
The Usefulness of Mean and Median Frequencies in Electromyography Analysis

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1. Introduction

Rich useful information can be obtained from the muscles and researchers can use such information in a wide class of clinical and engineering applications by measuring surface electromyography (EMG) signals (Merletti & Parker, 2004). Normally, EMG signals are acquired by surface electrodes that are placed on the skin superimposed on the targeted muscle. In order to use the EMG signal as a diagnosis signal or a control signal, a feature is often extracted before performing analysis or classification stage (Phinyomark et al., 2012a) because a lot of information, both useful information and noise (Phinyomark et al., 2012b), is contained in the raw EMG data. An EMG feature is a distinct characteristic of the signal that can be described or observed quantitatively, such as being large or small, spiky or smooth, and fast or slow. Generally, EMG features can be computed in numerical form from a finite length time interval and can change as a function of time, i.e. a voltage or a frequency. They can be computed in several domains, such as time domain, frequency domain, time-frequency and time-scale representations (Boostani & Moradi, 2003). However, frequency-domain features show the better performance than other-domain features in case of the assessing muscle fatigue (Al-Mulla et al., 2012). Mean frequency (MNF) and median frequency (MDF) are the most useful and popular frequency-domain features (Phinyomark et al., 2009) and frequently used for the assessment of muscle fatigue in surface EMG signals (Cifrek et al., 2009).

This chapter presents a usefulness of MNF and MDF in electromyography analysis. The successful muscular fatigue assessment based on MNF and MDF methods is presented together with the principle and theory of MNF and MDF in this chapter, and also up-to-date literature reviews of MNF and MDF in the analysis of EMG signals. In order to analyse the EMG signals during dynamic movements, the effects of muscle force and muscle geometry

(joint angle) should have paid more attention (Cechetto et al., 2001; Doheny et al., 2008). In the literature, such effects on MNF and MDF have still been inconclusive (Doheny et al., 2008; Phinyomark et al., 2012c). A summary of the conflicting results mentioned in the literature is also presented. The possible reasons for the conflicting results in both effects are discussed. In addition to the clinical applications, the classification of EMG signals during upper-limb movements for using in the engineering applications (Oskoei & Hu, 2007) is proposed in this chapter.

The rest of this chapter is as follows: Section 2 presents the principle and theory of MNF and MDF, and the relations between MNF (and MDF) and other EMG frequency-domain features are also described and discussed. In Section 3, the extensive review and careful survey of the up-to-date experiments for the assessing muscle fatigue using MNF and MDF in numerous applications are summarized, and moreover, the recent trend of MNF and MDF in the assessment of muscle fatigue is discussed in this section. On the other hand, the effects of muscle force and muscle geometry are described respectively in Section 4 and Section 5, with the re-evaluating results for both effects using the new EMG data set. In addition, a number of techniques that are possible to make the consistent results for both effects are suggested. In Section 6, the usefulness of MNF and MDF in the EMG pattern classification is proposed with the related works. The modified MNF and MDF in order to improve the robustness property for the classifying EMG signals are also presented. Lastly, the conclusion and future trends of using MNF and MDF to analyse EMG signals are presented in Section 7.

2. Principle and theory of mean and median frequencies

Frequency-domain or spectral-domain features are usually used in the assessing muscle fatigue and analysing MU recruitment (Oskoei & Hu, 2008). To transform the EMG signal in the time-domain to the frequency-domain, a Fourier transform of the autocorrelation function of the EMG signal is employed to provide the power spectrum (PS) or the power spectral density (PSD). Although PSD can be estimated by different methods, i.e. modern, parametric or model-based, the most commonly used PSD estimator in the EMG signal analysis is the Periodogram. It is defined as the square of absolute value of the Fourier transform of EMG signal divided by the signal length. Another stable and accurate PSD estimator is the autoregressive (AR) model (Zhang et al., 2010). Different kinds of statistical variables are applied to the PSD of EMG signal and the two popular used variables of PSD are mean and median. However, there are several possible statistical variables that can be applied to the PSD of EMG signal, such as summation or total, and peak value. Definitions of other statistical variables are presented in Section 2.2.

2.1. The definition of mean and median frequencies

MNF is an average frequency which is calculated as the sum of product of the EMG power spectrum and the frequency divided by the total sum of the power spectrum (e.g. Oskoei & Hu, 2008; Phinyomark et al., 2012a). MNF has a similar definition as several features, i.e.

the central frequency (f_c), centroid and the spectral center of gravity, in a number of studies (Du & Vuskovic, 2004; Farina & Merletti, 2000). In addition, MNF is also called as mean power frequency and mean spectral frequency in several works. The definition of MNF is given by

$$MNF = \frac{\sum_{j=1}^M f_j P_j}{\sum_{j=1}^M P_j}, \quad (1)$$

where f_j is the frequency value of EMG power spectrum at the frequency bin j , P_j is the EMG power spectrum at the frequency bin j , and M is the length of frequency bin. In the analysis of EMG signal, M is usually defined as the next power of 2 from the length of EMG data in time-domain.

MDF is a frequency at which the EMG power spectrum is divided into two regions with equal amplitude (e.g. Oskoei & Hu, 2008; Phinyomark et al., 2012a). MDF is also defined as a half of the total power, or TTP (dividing the total power area into two equal parts). The definition of MDF is given by

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^M P_j = \frac{1}{2} \sum_{j=1}^M P_j. \quad (2)$$

The behaviour of MNF and MDF is always similar. However, the performance of MNF in each of the applications is quite different compared to the performance of MDF, although both features are two kinds of averages in statistics. More details about the performance of both features are discussed in Section 3 to Section 6.

It should be noted that MNF is always slightly higher than MDF because of the skewed shape of EMG power spectrum (Knaflitz et al., 1990), whereas the variance of MNF is typically lower than that of MDF. In theory, the standard deviation of MDF is higher than that of MNF by a factor 1.253 (Balestra et al., 1988). However, the estimation of MDF is less affected by random noise, particularly in the case of noise located in the high frequency band of EMG power spectrum, and more affected by muscle fatigue (Stulen & De Luca, 1981).

2.2. The relations between mean and median frequencies and other EMG frequency-domain features

Other spectral variables that have been applied in the analysis of EMG signal are total power (TTP), mean power (MNP), peak frequency (PKF), the spectral moments (SM), frequency ratio (FR), power spectrum ratio (PSR), and variance of central frequency (VCF) (Phinyomark et al., 2012a). The definition of all variables is presented in the following.

