. During isokinetic contractions, EMG signals present strong nonstationarities. Hilbert-Haung transform (HHT) and autoregressive (AR) model have been known more suitable than Fourier or wavelet transform for nonstationary signals. Moreover, several analyses have been performed within each active phase during isokinetic contractions. Thus, the aims of this study were i) to determine which one was better suitable for the analysis of MNF between HHT and AR model during repetitive maximum isokinetic extensions and ii) to investigate whether the analysis could be repeated for sequential fixed epoch lengths. Seven healthy volunteers (five males and two females) performed isokinetic knee extensions at 60°/s and 240°/s until 50% of the maximum peak torque was reached. Surface EMG signals were recorded from the rectus femoris of the right thigh. An algorithm detecting the onset and offset of EMG signals was applied to extract each active phase of the muscle. Following the results, slopes from the least-square error linear regression of MNF values showed that muscle fatigue of all subjects occurred. The AR model is better suited than HHT for estimating MNF from nonstationary EMG signals during isokinetic knee extensions. Moreover, the linear regression can be extracted from MNF values calculated by sequential fixed epoch lengths ($p > 0.01$).

Keywords : Muscle fatigue, Mean frequency, Hilbert-huang transform, Autoregressive Model, Isokinetic contraction

1. Introduction

In the working population, muscle fatigue and musculoskeletal discomfort are common, which, in the case of insufficient recovery may lead to musculoskeletal pain. The risk of musculoskeletal disorders may be higher in agricultural workers

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because of the longer working hours (Hasaldar et al., 2007). Farming is a physically arduous occupation and this places farm workers at potential risk of musculoskeletal disorders such as osteoarthritis of the hip and knee, low back pain, neck and upper limb complaints, and hand-arm vibration syndrome (Walker-Bone and Palmer, 2002).

For example, while performing the top dressing of fertilizer activity majority of the women complained severe pain in shoulder joint, upper arm, low back, wrist/hands and knees as they had to carry the basket filled with 4-5 kg of fertilizer either in hands or tie the fertilizer cloth bag around their waist (Hasaldar et al., 2007). These work-related musculoskeletal disorders resulting from many risk factors-static positioning, forward bending, heavy lifting and carrying, kneeling and etc. - are among the most costly health care problems facing society today (Marras et al., 2009).

Workers suffering from musculoskeletal pains need to be rehabilitated for recovery. Isokinetic testing has been used in physical strengthening, rehabilitation and post-operative orthopedic surgery for over three decades because it is possible to do cyclic contractions by controlling the speed of contraction or the range of motion. Noninvasive measurements of surface electromyography (EMG) are being increasingly used for diagnosing neuromuscular and musculoskeletal disorders. Especially, the mean frequency (MNF) showed consequently higher correlation coefficients with peak torque during isokinetic contractions (Gerdle et al., 2000). MNF has been widely used to characterize muscle fatigue. It is well known that the EMG spectrum shifts towards lower frequencies when muscle fatigue increases (Arendt-Nielsen and Sinkjaer 1991; Xie and wang 2006). When the muscle contracts in dynamic conditions, the EMG signal generated by the muscle may no longer be considered a stationary process.

Recently, the availability of spectral estimation techniques specifically designed for nonstationary signal analysis has made it possible to extend the employment of muscle fatigue assessment to cyclic dynamic contractions. Knaflitz and Bonato (1999) introduced instantaneous spectral parameters based on the time-frequency transforms of the Cohen Class for muscle fatigue. Molinari et al. (2006) adopted the Choi-Williams time-frequency transform to assess the progression of muscle fatigue. Alternately, Coburn et al. (2006) and Beck et al. (2007) used discrete Fourier transform because Fourier-based determinations of the frequency content are formally equivalent to those of time-frequency methods such as wavelet transformation. Xie and Wang (2006), however, concluded that the Hilbert-Haung transform (HHT) and autoregressive (AR) model were more suitable than Fourier or wavelet transform to estimate the MNF of nonstationary EMG signals during sustaining contraction at 60% maximum voluntary contraction (Xie and wang, 2006). In case of isokinetic experiments, most analyses have been performed within each limited active phase of muscle (Coburn et al., 2006; Beck et al., 2007) or each single signal burst in epochs corresponding to a specific angular displacement (Knaflitz and Bonato 1999; Molinari et al., 2006).

