

## A Review of Electromyography Signal Analysis Techniques for Musculoskeletal Disorders

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### ABSTRACT

A Social Security Organisation (SOCISO) Malaysia has reported that the incidence of work related to musculoskeletal disorders (MSDs) has been growing planetary in the manufacturing industry. MSDs are the result of repetitive, forceful or awkward movements on our body and or body parts of bones, joints, ligaments and other soft tissues. Workplace pains and strains can be serious and disabling for workers, causing pain and suffering ranging from discomfort to severe disability. To overcome this problem, electromyography is proper to use in Health Screening Program (HSP) it to monitor and diagnose the muscle's performance for their patient and know the exact localization of muscle pain. The previous researchers has been explore of several in EMG analysis techniques and features proposed in time, frequency and time-frequency domain analysis. This review of common EMG signal processing techniques is proposed by assembling from simple to complex analysis techniques to give the overview information for the other researcher. This is because; the suitable selection of a method and its features settings will ensure readability of the time-frequency representations and reliability of results. The strongest correspond with time-frequency characteristic and resolution also reducing cross term for bilinear will consider it as the optimal method.

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## 1. INTRODUCTION

### 1.1. Musculoskeletal Disorders (MSDs)

Musculoskeletal Disorders (MSDs) are widespread in the world and as the second most common cause of disability in the work setting and able to give an impact on fatigue and the productivity of the workers [1]. MSDs is involving the injuries and sicknesses that will be affected the human body's movement or musculoskeletal system as muscles, tendons, ligament, nerves, discs, blood vessel and others [2], [3]. Workplace pains and strains can be serious and disabling for workers, causing pain and suffering ranging from discomfort to severe disability because of MSDs problems [4], [5]. All of these disorders are responsible for 40-50% of the costs of all work-related diseases. Additionally, 50% of all the absences more than three days are coming from work and 49% of absences more than two weeks are caused by MSDs [6]. The impact of MSDs can be complicated and give bad effect, and overall health recovery may take a long time, extending beyond the treatment and rehabilitation phase [2]. The new term work-related

musculoskeletal disorder has fewer etiological implications where it's affecting the back, lower limbs, and especially upper limbs and neck, can be extremely costly if not addressed appropriately [1]. It is important to prevent the MSDs lower or upper limbs that would give direct and indirect effect for the individual and also productive for the company. There is a strong link between exposure to the work-related risk factors for MSD and the development of these disorders.

However, these injuries can be prevented by taking appropriate steps to eliminate or reduce the exposure to the work-related risk factors that can minimize the risk of MSDs in the workplace and then the prevention can be simple and inexpensive by often making straightforward and basic changes can reduce MSD risks significantly [7]. Social Security Organisation (SOCISO) has classified occupational diseases into hearing impairment, musculoskeletal disorder, vibration disorder, skin diseases and occupational asthma [2], [8], [9]. Statistic of industrial accidents in Malaysia recorded 57,639 cases compared to 55,186 for the previous year. Musculoskeletal disorder is one of the critical occupational injuries and disabilities. In 2006, it showed an increment of 174% from 31 to 85 cases [10]. The effect of MSDs can be progressed from mild to severe disorder [10], [11]. There has been an increasing effort in recent years to investigate the causes of MSDs and to take action to prevent them. In order to prevent low back disorders we must first understand the concept and method that able to detect the symptoms that will contribute to MSDs problem. This literature review provides new insight on the critical literature and issues that have contributed to the results of previous research to being used as the guidance for the future researcher.

These are some working related MSDs by various researches done in previous years on postures/task performed and type of analysis of MSDs. It is summarized in Table 1.