1. TTP is an aggregate of EMG power spectrum (Phinyomark et al., 2012a). This feature is also defined as the energy and the zero spectral moment (SM0) (Du & Vuskovic, 2004). Its equation can be expressed as

$$TTP = \sum_{j=1}^M P_j = SM0 . \quad (3)$$

2. MNP is an average power of EMG power spectrum (Phinyomark et al., 2012a). It can be defined as

$$MNP = \sum_{j=1}^M P_j / M . \quad (4)$$

3. PKF is a frequency at which the maximum EMG power occurs (Phinyomark et al., 2012a). It can be expressed as

$$PKF = \max(P_j), \quad j=1, \dots, M . \quad (5)$$

4. SM is an alternative statistical analysis way to extract feature from the power spectrum of EMG signal. Normally, the first three moments (SM1-SM3) are employed as the EMG features (Du & Vuskovic, 2004). Their equations can be defined as

$$SM1 = \sum_{j=1}^M P_j f_j; \quad SM2 = \sum_{j=1}^M P_j f_j^2; \quad SM3 = \sum_{j=1}^M P_j f_j^3 . \quad (6)$$

5. FR is used to discriminate between relaxation and contraction of the muscle using a ratio between low- and high-frequency components of EMG signal (Han et al., 2000; Phinyomark et al., 2012a). The equation is defined as

$$FR = \sum_{j=LLC}^{ULC} P_j / \sum_{j=LHC}^{UHC} P_j , \quad (7)$$

where *ULC* and *LLC* are respectively the upper- and the lower-cutoff frequency of low-frequency band, and *UHC* and *LHC* are respectively the upper- and the lower-cutoff frequency of high-frequency band. The cutoff frequency between low- and high-frequencies can be defined by two ways: the experiment (Han et al., 2000) and the MNF value (Oskoei & Hu, 2006).

6. PSR is a ratio between the energy P_0 which is nearby the maximum value of EMG power spectrum and the energy P which is the whole energy of EMG power spectrum (Qingju & Zhizeng, 2006). It can be seen as an extended version of PKF and FR. The equation can be expressed as

$$PSR = \frac{P_0}{P} = \sum_{j=f_0-n}^{f_0+n} P_j / \sum_{j=-\infty}^{\infty} P_j , \quad (8)$$

where f_0 is defined as the value of PKF and n is the integral limit.

7. VCF is defined by using a number of the spectral moments (SM0-SM2) and MNF. It can be computed by the following equation

$$VCF = \frac{1}{SM0} \sum_{j=1}^M P_j (f_j - MNF)^2 = \frac{SM2}{SM0} - \left(\frac{SM1}{SM0} \right)^2. \quad (9)$$

TTP, MNP, and SM are frequency-domain features that extract the same information as time-domain features based on the energy information (Phinyomark et al., 2012a). Hence, the discriminant of TTP, MNP and SM in space has the similar pattern as the time-domain features based on the energy information, i.e. integrated EMG (IEMG), root mean square (RMS), mean absolute value (MAV), and variance of EMG (VAR). Due to the fact that muscle fatigue results in an increase of EMG signal amplitude, time-domain features based on energy information, i.e. IEMG, MAV and RMS, can track this behaviour. Thus, TTP, MNP and SM can also be used as an indicator of muscle fatigue, although EMG signal amplitude, itself, is rarely used to detect muscle fatigue. However, these features can be used in a combination with the spectral analysis i.e. MNF and MDF. On the other hand, all spectral features except PSR have the different discriminant patterns in feature space compared with MNF and MDF. In case of $n = 20$, the pattern of PSR is an inverse case of MNF and MDF patterns (Phinyomark et al., 2012a).

3. Assessing the muscle fatigue using mean and median frequencies

Muscle fatigue is generally defined as an activity induced loss of the ability to produce force with the muscle. Usually, the muscle fatigue is a result of prolonged or repetitive works (De Luca, 1984). It should be noted that the usual term “muscle fatigue” is generally meaning in fact “local muscle fatigue” (Chaffin, 1973). Undetected fatigue for a long-time can cause injury to the subject and is often irreversible. If an automated muscle fatigue detection system in wearable technology was feasible, it could be employed as an indicator to reduce the chances of work-place injury and aid sporting performance (Al-Mulla et al., 2012). Among a number of sources and techniques (Al-Mulla et al., 2011), e.g. acoustic-myography (AMG), mechano-myography (MMG), near-infrared spectroscopy (NIRS), sono-myography (SMG) and ultrasound, the EMG signal is used even more often and has several advantages, such as a non-invasiveness, an ability to monitor fatigue of a particular muscle and a real-time muscle fatigue monitoring during the performance of defined work (Petrofsky et al., 1982).

The assessment of muscle fatigue with surface EMG signals can be applied in a wide class of applications, such as muscle fatigue during repeated cycling sprints (Hautier et al., 2000), muscle fatigue in children with cerebral palsy (Leunkeu et al., 2010), muscle fatigue during playing the PC games (Oskoei et al., 2008), and the low back pain in helicopter pilots (Balasubramanian et al., 2011). Several classical and modern signal processing techniques have been applied (Cifrek et al., 2009), such as the RMS, the zero-crossing rate (ZCR), the averaged instantaneous frequency, wavelet analysis, fractal analysis, and also MNF and MDF.

Among such techniques, MNF and MDF so far have been hailed as the gold standard for muscle fatigue assessment with surface EMG signals due to the fact that muscle fatigue results in a downward shift of frequency spectrum of the EMG signal. Moreover, during the fatigue of muscle, several changes have been found, i.e. a relative decrease in signal power at high-frequency, a small increase in signal power at low-frequency, an increase in spectrum slope at high-frequency, and a decrease in spectrum slope at low-frequency (Petrofsky et al., 1982; Sato, 1982; Viitasalo & Komi, 1977). There are several possible reasons for the changes in the EMG signal, such as the modulation of recruitment firing rate, the grouping and slowing of CV, and synchronization of the signal (De Luca, 1979; Hermens et al., 1984; Viitasalo & Komi, 1977).

