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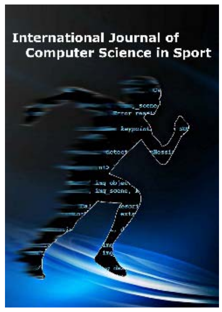

Comparison of Different Time-Frequency Analyses Techniques Based on sEMG-Signals in Table Tennis: A Case Study

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Abstract

The surface EMG signal in the action of dynamic contraction has more movement interference compared to sustained static contractions. In addition, the recruitment and de-recruitment of motor units causes a faster change in the surface EMG signal's proprieties. Therefore, more complex techniques are required to extract information from the surface EMG signal. The standardized protocol for surface myoelectric signal measurement in table tennis was a case study in this research area. The Autoregressive method based on the Akaike Information Criterion, the Wavelet method based on intensity analysis, and the Hilbert-Huang transform method were used to estimate the muscle fatigue and non-fatigue condition. The result was that the Hilbert-Huang transform method was shown to be more reliable and accurate for studying the biceps brachii muscle in both conditions. However, the Wavelet method based on intensity analysis is more reliable and accurate for the pectoralis major muscle, deltoideus anterior muscle and deltoideus medialis muscle. The results suggest that different time-frequency analysis techniques influence different muscle analyses based on surface EMG signals in fatigue and non-fatigue conditions.

KEYWORDS: MUSCLE FATIGUE, SURFACE EMG, TABLE TENNIS

Introduction

An electromyography (EMG) signal records valuable information with respect to the timing of the muscle, and reflects the relationship between muscular contraction and the central nervous system. The biochemical and physiological changes in skeletal musculature lead to the different properties of an EMG signal. It was observed a century ago that the properties of an EMG signal change during muscle contraction (Piper, 1912). The effect of the muscle contraction is an increase in the concentration of lactic acid. Aside from the type and size of the dominant muscle fibers, the force level and the type of contraction (static or dynamic) influences the net lactate concentration (Cifrek, Medved, Tonković, & Ostojić, 2009). In addition, the concentration of the lactates changes the intracellular pH. Consequently, there is a change in muscle fiber conduction velocity and the shape of the motor unit action potential waveform (Basmajian & Luca, 1985).

The EMG signal can be divided into two types, according to the recording electrodes. If the electrodes are placed on the skin, it is regarded as surface electromyography (sEMG). If the electrodes are inserted into the muscle, it is considered as intramuscular electromyography (González-Izal, Malanda, Gorostiaga, & Izquierdo, 2012).

In the sixties, researchers found that the amplitude of EMG signalincreases to the muscle fatigue point and then decreases. In addition, muscle fatigue can be divided into central and peripheral fatigue.The central factors of fatigue decrease the voluntary activation of the muscle by decreasing the number of recruited motor units and their discharge rate. Furthermore, the peripheral factors of muscle fatigue consist of alterations in neuromuscular transmission, muscle action potential propagation and the contractile strength of the muscle fibers (Boyas & Guével, 2011; González-Izal et al., 2012). In 1970, one of the first mathematical models of muscle fatiguewas proposed based on sEMG signals of muscle fiber conduction velocity (Lindström, Magnussen, & Petersen, 1970). However, the estimation of muscle fatigue is a complex process due to the various cases, mechanisms and forms of manifestation.

The recording of an sEMG signal based on the two different types of muscle contraction can be considered isometric and dynamic. The factors that influence the sEMG include non-physiological anatomic, detection system, geometrical, physical, physiological fiber membrane properties and motor unit properties (Farina, Merletti, & Enoka, 2014). In addition, the other important influence factor is crosstalk, which has been investigated by many researchers. Crosstalk is a signal recorded over one muscle that is actually generated by a nearby muscle and conducted through the intervening volume to the recording electrodes (DeLuca & Merletti, 1988).

The electrical manifestations of muscle fatigue are quantified by first estimating the power spectral density function of the signal within subsequent epochs, and then computing either the mean or the median frequency of each spectral estimate (Knaflitz & Bonato, 1999). The attitude of the frequency changes, and the spectral parameter derived from the sEMG signal is used to track muscular changes in the fatigue condition (Merletti, Knaflitz, & Luca, 1990). The traditional spectrum analysis of the sEMG signal is done by the Fourier transform and Autoregressive method (Cooley & Tukey, 1965; Lo Conte & Merletti, 1995b, 1995a; Merletti, Gulisashvili, & Lo Conte, 1995) However, the sEMG signal in the dynamic contraction task has more movement interference, such as crosstalk and electrical activity. In addition, the factor of rapid changes in the recruitment and de-recruitment of motor units causes a faster change in the sEMG signal proprieties than occurs in a static condition (González-Izal et al., 2012). Therefore, more complex techniques are required to extract information from the sEMG signal in fatigue and non-fatigue conditions.

The analysis models in this investigation include the Autoregressive method based on the Akaike Information Criterion, a modified Wavelet method based on intensity analysis, and the Hilbert-Huang transform method. An Autoregressive modeling-based spectral estimation procedure overcome the problems of lower resolution and 'leakage' effects inherent in the Fast Fourier transforms. And the order of autoregressive model is optimized by the Akaike information criterion (Muthuswamy & Thakor, 1998). The Modified Wavelet method based on intensity analysis resolves the events within the EMG signal. The time and frequency distribution are resolved well in the intensity patterns (Tscharner, 2000). The Hilbert-Huang transform has been applied to analysis signals in a variety of areas (Huang, Wu, Qu, Long, & Shen, 2003; Peng, Tse, & Chu, 2005; Rai & Mohanty, 2007). Intrinsic modes of function were calculated through empirical mode decomposition, and then a Hilbert transform was applied to each intrinsic mode of function and weighted sum. The result of some case studies showed the Hilbert Huang transform to be much sharper than other traditional time-frequency analysis methods (Huang & Shen, 2014).