When workers suffering from musculoskeletal pains do isokinetic exercise for rehabilitation, an appropriate method is required to analyze nonstationary signal for muscle fatigue assessment. Thus, the aims of this study were i) to determine which one was better suitable for the analysis of MNF between HHT and AR model during repetitive maximum isokinetic knee extensions and ii) to investigate whether the analysis could be repeated for sequential fixed epoch lengths.

2. Materials

Seven healthy volunteers (five males and two females) with no history of lower limb disorders participated in expiriments (MacIsaac et al., 2001) and all of them had no previous experience with isokinetic exercise devices (Biodex System 3 Pro). They used their dominant (right) leg during isokinetic exercises. The range of motion was set to approximately 90° from neutral position (about 90° flexion) to full extension (0° flexion). The subjects were familiar with the dynamometer at a passive mode, in accordance with trainer's directions. Prior to a real isokinetic test, they performed a warm-up of three submaximal isokinetic muscle actions. Angular velocities were 60°/s for slow velocity and 240°/s for fast velocity (Coburn et al., 2006). Subjects were instructed to perform the contractions always exerting their maximal effort until 50% of the maximum peak torque was reached. EMG (BMH-D100, BME KOREA) signals were recorded from the rectus femoris of the thigh by surface electrode.

3. Signal Processing

The raw EMG signals were digitized at 1kHz and amplified with a gain of 3000, and were digitally band-pass filtered (fourth-order Butterworth) at 10-500Hz. We analyzed two types of data segments, one was a set of burst-detected onset and offset of each active phase of muscle, and the other was data with three fixed epoch lengths including at least one contraction cycle: epoch length of one contraction (1 cycle), 4/3 and 5/3 cycle. For EMG onset and offset detection (Hodges et al., 1996), all EMG traces were full wave rectified prior to analysis and then the EMG onset and offset were determined visually by selecting two spots within resting EMG occured at before and after each active phase. After data segmentation, each EMG segment was processed with a Hamming window and then HHT and an AR Model for the estimation of MNF.

A. HHT

HHT consists of two parts: the Empirical Mode Decomposition (EMD) and the Hilbert Spectral Analysis. The key part of the method is the EMD technique, which allows any complicated data set to be decomposed into a finite and often small number of intrinsic mode functions (IMFs). Since the decomposition is based on the local characteristic time scale of the data, it is applicable to nonlinear and nonstationary processes.

The original signal x(t) can be expressed as follows (Huang et al., 1998; Xie and Wang, 2006):

$$x(t) = \sum_{j=1}^{n} c_j(t) + r_n(t) \tag{1}$$

where n is the number of IMFs, $r_n(t)$ is the final residue and functions $c_j(t)$ are nearly orthogonal to each other, and all have zero means. After the decomposition, the IMFs are submitted to Hilbert transform, which is defined as:

$$y(t) = \frac{1}{\pi} P \int \frac{x(t')}{t - t'} dt' \tag{2}$$

where P indicates the Cauchy principle value. Finally, the mean frequency of the original signal is calculated (Xie and Wang, 2006).

B. AR Model

The method of AR model assumes that each sample of the signal is described as a linear combination of present and some past outputs. The AR model (Kay and Marple 1981; Capponi et al., 1988) is

$$y_k = \sum_{i}^{p} a_{pi} y_{k-i} + u_k \tag{3}$$

where $y_k = y(t_k) = y(kT_c)$ and Tc is the sampling interval, a_{pi} are the coefficients of the AR portion of the model of order p, and u_k is a sample of white noise. Many algorithms have been proposed for the estimation of api parameters. In the case of nonstationary signals, it is necessary to use a sequential algorithm (Capponi et al., 1988). It relies on the forward and backward prediction errors.

Determining the optimal AR model order is an important part of the whole procedure since too low a model order tends to smooth the actual spectrum and too high an order tends to introduce spurious peaks in the power spectrum. We determined AR model order using the Akaike information criterion (AIC) (Aiaike, 1974).