Using MNF and MDF to detect muscle fatigue in static contractions is clearly known because during static contraction the EMG signals may be assumed to be stationary during short-time intervals (0.5-2s). On the other hand, in dynamic contractions, the EMG signal information has been changed as a function of time that cannot be analyzed by simply applying FFT and most recently EMG studies have been applied to the study of dynamic contraction. The instantaneous mean and median frequency (IMNF and IMDF) are introduced to fulfill the requirement (Roy et al., 1998) by using time-frequency or time-scale approaches, such as short-time Fourier transform (STFT) (Cifrek et al., 2000; Thongpanja et al., 2010, 2011), Wigner distribution (WD), Choi-Williams distribution (CWD) (Knaflitz & Bonato, 1999), time-varying autoregressive approach (TVAR) (Zhang et al., 2010), and continuous wavelet transform (CWT) (Karlsson et al., 2000).

Further, there are several ways to use IMNF and IMDF to detect muscle fatigue. For example, Georgakis et al. (2003) demonstrated that the performance of the average of IMNF and IMDF is better than the traditional MNF and MDF. On the other hand, a slope of the regression line that fits the maximum values of IMNF and IMDF during cyclic contractions is used as a fatigue index in Cifrek et al. (2000).

Many research works reported on the effectiveness of MNF and MDF applied to EMG signal as a mean of identifying muscle fatigue. The experimental conditions for several studies (based on literature published between 1980-2011) are summarized in Table 1. Most of the studies have been performed MNF and MDF to detect the muscle fatigue in primarily static muscle contraction but also in dynamic muscle contraction.

In Table 1, most of the studies recorded EMG data from 10 subjects and the volunteers between 20 and 30 years of age (young subjects) are the main target. However, in Masuda et al. (1999), age of the subjects is ranged from 19 to 73 years (both young and older subjects). EMG signals obtained from young and older subjects are quite different, as mentioned in Tavakolan et al. (2011) that the difference in classification accuracy obtained from the young and older subjects is approximately 7%. Although Kalra et al. (2012) found that MDF of EMG is not significantly impacted by age at 50-100%MVC of the BB muscle, the effect of age needs to be carefully considered in future research. In addition to the effect of age, the effect of gender is another factor that should be paid more an interest (Kalra et al., 2012).

Reference	N	Age	Muscle	ID	Force levels	RT	Filter
Petrofsky & Lind (1980b)	10	23.2±2.3	BR	40	25, 40, 70%MVC	F	-
Gerdle et al. (1990)	9	30-40	BB	-	20, 40, 60, 80, 100%MVC	-	-
Merletti & Roy (1996)	6	-	TA	-	50, 60, 70, 80%MVC	90-170	-
Mannion & Dolan (1996)	10	-	RF, VL	-	20, 30, 40, 50, 60%MVC	F	-
Potvin (1997)	15	24±3	BB	30	7kg	F	15-450
Masuda et al. (1999)	19	19-73	VL	5	50%MVC	F	5-1000
Rainoldi et al. (1999)	10	30.2±6.1	BB	10	10, 30, 50, 70%MVC	30	10-450
Cifrek et al. (2000)	10	22.9±1.5	RF, VL, VM	30	50%MVC	F	20-480
Bonato et al. (2001)	-	-	FDI	5	10%MVC	150	8-450
MacIsaac et al. (2001)	7	26±7	BB	40	20-30%MVC	F	1-1000
Arnall et al. (2002)	10	-	PS	-	40, 50, 60%MVC	60	-
Allison & Fujiwara (2002)	10	29.4±4.8	BB	25	60%MVC	C1	20-500
Bilodeau et al. (2003)	14	22-43	RF, VL, VM	20	100%MVC	C2	15-4000
Georgakis et al. (2003)	30	-	RF, VL, VM	20	60%MVC	60	10-500
Clancy et al. (2005)	12	31.4±11.1	FDS, ECR	-	10, 20, 30, 40, 50, 60, 70, 80, 90%MVC	F	25-1350
Ravier et al. (2005)	10	24±1.5	BB	75	70%MVC	F	2-600
Zaman et al. (2011)	11	24±4	BB	5	40%MVC	F	-
Soares et al. (2011)	10	24±2.8	BB	5	40%MVC	90	-

Table 1. A survey of the experimental conditions in related works about muscle fatigue assessment with surface EMG signals using MNF and MDF in chronological order. Note that *N* is the number of subjects; ID is the inter-electrode distance (mm); RT is the recording time (s); Filter is the specification of filtering (Hz); MVC is maximum voluntary contraction; F is the EMG data is recorded until the subject cannot support the required force level; C1 is the EMG data is recorded until force is below 35%MVC; C2 is the EMG data is recorded until force is below 50%MVC; BR is brachioradialis; BB is biceps brachii; TA is tibialis anterior; RF is rectus femoris; VL is vastus lateralis; VM is vastus medialis; FDI is first dorsal interosseous; PS is paraspinal; FDS is flexor digitorum superficialis; ECR is extensor carpi radialis.

The next interested factor in Table 1 is the recording time. Because in the analysis of muscle fatigue, the EMG signals recorded during the fatigue of muscle are needed. Most of the studies used a level of force as the threshold to finish the recording. In other words, the EMG data have been recorded until the subject cannot maintain the required force level. However, several studies define the specific recording times that range from 30s to 170s.

Other factors are varied, such as the inter-electrode distance (5-75 mm), the levels of force (10-100%MVC), and the specification of filtering (1-1350 Hz). However, most of the studies paid more an interest to the study of biceps brachii muscle. The evaluating performance between each pair of the methods and the muscles should be done in future study.

4. Effect of muscle force on mean and median frequencies

In order to make a reliably automate the muscle fatigue determination, the knowledge of the effects of time-varying factors on MNF and MDF is very important. Two time-varying factors, muscle force and muscle geometry, are the major factors due to the activities that involve dynamic muscle contractions (muscle force and/or geometry are changing) (Cechetto et al., 2001). It should be noted that the number and firing rate of active motor units (MUs) do not significantly affect MNF and MDF in both experimental and theoretical studies (Engelhart & Parker, 1994; Solomonow et al., 1990).

The individual effects of muscle force and muscle geometry on MNF and MDF have been investigated in many previous researches. The effect of muscle force is discussed in this section, while the effect of muscle geometry will be discussed in the next section.