The standardized protocol of surface myoelectric signal measurement during a game of table tennis was established by (Baca et al., 2007). The test system consists of a table, a ball machine, balls, a force plate, a kinematic system, a surface EMG system and a heart-rate monitor. The subject performed top-spin strokes into the right-hand corner. The production of top-spin strokes is an important factor in determining the effectiveness of a return, and the report showed a lift coefficient of stroking ball between 0.7 and 0.4 influnces speed increased from 15 to 40 m/s(Lees, 2003). In addition, in international-level table tennis, top-spin strokes are the most important of winning tactical strategies (Lees, 2003). During the experiment, the player executes 24 consecutive sequences of 12 top-spin strokes (2 for familiarization and 10 for analysis). The frequency of the ball machine was set to 60 balls per minute. The opposite side of the table (1/4 table) was set to be the target area. The player has to hit the ball with maximum speed as well as maximum precision. In the first two series, there is 1-minute rest. Then the fatigue condition started, with 10 seconds rest between each series. If the play was manually observed to be unsuccessful in 30% of the player's strokes, it defined the last series as fatigue (Baca et al., 2007).

The purpose of this study was to compare different muscle analysis models based on sEMG signal and evaluate different muscles under the fatigue and non-fatigue conditions in table tennis.

Methods

Figure 1 shows a schematic drawing of the system setup (Baca et al., 2007). Based on the proposed fatigue protocol executing top-spin strokes in table tennis, as illustrated in Figure 2, four top-level young Austrian players participated in the experiment (Baca et al., 2007). According to the SENIAM protocol (Hermens, Freriks, Disselhorst-Klug, & Rau, 2000), the right-hand muscles of subjects including biceps brachii (RBB), pectoralis major (RPM), deltoideus anterior (RDA), and deltoideus medialis (RDM) were measured and analyzed by a surface EMG system (Delsys). The recording of EMG data was observed by two experienced technician The electrodes were placed over the midline of the belly muscle between the motor point and the myotendinous junction (Roy, Luca, & Schneider, 1986). The crosstalk between adjacent muscles was ensured negligible. The signals were recorded with a Tringo IM sensors (Delsys) electromyograph (bandwidth 20±50 – 450±50 Hz, 16 bit resolution, Noise< 0.75 uV, 1000 Hz sampling rate).

Three different methodologies were applied in order to calculate the mean frequency from RBB, RDA, RDM and RPM muscles. The epoch length of each EMG signal series was 15.5s.

To ensure the main movement of muscle activity, the movement cycles were analysied after 0.4s.Then, the 0.1s epoch length of each series was computed as a mean frequency. Therefore, the number of mean frequencies in each series was 106 in total. Following this, the mean frequency values were regressed by a least-square error linear regression method. It provided the slope and point of intercept of mean frequency values in each epoch. Ultimately, statistical analysis was performed, including mean, standard deviations, standard deviations error mean, and 95% confidence interval.