4. Results and Discussion

All of their repetitive numbers were different since seven healthy subjects performed isokinetic knee extensions until 50% of the maximum peak torque was reached. In Fig. 1, (a) and (b) show the filtered EMG signal of one male subject (M4) at 60°/s and lines of onset and offset of (a), respectively.

Burst or fixed epochs in the entire EMG signal were presented relative to a normalized range (100%) during MNF plotting so that MNF slopes were not affected by data segments. Fig. 2 showed the mean frequency derived from HHT (a) and AR model (b) for one male (M4) after onset and offset detection of EMG signal. The AR model order is 15. The mean frequency was on the decrease. All of mean frequencies from burst and fixed epochs showed a decline.

Table 1 and 2 presented the linear regression of the MNF values calculated from burst. All of MNFs showed a decline. In addition, R-squares of the linear regression of MNF at 60°/s were larger than those at 240°/s overall. Slopes from the linear regression of the MNF values indicated that the muscle fatigue of some subjects (M1,M2, M4,F2) occurred faster during 60°/s than 240°/s. R-squares of the linear regression between HHT

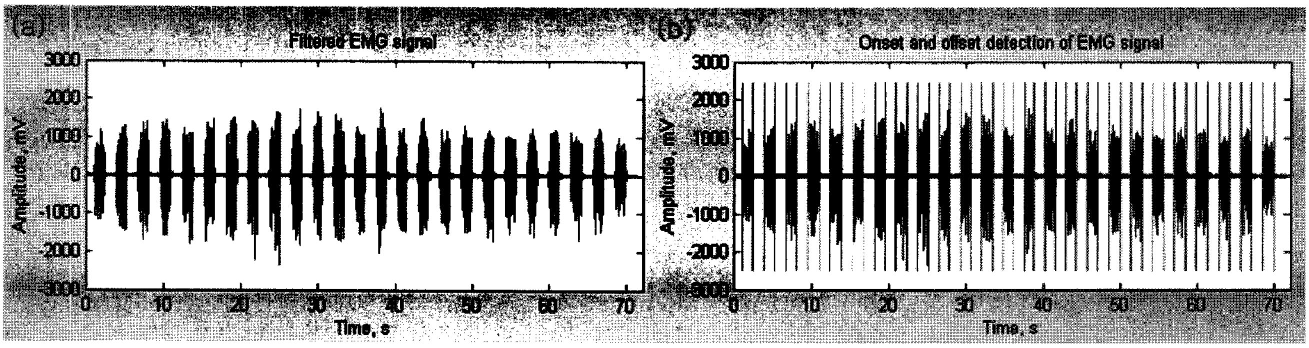

Fig. 1 Example of a signal collected during maximum isokinetic knee extensions. (a) Filtered EMG signal and (b) onset and offset detection of signal (a).