At present, the conflicting results of MNF and MDF with the muscle force effect exist in the literature. The difference in the experimental conditions for most of the studies is presented in Table 2. Maybe it is the possible reasons for the conflicting results of MNF and MDF on muscle force effect. It can be observed from the table that three different cases exist for the effect of muscle force on MNF and MDF.

- In the first case (CF1), MNF and MDF are unaffected or only weakly affected by changes in muscle force or load levels (Bilodeau et al., 1991; Cechetto et al., 2001; Hagberg & Ericsson, 1982; Inbar et al., 1986; Merletti et al., 1984; Petrofsky & Lind, 1980a, 1980b; Viitasalo & Komi, 1978).
- In the second case (CF2), MNF and MDF increase as muscle force levels increase (Doheny et al., 2008; Gander & Hudgins, 1985; Gerdle et al., 1990; Hagberg & Ericsson, 1982; Hagberg & Hagberg, 1989; Moritani & Muro, 1987; Muro et al., 1982; Van Boxtel & Schomaker, 1984).
- In the third case (CF3), MNF and MDF decrease as muscle force levels increase (Kaplanis et al., 2009; Rainoldi et al., 1999).

Each of the first two cases is found in eight publications, while the third case exists only in two publications. However, the third case is found in the most recent study (Kaplanis et al., 2009) which used the EMG data recorded from 94 subjects (the largest EMG data compared with other publications).

Reference	N	Age	Muscle	ID	Force levels	RT	Filter	CF
Viitasalo & Komi (1978)	7	-	RF,VL,VM	-	-	-	-	1
Petrofsky & Lind (1980a)	8	22-52	FCR	40	5-100%MVC	3	-	1
Petrofsky & Lind (1980b)	10	23.2±2.3	BR	40	10, 20, 40, 60, 80, 100%MVC	3	-	1
Hagberg & Ericsson (1982)	4	21-24	BB,BR,BL	20	5, 10, 15, 20, 25, 30, 40, 50, 80%MVC	3-5	0.2-2000	1,2
Muro et al. (1982)	5	32.5±8.2	BB	-	0.25, 0.5, 1, 2, 3kg	10	-	2
Merletti et al. (1984)	26	22.6±6.4	FDI	10	20, 80%MVC	3-5	30-350	1
Van Boxtel & Schomaker (1984)	19	18-32	FL,CS	15	20, 40, 60, 80%MA	3	3-520	2
Gander & Hudgins (1985)	6	20-40	BB	-	1-10Nm	8.2	-	2
Inbar et al. (1986)	9	30-40	BB,ED	35	30, 50, 70, 90%MVC	6	1-1000	1
Moritani & Muro (1987)	12	26.3±2.5	BB	6	0-80%MVC	5	< 520	2
Hagberg & Hagberg (1989)	14	36±8	TZ	30	0-100%MVC	10-15	5-500	2
Gerdle et al. (1990)	9	30-40	BB	-	20, 40, 60, 80, 100%MVC	1-2	-	2
Bilodeau et al. (1991)	14	30.2±7.8	TB,AN	6	10, 20, 40, 60, 80%MVC	3	16-800	1
Rainoldi et al. (1999)	10	30.2±6.1	BB	10	10, 30, 50, 70%MVC	30	10-450	3
Cechetto et al. (2001)	12	31.1±10	BB	40	20, 30, 40, 50, 60%MVC	5	0.1-3000	1
Doheny et al. (2008)	12	24.8±2.8	BB,BR,TB	10	10, 20, 30, 40, 50, 60, 70%MVC	8	20-450	2
Kaplanis et al. (2009)	94	5-69	BB	10	10, 30, 50, 70, 100%MVC	5	20-500	3

Table 2. A survey of the experimental conditions in related works about the effect of muscle force on MNF and MDF in chronological order. Note that CF is one of three conflicting cases for muscle force effect; MA is maximum amplitude; FCR is flexor carpi radialis; BL is brachialis; FL is frontalis; CS is corrugator supercilii; ED is extensor digitorum; TZ is trapezius; TB is triceps brachii; AN is anconeus.

There are several possible reasons for the conflicting results presented above.

Firstly, the different muscles studied have the different muscle fibre composition and distribution, and also the different tissue filter effects (Farina et al., 2002). The EMG power spectrum can be changed by both of which. Moreover, the difference of subject gender can produce the differences in fibre diameters and types (Sabbahi et al., 1981). Hence, the difference in the type and distribution of muscle fibres should be one of the major reasons, although the conflicting results exist in the same muscle i.e. the biceps brachii.

Secondly, the electrode locations over the muscle are different in the experiments. Komi and Viitasalo (1976) mentioned that MNF increase with muscle force levels unless the electrodes were located over the motor point area.

Thirdly, the inter-electrode distance (ID) of the bipolar surface electrodes may be the possible reason for the conflicting results. However, based on the observation throughout Table 2, the different inter-electrode distances are also found in the same case (all cases).

Fourthly, Bilodeau et al. (1992) found the different results between two genders for MDF but not for MNF. The difference in skinfold layer is the main contributor for the differences between two genders in that study. On the other hand, Kaplanis et al. (2009) found that no significant differences exist between values based on gender and age.

Other possible reasons are the limited and different number of subjects (i.e. 4–94 subjects), the level of force exhibited (i.e. %MVC or weight in kg), the range of joint angle exhibited (i.e. 0–150 degrees of extension), the difference in recording time (i.e. 1–30s), the existence of fatigue that resulting from the longer recording times (Lariviere et al., 2001), and the method of statistical analysis used.

To confirm the effect of muscle force on MNF and MDF, the relationship between MNF (and also MDF) and muscle force level was re-evaluated by the new EMG data (Phinyomark et al., 2012c). Figs. 1(a), 1(c) and 1(e) illustrate the relationship between muscle force level and MNF at the constant angle, while Figs. 1(b), 1(d) and 1(f) display the relationship between muscle load level and MDF at the same condition.

Three conflicting cases were found in our experiments for the effect of muscle force on MNF and MDF. The results are the subject-dependent. It is similar as the three conflicting cases which were found in the literature. To answer the question “why’s the subject-dependent?”, several related anthropometric variables obtained from the volunteers should be intended to find the possible reasons (Phinyomark et al., 2012c). The preliminary study showed that a number of anthropometric variables have a correlation with the conflicting results, such as standing height, hand breadth, body mass, and forward grip reach.