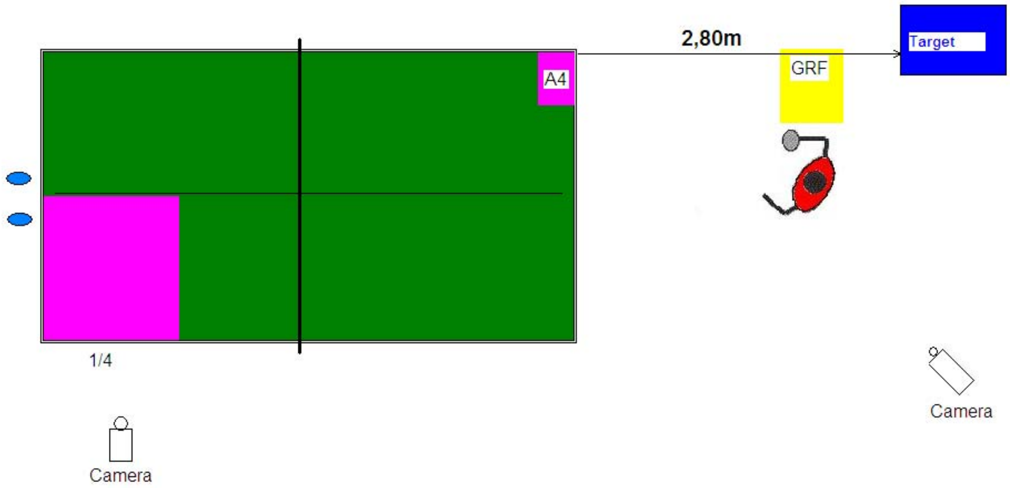


Figure 1. Schematic drawing of the system setup

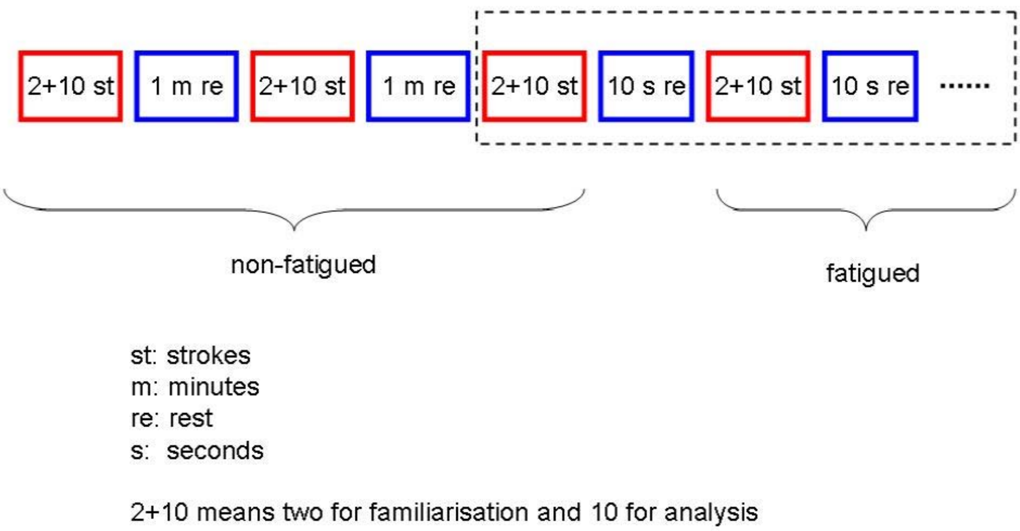


Figure 2. The scheme of fatigue protocol in Table Tennis

Figure 3. The scheme of fatigue protocol in Table Tennis

The Autoregressive Method Based on Akaike Information Criterion

The spectral estimation based on the Autoregressive model (AR) extracts the important information hidden in the biological signal. It yields a better solution for dealing with the problem of spectrum leakage (Ganter et al., 2007; Güler, Kiymik, Akin, & Alkan, 2001; Muthuswamy & Thakor, 1998). The three main steps of spectrum estimation based on AR model are as follows: optimal model order determination, AR parameters estimation, and estimating the power spectral density using the above parameters (Subasi, Yilmaz, & Ozcalik, 2006). The AR modelling of a time series is based on an assumption that the most recent data points contain more information than other data points, and that each value of the series can be predicted as a weighted sum of the previous values of the same series plus an error term (Takalo, Hytti, & Ihalainen, 2005). The algorithm for AR modeling is given by:

$$x(k) = -\sum_{i=1}^{N} a_i x(k-i) + e(k)$$

where a_i is the weighting coefficient, N is the model order, k is the sample time and e represents the prediction error.

The order of the AR model directly influences the accuracy of the spectrum estimation. Therefore, the Akaike information criterion (AKI), based on minimizing an information theoretic criterion, applies to determine the AR model order. The AKI is defined as follows:

$$E_N(i) = \sum_{k=0}^{N} a_N(k) x(i-k)$$

$$AKI(N) = p \ln(E_N) + 2N$$

where E_N is the forward prediction error, $a_N(k)$ is a parameter in the AR model of order N, N is the model order, and p is the number of data points (Akaike, 1974).

The AR parameter estimation algorithm is based on the Burg algorithm (Burg, 1967). After estimating the AR parameters, the power spectrum of the data sequence can be estimated. It is given by:

$$P_{AR}(f) = \frac{n_p^2 \Delta t}{|1 + \sum_{k=0}^{p} a_p(k) \exp(-j2\pi f k \Delta t)|^2}$$

where n_p^2 is the forward prediction error energy, p is the AR model, t is the sampling period of data sequence and f is the frequency. Thus, the mean frequency of power spectrum (MNF) can be calculated. It is defined as:

$$MNF = \frac{\int_0^\infty fP(f)df}{\int_0^\infty (f)df}$$

Wavelet Method Based on Intensity Analysis

The point of disadvantages of traditional signal analyses such as Short Time Fourier Transformation, the intensity analysis for sEMG by wavelets was developed by Tscharner (Tscharner, 2000). The main theory of this analysis is to use a filter bank of non-stationary sEMG signal as a function of both time and frequency. In addition, the filter bank is redefined based on the Wavelet method by rescaling a given mother wavelet using center frequencies with non-constant relative bandwidth (Borg, 2010). It also proposes a variation on frequency bands with time to suit the sEMG signal investigation. It is defined in frequency space by:

$$F\varphi(f, cf, scale) := \left(\frac{f}{cf}\right)^{cf*scale} * e\left(\frac{-f}{cf}+1\right)^{cf*scale}$$

where F represents the operator for the Fourier transform, f is the frequency in Fourier, cf is the center frequency, and scale is the scaling factor. In Tscharner's approach, the center frequencies are calculated as follows:

$$cf_j := \frac{1}{scale} * (j+q)^r$$

where j =0, 1…J, scale 0.3, q 1.45 and r 1.959 are the values of parameters fixed by Tscharner. Moreover, the criterion for the best combination of q and r is a restricted frequency range between 20 and 200 Hz. The other criterion, to normalize the geometrical mean of all even and all odd wavelets in frequency space, remains minimal. The normalized geometrical mean was calculated as follows:

$$gm_j := \frac{\sum_{f=0}^{\infty} F\varphi(f, cf_j) * F\varphi(f, cf_{j+2})}{\sum_{f=0}^{\infty} F\varphi(f, cf_j) * F\varphi(f, cf_j)}$$

Hilbert-Huang Transform Method

The Hilbert-Huang Transform (HHT) is the new method for analyzing the time-frequency technique in non-linear and non-stationary signals. It has been widely applied in different fields of signal processing. The HHT consists of empirical mode decomposition (EMD) and the Hilbert spectral analysis method. Then, the mean frequency of signals is estimated based on HHT.