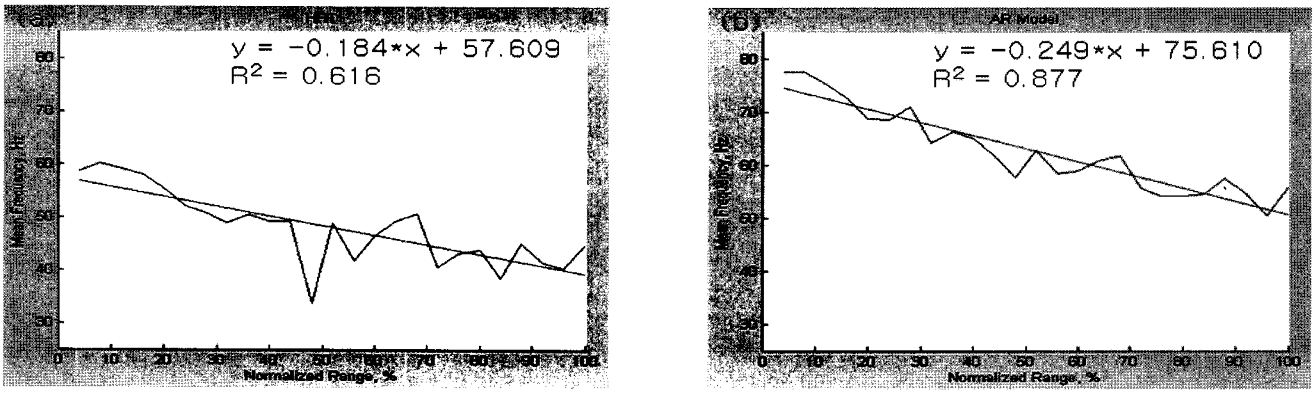

Fig. 2 The mean frequency derived from HHT (a) and the AR model (b) after onset and offset detection of the EMG signal. Angular velocity was 60°/s and repetition number was 25.

Table 1 Linear regression of MNF values in each subject after onset and offset detection of the EMG signal. Angular velocity was 60°/s. MNFS: MNF slope, IMNF: initial MNF, M: male, F: female

Angular Velocity	HHT			AR		
60°/s	R2	MNFS	IMNF	R2	MNFS	IMNF
M1	0.603	-0.098	36.553	0.701	-0.124	46.983
M2	0.613	-0.140	58.458	0.717	-0.203	72.421
M3	0.429	-0.055	45.248	0.653	-0.098	58.205
M4	0.616	-0.184	57.609	0.877	-0.249	75.610
M5	0.474	-0.101	45.481	0.644	-0.144	59.160
F1	0.328	-0.082	51.258	0.713	-0.102	63.868
F2	0.648	-0.155	50.846	0.717	-0.220	67.098

Table 2 Linear regression of MNF values in each subject after onset and offset detection of the EMG signal. Angular velocity was 240°/s. MNFS: MNF slope, IMNF: initial MNF, M: male, F: female

Angular Velocity	HHT			AR		
240°/s	R2	MNFS	IMNF	R2	MNFS	IMNF
M1	0.021	-0.026	48.965	0.026	-0.026	60.244
M2	0.356	-0.123	65.522	0.242	-0.099	78.514
M3	0.344	-0.120	52.356	0.392	-0.144	63.579
M4	0.064	-0.039	59.651	0.325	-0.107	75.380
M5	0.349	-0.135	62.461	0.511	-0.153	77.553
F1	0.376	-0.116	57.378	0.666	-0.165	67.500
F2	0.260	-0.117	73.742	0.462	-0.155	89.508

and AR at 60°/s were statistically different at 1% significant level ($p=0.004$) and those at 240°/s were not ($p=0.071$). For both training velocities, there was a significant difference ($p<0.001$). Moreover, the coefficients of variation (CoV: standard deviation over absolute mean) of the AR model (60°/s: 0.107, 240°/s: 0.548) were smaller than HHT (60°/s: 0.228, 240°/s: 0.588). As a result, an AR model was better than HHT for estimating MNF. These results are different from those of Xie and Wang (2006). We deduce this may be due to the following two aspects. First, the AR model order may be different. Second, the linear regression depends on MNFs and MNFs depends on EMG signals during isokinetic exercise.

At 60°/s, MNFS and initial MNF (IMNF) from all epoch lengths using HHT and an AR model were not different from burst at 1% significant level. In the case of 240°/s, however, the IMNF from 5/3 cycle alone using HHT was different from burst (MNFS: $p=0.617$, IMNF: $p<0.001$). For both training velocities, the least-square error linear regression of the MNF values from all epoch lengths was statistically similar to that of burst ($p>0.01$).

5. Conclusions

In the working place, muscle fatigue and musculoskeletal pain result from risk factors like a static positioning, forward bending, heavy lifting and carrying, kneeling and so on. Isokinetic testing is good for rehabilitation of workers with musculoskeletal disorders. When the muscle contracts in dynamic conditions, the EMG signal generated by the muscle may no longer be considered a stationary process. An appropriate method is required to assess muscle fatigue during isokinetic exercise. Thus, in this study, we determined which method was better suitable for the analysis of mean frequency from EMG during repetitive maximum isokinetic knee extensions between HHT and AR model and investigated whether spectral analysis could be repeated for sequential fixed epoch lengths. The results were following:

(1) AR model was better suitable than HHT for estimating MNF from nonstationary EMG signals during isokinetic knee extensions.
(2) For both training velocities, the least-square error linear regression of the MNF values from all epoch lengths using HHT and AR model had no difference, as compared to bursts.