In order to modify MNF and MDF to have the consistent results (the same case), a modification of traditional MNF and MDF should be done. In one of our previous works (Thongpanja et al., 2010), we found that if a concept of using consecutive fast Fourier transform (FFT) is used instead of using a whole signal FFT, a certain relationship between MNF (and MDF) and muscle force level (the third case) can be found in the middle range of consecutive feature series for all trials and subjects, as an example is shown in Fig. 2. This is

not found for traditional MNF and MDF. This finding can be applied for the EMG signals recorded from the biceps brachii (Thongpanja et al., 2010, 2011) and also the flexor pollicis longus (Thongpanja et al., 2012). To easily observe and use in applications, five statistical variables consisting mean, median, variance, the RMS and kurtosis are used to apply with the selected efficient range of consecutive feature series. The results showed that the consistent results exist across the subjects (subject-independent) by applying mean and median variables (Thongpanja et al., 2011, 2013). The optimization of such techniques can be found more details in Thongpanja et al. (2013).

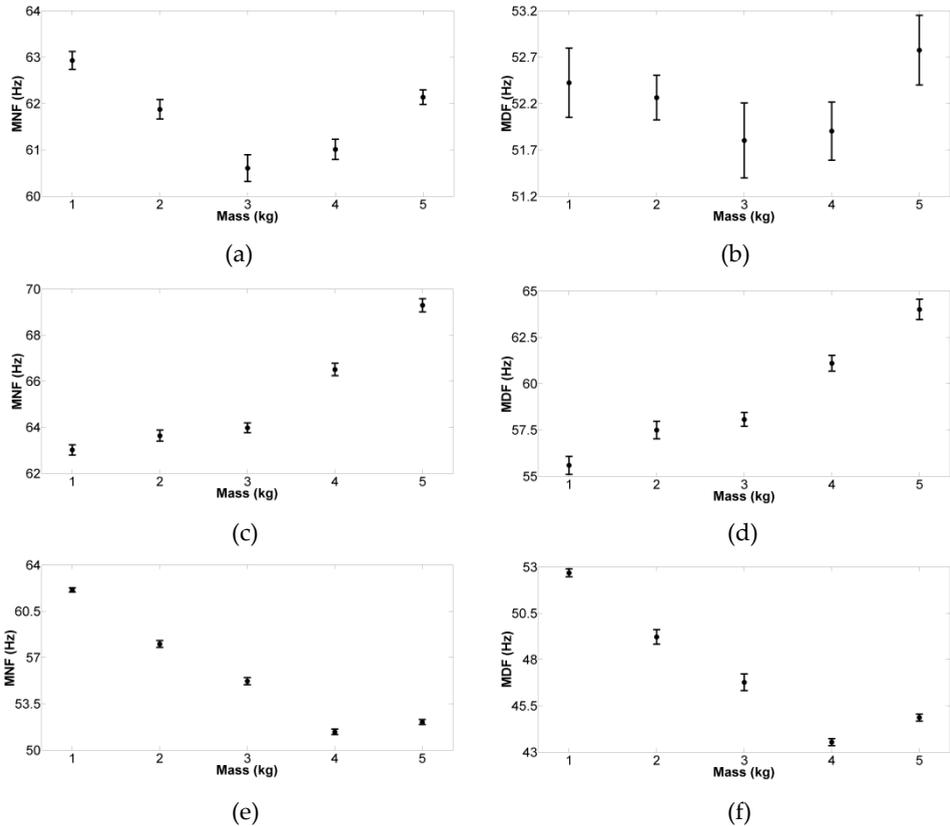


Figure 1. (a, c, e) MNF and (b, d, f) MDF of EMG signals recorded at a constant joint angle (90°) as a function of muscle force (1-5 kg) for three subjects. (a-b) the first case in muscle force effect or CF1 (c-d) the second case in muscle force effect or CF2 (e-f) the third case in muscle force effect or CF3. The error bars shown are given by the standard deviation of the mean value.

5. Effect of muscle geometry on mean and median frequencies

Muscle geometry is another main factor that does significantly affect MNF and MDF. Generally, the effect of muscle geometry including electrode configuration, fibre diameter and subcutaneous tissue thickness has been evaluated by the resulting from changes in joint

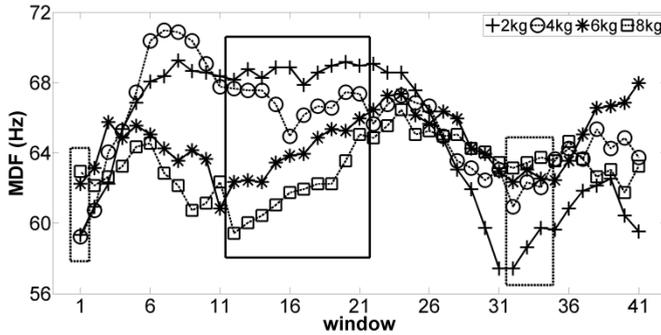


Figure 2. The consecutive MDF feature series computed from the EMG signals recorded from the biceps brachii during dynamic muscle contractions (0-150 degrees of extension). Four load levels are applied: 2, 4, 6 and 8 kg. The FFT is computed using the window size of 512 samples and window overlapping of 64 samples. Note that the second case exists in the beginning and the end ranges (the dashed line boxes) and the third case exists in the middle range (the solid line box).

angle or muscle length (Merletti et al., 1999). Changing in such factors can vary producing a time-varying EMG spectrum. In the literature, two different cases exist for the effect of muscle geometry on MNF and MDF.

In the first case (CG1), MNF and MDF are unaffected by changes in joint angle or muscle length (Sato, 1976). A number of the studies showed no significant change in the power spectrum of EMG signals acquired from the biceps brachii under constant load while joint angle varied. It is also found for the EMG signals recorded from the trapezius, deltoid and the infraspinatus (Gerdle et al., 1988).

In the second case (CG2), MNF (and MDF) increases as muscle length or joint angle (degrees of extension) decreases (Inbar et al., 1987; Shankar et al., 1989). This case exists in most of the studies for EMG signals acquired from the biceps brachii (Cechetto et al., 2001; Doheny et al., 2008; Moritani et al., 1988; Okada, 1987; Potvin, 1997), and is also found for EMG signals acquired from other muscles, such as the tibialis anterior (Merletti et al., 1993), the brachioradialis (Doheny et al., 2008), and the triceps brachii (Doheny et al., 2008; Okada, 1987). The second case, however, is found frequently in the recent studies compared to the first case.