Empirical Mode Decomposition method

EMD decomposes a complicated time-series signal into a finite number of its individual characteristic oscillations. Each oscillation mode consists of a narrow band of frequency called intrinsic mode of functions (IMFs). Each IMF satisfies two conditions. First, the number of extremes and the number of zero crossings must either be equal or differ at most by one; and second, the mean value of the envelope defined by the local maxima and minima is zero at any point (Huang et al., 1998). According to the discussion, the EMD algorithm for adapting the IMFs can be summarized in the following steps:

(1) The determination of all extreme points of signal x (t) separately as the local maxima and minima by the cubic spline lines method.

(2) The local mean value, by averaging the upper envelope and lower envelope.

(3) Generating a resultant signal:

$$h_1(t) = x(t) - m_1(t)$$

(4) The resultant signal must satisfy the two mentioned conditions. The above process steps are repeated until the IMF conditions are satisfied.

(5) The left signal decomposes continuously until the residue is a monotonic function. It shows the mean trend or a constant of signal as no more IMFs can be extracted from the monotonic function.

Then, the sum of all IMFs and the residue of original signal x(t) is represented as:

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

where n is the number of IMFs, and the final residue is the mean trend or a constant.

Hilbert Transform

A Hilbert transform is used to compute instantaneous frequencies and amplitudes. The IMF signals were calculated in this process. The Hilbert transform function x (t) is defined as follows:

$$H(x(t)) = y(t) = \frac{1}{\pi} PV \int_{-\infty}^{+\infty} \frac{X(t')}{t - t'} dt$$

where PV indicates the Cauchy principal value. The original time-series and its Hilbert transform are the real and imaginary part. The analytic signal obtained with the Hilbert transform is defined as:

$$z(t) = x(t) + iy(t) = a(t)e^{i\theta(t)}$$

where

$$a(t) = \sqrt{x^2(t) + y^2(t)}$$

$$\theta(t) = arc\tan(\frac{y(t)}{x(t)})$$

Moreover, w (t) is given as

$$w(t) = \frac{d\theta(t)}{d(t)}$$

The time-dependent amplitude and frequency of each IMF are extracted after the Hilbert transform is applied to it.

The Hilbert transform designates the frequency time distribution of the amplitude as follows:

$$H(w,t) = \mathrm{Re}\, alpart \sum_{i=1}^{n} a_i(t) e^{i\theta}$$

The mean frequency of each instantaneous frequency (MIF) is defined as:

$$MIF(j) = \frac{\sum_{i=1}^{n} w_j(i) a_j^2(i)}{\sum_{i=1}^{n} a_j^2(i)}$$

where n is the data point of each instantaneous frequency. Then, the measurement of the relative magnitude of each frequency band is computed by the tow norms of each instantaneous frequency amplitude value. The amplitude norm of this band caculatesthe mean frequency, and the results estimate the mean frequency based on EMD. So, the mean frequency of the original signal is defined by:

$$MIF = \frac{\sum_{j=1}^{n} \| a_j \| MIF(j)}{\sum_{j=1}^{n} \| a_j \|}$$

Results

Muscle fatigue is defined as an activity-induced loss of the ability to produce force with the muscle (Luca, 2016). The measurement of muscle fatigue with an sEMG signal, which is non-invasive and a real-time muscle fatigue monitor, is widely applied in different research areas. The variables of the sEMG power spectrum are developed to analyze the muscle fatigue index, such as mean frequency (MNF). According to the result of the downward shift in the frequency spectrum of the EMG signal, MNF is regarded as a gold standard for muscle fatigue assessment (Phinyomark, Thongpanja, & Hu, 2012). MNF is an average frequency value which is calculated as the sum of the product of the EMG power spectrum and frequency, divided by the total sum of spectrum intensity. The MNF variable derived though three different time frequency analyses. And then, the slope and point of intercept in each MNF by a least-square error linear regression were compared.. Figure 4 shows mean frequency derivated via HHT in the RBB muscle of subject 3. The linear regressions of each of these 10 data were applied to exact the slope and intercept. The result is illustrated in Figure 5. The analysis methods were repeated for other muscles. Figure 6 shows the four different muscles' slope and point of intercept parameters of the linear regression of the mean frequency in subject 3. It was calculated by Hilbert-Huang transform; the Wavelet based on intensity analysis and the Autoregressive method based on Akaike Information Criterion in fatigue condition.

Tables 1–4 show mean, standard deviation, and standard error of the meanstandard deviations error mean in slope and point of intercept parameters of the linear regression of the mean frequency in four different muscles of subject 3. Table 1 shows that the standard deviation and error mean in slope (SD = 0.049, SEM = 0.1223) and point of intercept (SD = 1.9983, SEM = 0.5542) are the lowest using the HHT method. It indicates that the stability of the estimates of slope and intercepts in RBB P3 muscle using HHT method is better than the others, verifying the research finding in (Xie & Wang, 2006).