These results could play an important role in investigations of muscle behavior in several medical disciplines such as neurology, rehabilitation, and orthopaedics, or in sports biomechanics, especially, including dynamic and highly fatiguing contractions. These could be also applied to develop prediction model of muscule fatigue.

REFERENCES

1. Aiaike, H. 1974. A new look at the statistical model identification. IEEE Transactions on Automatic Control AC-19 (6):716-723.
2. Arendt-Nielsen, L. and T. Sinkjaer. 1991. Quantification of human dynamic muscle fatigue by electromyography and kinematic profiles. Journal of Electromyography and Kinesiology 1:1-8.
3. Beck, T. W., T. J. Housh, M. Mielke, J. T. Cramer, J. P. Weir, M. H. Malek and G. O. Johnson. 2007. The influence of electrode placement over the innervation zone on electromyographic amplitude and mean power frequency versus isokinetic torque relationships. Journal of Neuroscience Methods 162(1-2):72-83.
4. Capponi, M., T. D'Alessio and M. Laurenti. 1988. Sequential estimation of power spectra for non stationary myoelectric signals. Electroencephalography & Clinical Neurophysiology 28:427-432.
5. Coburn, J. W., T. J. Housh, M. H. Malek, J. P. Weir, J. T. Cramer, T. W. Beck and G. O. Johnson. 2006. Neuromuscular responses to three days of velocity-specific isokinetic training. Journal of Strength and Conditioning Research 20(4):892-898.
6. Gerdle, B., B. Larsson and S. Karlsson. 2000. Criterion validation of surface EMG variables as fatigue indicators using peak torque A study of repetitive maximum isokinetic knee extensions. Journal of Electromyography and Kinesiology 10:225-232.
7. Hasalkar, S., R. Shivalli and R. Budihal. 2007. Musculo-skeletal disorders of the farm women while performing the top dressing of fertilizer activity. Journal of Human Ecology 21(2):109-112.
8. Hodges, P. W. and B. H. Bui. 1996. A comparison of computer-based methods for the determination of onset of muscle contraction using electromyography. Electroencephalo-graphy & Clinical Neurophysiology 101:511-519.
9. Huang, N. E., Z. Shen, S. R. Long, M. L. C. Wu, H. H. Shih, Q. N. Zheng, N. C. Yen, C. C. Tung and H. H. Liu. 1998. The empirical mode decomposition and the Hilbert spectrum for non-linear and non-stationary time series analysis. Proceeding of the Royal Society of London Series A 454:903-995.
10. Kay, S. M. and S. L. Marple. 1981. Spectrum analysis-a modern perspective. Proceedings of the IEEE 69(11):1380-1419.
11. Knaflitz, M. and P. Bonato. 1999. Time-frequency methods applied to muscle fatigue assessment during dynamic contractions. Journal of Electromyography Kinesiology 9(5):337-350.
12. MacIsaac, D., P. A. Parker, R. N. Scott. 2001. The short-time Fourier transform and muscle fatigue assessment in dynamic contractions. Journal of Electromyography and Kinesiology 11(6):439-449.
13. Marras, W. S., R. G. Cutlip, S. E. Burt and T. R. Waters. 2009. National occupational research agenda (NORA) future directions in occupational musculoskeletal disorder health research. Applied Ergonomics 40:15-22.

14. Molinari, F., M. Knaflitz, P. Bonato and M. V. Actis. 2006. Electrical manifestations of muscle fatigue during concentric and eccentric isokinetic knee flexion-extension movements. IEEE Transactions on Biomedical Engineering 53(7):1309-1316.
15. Walker-Bone, K. and K. T. Palmer. 2002. Musculoskeletal disorders in farmers and farm workers. Occupational Medicine 52(8):441-450.
16. Xie, H. and Z. Wang. 2006. Mean frequency derived via Hilbert-Huang transform with application to fatigue EMG signal analysis. Computer Methods and Programs in Biomedicine 82:114-120.