The experimental conditions for several studies are summarized in Table 3. The difference in the experimental conditions may be the reasons for the conflicting results presented in the literature.

Firstly, muscle types and electrode locations over the muscle are different in the experiments. Doheny et al. (2008) mentioned that this factor is one of the reasons for the second case effect. However, the conflicting results are also found in the same muscle i.e. the biceps brachii.

Secondly, Cechetto et al. (2001) proposed that the inter-electrode distance (ID) may be the possible reason for the conflicting results. However, based on the observation through Table 3, three different inter-electrode distances (10, 30 and 40 mm) are found in the same case (the second case).

Thirdly, it can be observed that the frequency band of EMG signals does not affect MNF and MDF.

Reference	N	Age	Muscle	ID	Force levels	Joint angles	Filter	CG
Gerdle et al. (1988)	23	20-30	TZ,DT, IF,BB	-	-	45°, 65°, 90°	-	1
Moritani et al. (1988)	12	-	BB	-	-	30°-150°	-	2
Merletti et al. (1993)	10	-	TA	-	-	0°, 15°, 30°, 45°	-	2
Potvin (1997)	15	24±3	BB	30	7kg	0°-140°	15-450	2
Cechetto et al. (2001)	12	31.1±10	BB	40	20, 30, 40, 50, 60%MVC	50°, 70°, 90°, 110°, 130°	0.1-3000	2
Doheny et al. (2008)	12	24.8±2.8	BB,BR, TB	10	10, 20, 30, 40, 50, 60, 70%MVC	45°, 60°, 75°, 90°, 105°, 120°	20-450	2

Table 3. A survey of the experimental conditions in related works about the effect of muscle geometry (joint angle) on MNF and MDF in chronological order. Note that CF is one of the two conflicting cases for the muscle geometry effect; DT is Deltoid; IF is infraspinatus.

Due to the incompleteness of captured information in the literature, in future study, a request to complete all interested information to the first author or the corresponding author should be done.

As the possible reasons mentioned above that are inconclusive, the main reason for the conflicting results should be the changes of muscle force with the muscle length. The same weight was used at all angles in most of the studies, therefore the changes in MNF and MDF were not due to changes in the muscle length, or joint angle, only but also to changes in the muscle force. In future work, EMG signals should be measured from the muscle under a constant force (varying loads) while joint angles varied.

To confirm the effect of muscle geometry on MNF and MDF, the relationship between MNF (and also MDF) and elbow joint angle was re-evaluated by the similar EMG data as used in Section 4. Figs. 3(a), 3(c) and 3(e) illustrate the relationship between joint angle and MNF at the constant load, while Figs. 3(b), 3(d) and 3(f) display the relationship between joint angle and MDF at the same condition.

Three conflicting cases were found in our experiments for the effect of elbow joint angle on MNF and MDF. The results are the subject-dependent. It is similar as the three conflicting cases which were found in the effect of muscle force on MNF and MDF. In the third case or CG3, MNF (and MDF) increases as muscle length or joint angle (degrees of flexion) increases, as can be observed in Figs. 3(e) and 3(f). In future work, several related anthropometric variables obtained from the volunteers should be intended to find the possible reasons, as mentioned in Section 4.

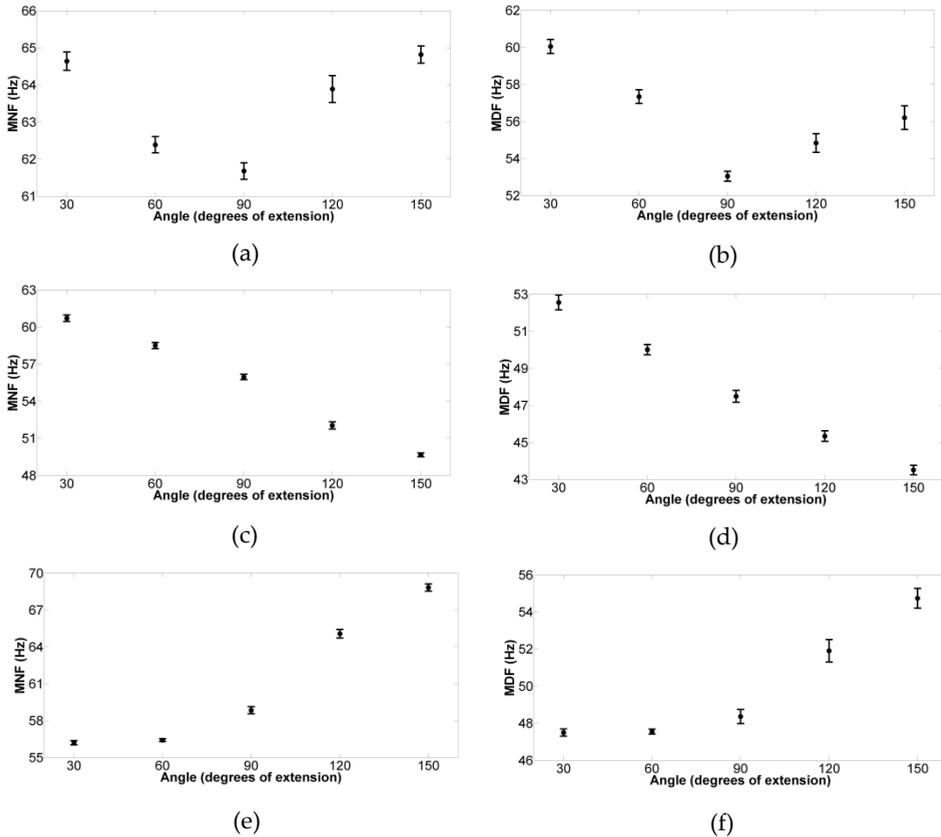


Figure 3. (a, c, e) MNF and (b, d, f) MDF of EMG signals recorded at a constant muscle force (3 kg) as a function of elbow joint angles (30-150 degrees of extension) for three subjects. (a-b) the first case in muscle geometry effect or CG1 (c-d) the second case in muscle geometry effect or CG2 (e-f) the third case in muscle geometry effect or CG3. The error bars shown are given by the standard deviation of the mean value.