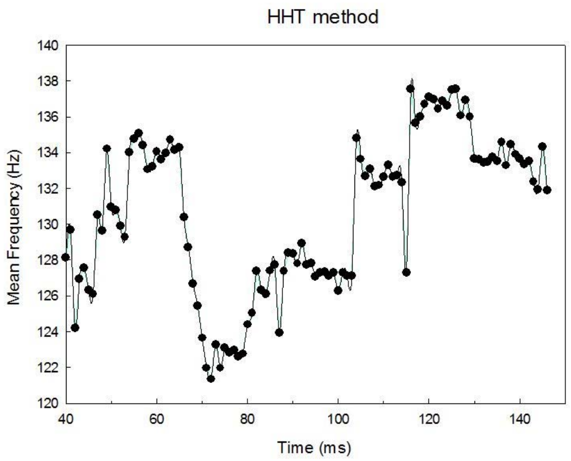
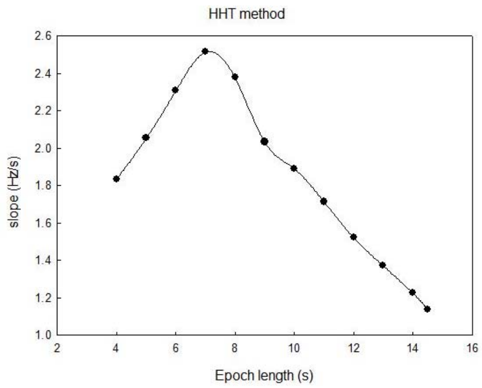


Figure 4. Mean frequency derivated via HHT in RBB muscle of subject 3



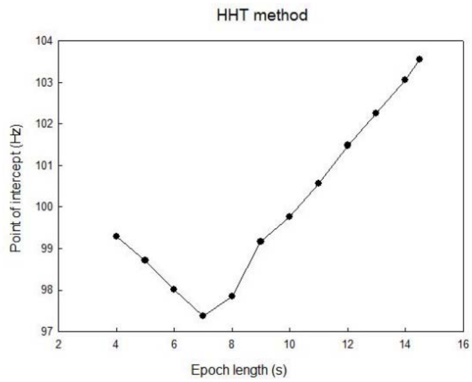


Figure 5. Slope and point of intercept parameters of the linear regression of the MNF calculated by HHT in one subject's RBB muscle

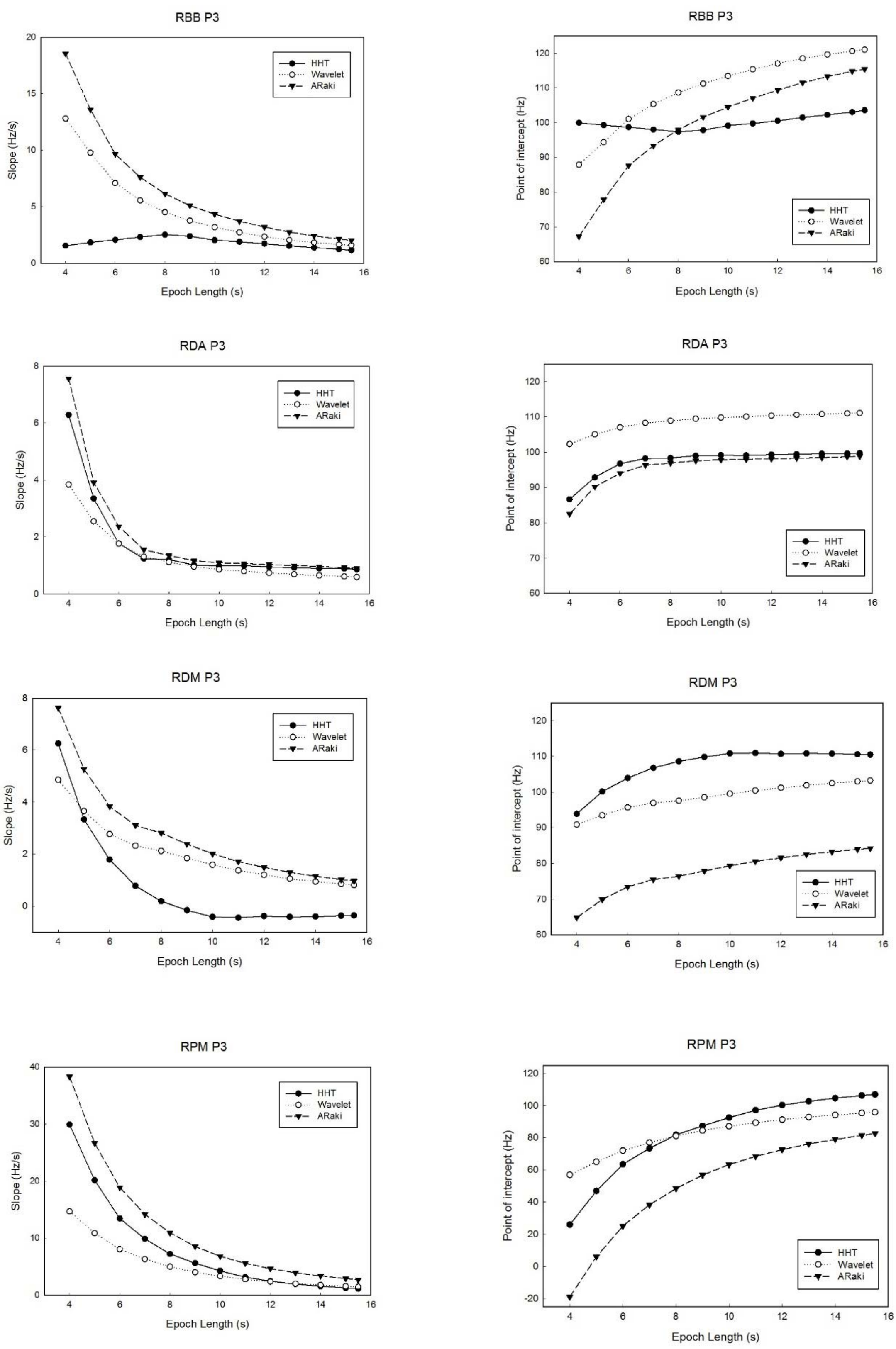


Figure 6. Slope and point of intercept parameters of the linear regression of the mean frequency calculated by Hilbert-Huang transform (HHT), Wavelet based on intensity analysis (Wavelet) and Autoregressive method based on Akaike Information Criterion (ARaki) for biceps brachii (RBB), pectoralis major (RPM), deltoideus anterior (RDA), and deltoideus medialis (RDM) of subject 3 in fatigue condition.

Table 1. The mean, standard deviation, and standard error of the mean in slope and point of intercept parameters of the linear regression of the mean frequency in the RBB muscles of subject 3.

		Slope			Point of intercept		
	n	**mean**	**SD**	**SEM**	**mean**	**SD**	**SEM**
AKI	13	6.2383	5.0109	1.3898	100.1264	14.9859	4.1563
HHT	13	1.8094	0.4409	0.1223	100.0795	1.9983	0.5542
WT	13	4.5202	3.4729	0.9632	110.3291	10.5192	2.9175

Note: AKI = Autoregressive method based on Akaike Information Criterion, HHT = Hilbert-Huang transform, WT = Wavelet based on intensity analysis, SD = Standard deviation, and SEM = standard error of the mean

However, it is obvious in Figure 6 that the estimates of slope and points of intercept in RDA, RDM and RPM muscles show a similar trend in these three methods. It indicates HHT may not be the best choice for estimating RDA, RDM and RPM muscles in fatigue condition. Tables 2–4. Show that the standard deviation and error mean in slope and point of intercept are the lowest with the WT method, compared with the other two methods.

Table 2. The mean, standard deviation, and standard error of the mean in slope and point of intercept parameters of the linear regression of the mean frequency in the RDA muscles of subject 3.

		Slope			Point of intercept		
	n	**mean**	**SD**	**SEM**	**mean**	**SD**	**SEM**
AKI	13	1.9120	1.8950	0.5256	95.8256	4.6765	1.2970
HHT	13	1.6406	1.5494	0.4297	97.5098	3.7556	1.0416
WT	13	1.2657	0.9536	0.2645	108.8304	2.6134	0.7248

Table 3. The mean, standard deviation, and standard error of the mean in slope and point of intercept parameters of the linear regression of the mean frequency in the RDM muscles of subject 3.

		Slope			Point of intercept		
	n	**mean**	**SD**	**SEM**	**mean**	**SD**	**SEM**
AKI	13	2.6653	1.9510	0.5411	77.9359	5.8614	1.6257
HHT	13	0.7179	2.0124	0.5581	107.5452	5.2585	1.4584
WT	13	1.9500	1.2122	0.3362	98.8379	3.8091	1.0564

Table 4. The mean, standard deviation, and standard error of the mean in slope and point of intercept parameters of the linear regression of the mean frequency in RPM muscles of subject 3.

		Slope			Point of intercept		
	n	**mean**	**SD**	**SEM**	**mean**	**SD**	**SEM**
AKI	13	11.3189	10.7885	2.9922	52.2699	31.7110	8.7951
HHT	13	7.8284	8.6881	2.4096	83.8238	25.1741	6.9820
WT	13	4.9238	4.0689	1.1285	83.3069	12.3616	3.4285

The other subjects have a similar result as subject 3 in fatigue condition. In order to qualify the results of all the subjects in both fatigue and non-fatigue conditions, the coefficient of variation (CoV: standard deviation over absolute mean) was used (Georgakis, Stergioulas, & Giakas, 2003; Xie & Wang, 2006). Then, the mean and itsconfidence intervals for the slope and intercept in both the fatigue and non-fatigue condition were derived from the individual t-estimates for all subjects, shown in Figure 7 and 8. The result demonstrated that the mean standard deviation of the RBB muscle of slope (SD = 1.7614, SEM = 0.4885) and points of intercept (SD = 1.13361, SEM = 0.314407) by HHT method in the fatigue condition and non-fatigue condition are the smallest. However, the lowest mean standard deviation of slope and points of intercept vaule in RDA, RDM and RPM muscles in both conditions derivated Wavelet method based on intensityanalysis.. The result suggests that the mean frequency derived from the HHT method in RBB muscles is nearly constant against the epoch length, and that the mean frequency derived for RDA, RDM and RPM muscles via the Wavelet method which is based on intensity analysis is better.

Discussion

Surface EMG is regarded as a non-invasive source of information on the state of skeletal muscle fatigue and non-fatigue. The spectrum analysis of a surface EMG signal can provide information on where the muscle fatigue or non-fatigue is. The surface EMG spectrum and amplitude are impacted by both force and fatigue. Fatigue was distinguished by four different cases (Cifrek et al., 2009). According to the effect of the relative muscle-electrode movement, the results obtained during dynamic contractions should also be treated with caution because of the limited information available (Felici et al., 2001).

The problem of lower resolution and ‘leakage’ effects based on Fast Fourier transforms was overcome by the AKI model (Muthuswamy & Thakor, 1998). It is useful when one needs to track the changes in a rapidly changing signal on-line in a reliable manner. However, compared HHT and WT with the following, the mean values of the CoV of slope and intercept by AKI in the non-fatigue condition for four muscles is the highest. In the fatigue condition, except for the mean values of the CoV of slope and intercept in RDA muscles, it is also highest. The result indicates that the AKI model is the worst technique for analyzing muscle in the fatigue and non-fatigue condition.