In order to modify MNF and MDF to have the consistent results (the same case), a modification of traditional MNF and MDF should be done. Figs. 4(a) and 4(b) show the sample in time-domain of EMG signals measured at the same constant force level with the elbow joint angles at 30° and 150° of extension, respectively. It was found that at narrow elbow joint angles, i.e. 30° of extension, the distribution of positive and negative amplitudes is asymmetry, but at wide elbow joint angles, i.e. 150° of extension, the distribution of positive and negative amplitude is symmetry. The power spectrum of each of the samples is respectively shown in Figs. 4(c) and 4(d). Based on the observation of the distribution, if the EMG signal is normalized by setting the highest value to 1 and the lowest value to -1 for an asymmetric signal, the EMG baseline should be shifted away from the true zero line, as can be observed in Fig. 5(a). On the other hand, the EMG baseline should not be shifted away from the true zero line in the case of normalized symmetric signal, as can be observed in Fig. 5(b). Hence, the values of MNF and MDF that are calculated from the normalized EMG signals measured at

the narrow joint angles should decrease, while the values of MNF and MDF that are computed from the normalized EMG signals measured at wide joint angles should be same as the old one. It can be observed throughout Figs. 5(c) and 5(d). As a result, the consistent results should exist across the subjects (subject-independent). The consistent case is the second case. In future work, the evaluation of this finding should be done with the large EMG data set.

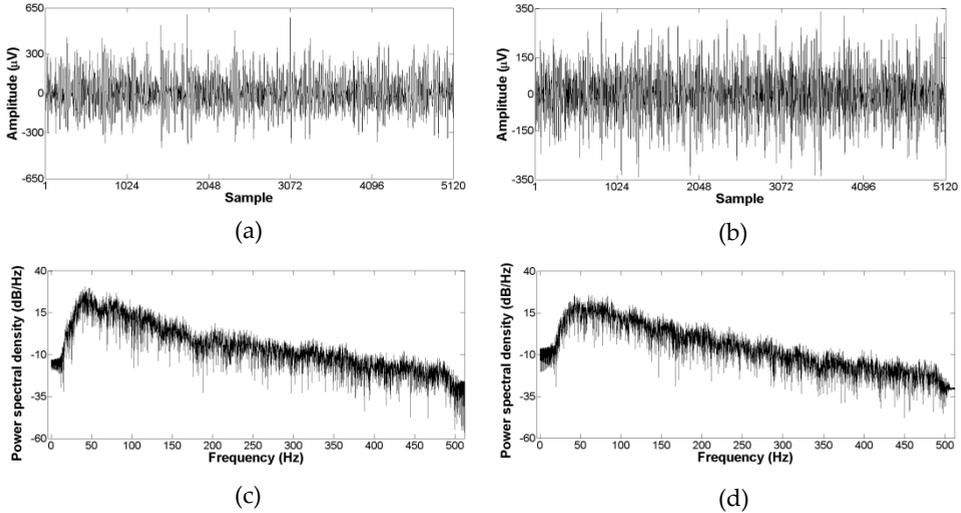


Figure 4. Samples of raw EMG signals recorded from the biceps brachii at (a) 30° and (b) 150° of extension in time-domain, and their power spectrum at (c) 30° and (d) 150° of extension. Note that a constant force (3kg) is performed for each angle.

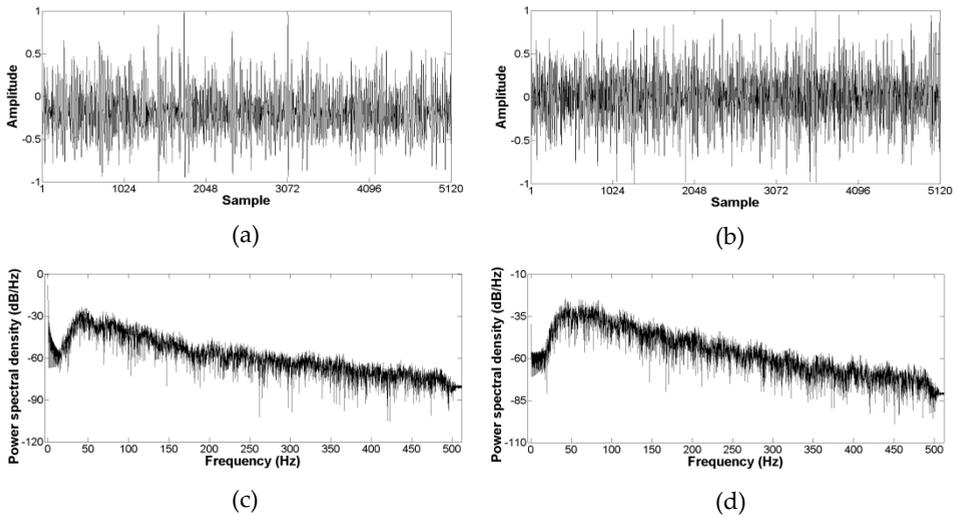


Figure 5. Samples of normalized EMG signals recorded from the biceps brachii at (a) 30° and (b) 150° of extension in time-domain, and their power spectrum at (c) 30° and (d) 150° of extension. Note that a constant force (3kg) is performed for each angle.

6. EMG pattern classification using mean and median frequencies

EMG pattern classification is applied in several potential applications, particularly in the engineering context. The multifunction myoelectric control system (MMCS) is a main engineering application (Oskoei & Hu, 2007; Zecca et al., 2002) consisting the control of prosthesis, industrial robot arms, electric wheelchairs, virtual keyboard and virtual mouse. To be successful in the classification of EMG signals, three main cascaded modules should be carefully considered: data-preprocessing, feature extraction, and classification methods, especially the selection of feature extraction methods (Boostani & Moradi, 2003; Phinyomark et al., 2012a).

Three criteria: maximum class separability, robustness and complexity, have been suggested and generally used to evaluate the EMG features for MMCS. Time-domain features have been usually used to make an optimal feature vector. However, only one feature per EMG channel is obtained from most of the frequency-domain methods (Boostani & Moradi, 2003), and their discriminant patterns in feature space are different from that of time-domain features (Phinyomark et al., 2012a). For a more powerful feature vector, an optimal frequency-domain feature should be combined with other successful time-domain features, such as the waveform length or WL (Oskoei & Hu, 2008), the RMS (Phinyomark et al., 2010), and the Willison amplitude or WAMP (Phinyomark et al., 2011).