In terms of its robustness against the size of the analysis window, Xie and Wang (2006) suggest the HHT approach is a better choice for analyzing muscle fatigue. The surface EMG signal in both fatigue and non-fatigue condition are qualified by estimating the slope and intercept of the mean frequency regression line. The empirical mode decomposition is utilized, and several instantaneous frequencies (IMFs) are obtained which relate to the motor unit firing, recruitment, muscle fiber conduction and other neuromuscular physiological factors (Xie & Wang, 2006). However, the result of the top-spin stroke table tennis experiment shows a better choice only for RBB muscle analysis in both the fatigue and non-fatigue condition.

The Wavelet method, based on intensity analysis, presents much more accuracy and reliability in both the fatigue and non-fatigue condition in RDA, RDM and RPM muscles. This method optimizes the analysis with respect to time- and frequency-resolution, respecting the limits given by the uncertainty relationship. If the signals contain events with a limited frequency band, the new definition of intensity is obtained, which detects the shape of an event. In addition, the power of an EMG signal generates a very good approximated event by intensity analysis. This method, proposed by Tscharner, has the advantage of being event- and intensity-oriented. It requires more detail with respect to the functional aspects of muscle activation, instead of EMG signal details (Tscharner, 2000).

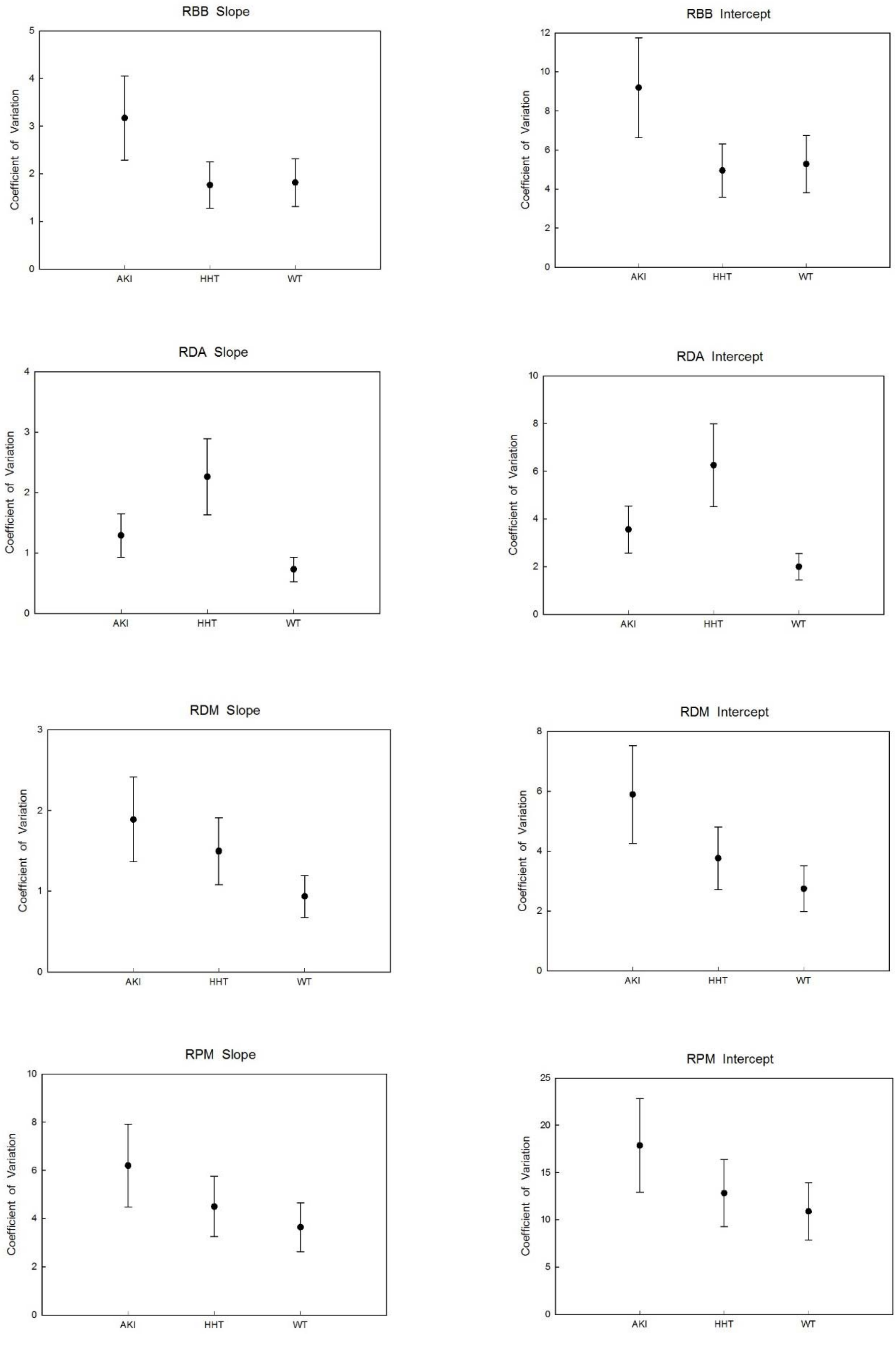


Figure 7. The mean CoV (5% significance level) values of slope and intercept derived by Hilbert-Huang transform (HHT). Wavelet based on intensity analysis (WT) and Autoregressive method based on Akaike Information Criterion (AKI) for each muscle of all the subjects in fatigue condition

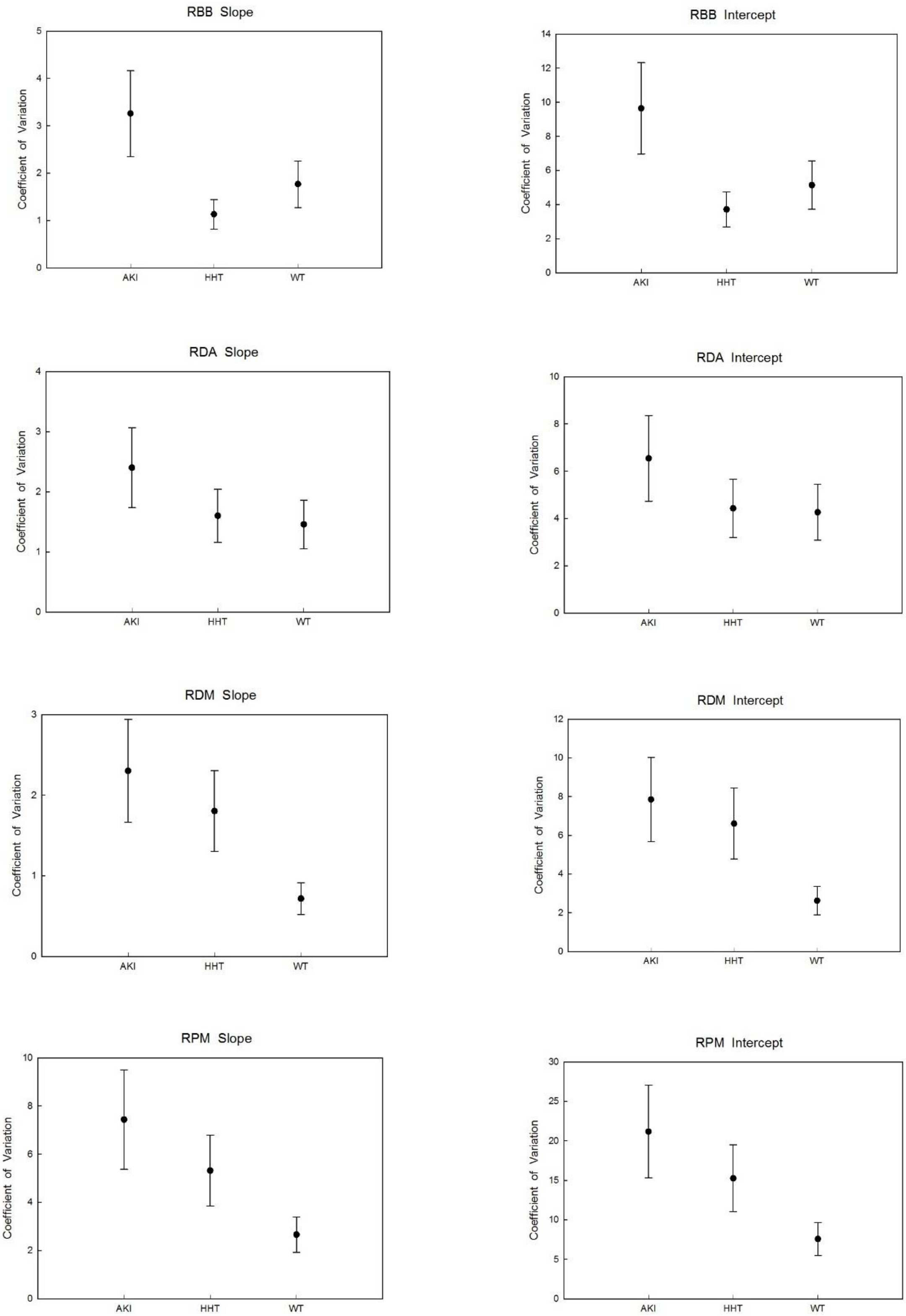


Figure 8. The mean CoV (5% significance level) values of slope and intercept derived by Hilbert-Huang transform (HHT). Wavelet based on intensity analysis (WT) and Autoregressive method based on Akaike Information Criterion (AKI) for each muscle of all the subjects in non-fatigue condition.

In the future, we will focus on the improvement of muscle fatigue analysis using the Hilbert-Huang transform model and the Wavelet method based on intensity analysis, as well as evaluating other racket sports. In addition, we could integrate artificial intelligence to estimate muscle fatigue based on the EMG signal. We believe that an effective muscle fatigue analysis model and evaluation system will help players to avoid excessive training injuries.

Conclusion

In this paper, we discussed the issue of assessing the electrical manifestations drive via mean frequency based on surface EMG signals in table tennis. Three different time-frequency techniques were employed to estimate the spectrum of the signal in the non-fatigue and fatigue conditions of four different muscles. This revealed that the Hilbert-Huang transform method for studying the biceps brachii muscle is the most reliable and accurate (Xie & Wang, 2006). However, the Wavelet method, based on intensity analysis, is more reliable and accurate for the pectoralis major muscle, deltoideus anterior muscle and deltoideus medialis muscle. The results suggest that different time-frequency analysis techniques are required to be quantified in different muscles based on surface EMG signal in the fatigue and non-fatigue condition.

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