First, the classification performance of the MNF and MDF features is discussed. Both features have the similar discriminant patterns, as can be observed from the scatter plots in Figs. 6(a) and 6(b). However, the MNF feature showed (a bit) better performance in class separation than the MDF feature. This can be confirmed by the classification accuracy obtained from the linear discriminant (LD) classifier. Mean and standard deviation of the classification accuracy obtained from MNF and MDF are $75.56 \pm 11.8\%$ and $70.54 \pm 10.4\%$, respectively (Phinyomark et al., 2012a). Such classification accuracies are computed based on the classification of six upper-limb movements (hand open or HO, hand close or HC, wrist extension or WE, wrist flexion or WF, forearm pronation or FP, and forearm supination or FS) and five EMG channels (the extensor carpi radialis longus, the extensor carpi ulnaris, the extensor digitorum communis, the flexor carpi radialis, and the biceps brachii) from twenty healthy subjects (ten men and ten women).

For other frequency-domain features, five features consisting TTP, MNP, SM1, SM2 and SM3 have the same discriminant patterns in feature space as features in time-domain i.e. the RMS and the WL (Phinyomark et al., 2012a). Therefore, these features are not recommended to be one of the optimal features due to their higher computational cost. Moreover, the discriminant pattern of PSR is an inverse case of MNF and MDF, but the classification accuracy of PSR is less than that of MNF and MDF.

On the other hand, three features consisting PKF, VCF, and FR have the different discriminant patterns by comparing with MNF, MDF, and also time-domain features. The classification accuracies obtained from the classifier of PKF and VCF are very low ($<50\%$), while the classification accuracy of FR (69.81%) is a bit less than that of MNF and MDF (Phinyomark et al., 2012a). Based on the results mentioned above, it can be concluded that MNF is an optimal frequency-domain feature for the EMG pattern classification.

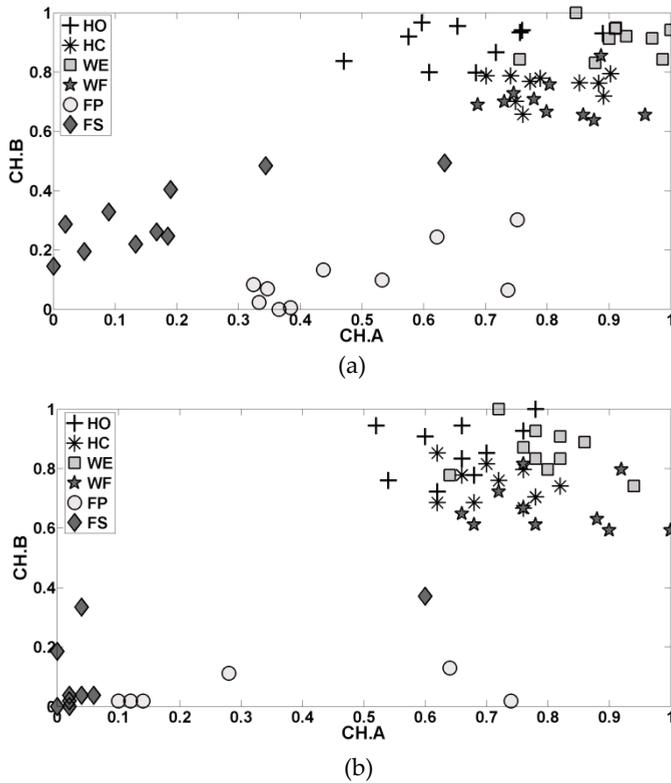


Figure 6. Scatter plots of (a) MNF and (b) MDF for 2 EMG channels (CH.A and CH.B) and 6 upper-limb movements (HO, HC, WE, WF, FP and FS) of a healthy subject. Note that CH.A is flexor carpi radialis muscle; CH.B is extensor carpi radialis longus muscle.

Further, in order to increase the robustness property of the MNF and MDF features, a modification of the MNF and MDF methods was proposed in one of our previous works (Phinyomark et al., 2009). The statistical variables (mean and median) were applied to the amplitude spectrum instead of the power spectrum, as used in the traditional methods, because the variation of the amplitude spectrum is less than that of the power spectrum. As a result, the variation of the modified MNF and MDF features is less than that of the traditional MNF and MDF features. These findings are confirmed using the real EMG data as presented in Phinyomark et al. (2009).

7. Conclusion and future trends

Mean frequency (MNF) and median frequency (MDF) are two useful and popular frequency-domain features for electromyography analysis both in clinical and engineering applications. MNF and MDF are frequently used as the gold standard tool to detect fatigue in the target muscles using EMG signals. The effectiveness of MNF and MDF under many

experimental conditions is presented and confirmed in this chapter, although the effects of muscle force and muscle geometry on MNF and MDF are inconclusive. However, the possible reasons for the conflicting results in both effects have been described and discussed in detail together with the possible techniques to make the consistent results for MNF and MDF with the both effects, as mentioned in the following.

- For the effect of muscle force, the selection of time-dependent MNF and MDF should be applied to the raw EMG data. As a result, MNF and MDF should increase as the muscle force or load increases.
- For the effect of muscle geometry or joint angle, the normalization technique should be applied to the raw EMG data. As a result, MNF and MDF should increase as the muscle length or joint angle (degrees of extension) decreases.

However, the question remains whether the conflicting results, i.e. subject dependent, are found for the effect of both muscle force and muscle geometry on MNF and MDF. To address this question, two further works should be investigated: (1) finding the correlation between related anthropometric variables obtained from the subjects and MNF (or MDF), and (2) requesting all interested information to complete all components in Tables 2 and 3, and finding the possible reasons from the complete experimental conditions.

In total, MNF and MDF features extracted from the EMG signal are the optimal variables to identify muscle fatigue, particularly for static muscle contraction. However, for dynamic muscle contraction, applying instantaneous MNF and MDF are recommended.

The recommendations above can be useful to apply for most electromyography applications, such as human-computer interaction (HCI), ergonomics, occupational therapy and sport science. In addition, applying both techniques can make the MNF and MDF features to be the universal indices than can identify all factors including muscle force, muscle geometry, and muscle fatigue.

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