Table 1. Postures/tasks and MSDs analysis

References	Postures/Task	MSDs analysis
Starovoytova. D [7]	Awkward postures in construction activities (working overhead, kneeling, back bending forward, squatting, neck bending, reaching)	Machine-operators' Posture via Rapid-Upper-Limb-Assessment (RULA)
Zurada et al. [12]	Low Back Disorders (manual handling)	Logistic regression (LR), neural networks (NN), k-nearest neighbor (kNN), decision trees (DT), and random forest (RF)
S.K.Das et al, [13]	Medical Practitioners (low back, neck, ankle/feet, knees, upper back, shoulders, wrist/hands)	Body composition measured by bioelectrical impedance, Waist-Hip Ratio (WHR)
Hashim et al, [14]	Awkward posture among workers in aerospace industry (push-pull)	Rapid-Upper-Limb-Assessment (RULA)
Ghosh et al, [15]	Work related musculoskeletal disorders and back muscle fatigue among the goldsmiths of India (Nech, Low Back, Wrist, Shoulder)	Rapid-Upper-Limb-Assessment (RULA)
Nurhayati et al, [16]	Upper Limb and Lower Back Muscle Activity During Prolonged Sitting	Maximum Voluntary Contraction (MVC), Statistical Analysis, Independent Samples T-Test
Nur et al, [17]	Upper limb and lower back muscle activities (right and left Levator Scapulae, Upper Trapezius, Anterior Deltoid and Erector Spinae)	Maximum Voluntary Contraction (MVC), Independent Samples T-Test
Shair et al, [18]	Upper limb disorders (ULDs), Manual Lifting	Time Distribution (TD), Frequency Distribution (FD), Time-Frequency Distribution (TFD), Linear TFD (Short-Time Fourier Transform (STFT), Wavelet Transform (WT), S-Transform), Bilinear TFD (Wigner-Ville Distribution (WVD), Choi-William Distribution (CWD)
Rafie et al, [19]	Upper Extremity Musculoskeletal Disorders in Dentists	Rapid-Upper-Limb-Assessment (RULA)

### 1.2. Electromyography Signal

The measurement of muscle signal from electromyography (EMG) is able to assist SOCSO in diagnose MSDs problem from earlier. Electromyography (EMG) is the analytical study of electrical activity produced by skeletal muscles [20]. It will measure the electrical potential between the surface skins to muscle contraction that represent neuromuscular activities and easier to use in research on physiology. EMG signal can be captured by two types of electrodes which are surface (non-invasive) and intramuscular fine wire (invasive) [18], [21]. Intramuscular fine wire is used to record EMG signal from deep muscle, however, it requires needle insertion into the muscle that need clinical assistant and cause pain to the subject. On the contrary, surface EMG electrode is easy to apply and free from pain [21]. EMG signal is described by its amplitude and frequency. The signals are complicated and non-stationary signal with highly complex time and frequency characteristics [21]. The amplitude of EMG signal is normally in the range of 0-10 millivolts (peak-to-peak) or 0-1.5 millivolts (root mean square) and the frequency is from 0- 500 Hz.

### 1.3. Signal filtering

Signal filtering is an important process that removes some unwanted components of features of the signal. The correct filter setting will significantly improve the visibility of a defect signal, incorrect setting of filter will distort the signal presentation then defect the signal completely. Generally, a filter will limit the frequency spectrum of recorded signal which are normally comprised of low frequency component and remove high pass filter. Most of the studies used frequency 1000 Hz and 2000 Hz [21]. Table 2 is shows the lists of sampling frequency, type of filter and bandwidth frequencies of previous researches for a few years.

Table 2. Sampling frequency, type of filter and bandwidth

References	Types of filter	Sampling frequency, fs (Hz)	Bandwidth (Hz)
Karthick et al, [22]	Butterworth filter	10000	10-400
Amanda et al, [23]	Bandstop filter	1000	0-500
Gurmanik et al, [24]	Bandpass filter/ low pass	20k/8000	3000-10k
Edward et al, [25]	Bandpass filter	4096	10-2000
Wang et al, [26]	Bandpass filter	1000	10-500
Isa. H et al, [27]	Bandpass filter	1000	85-500
E. Gokgoz et al, [28]	High and low pass filters	2000	2-10k
E. Shair et al, [29]	Low pass filter	1500	20-500
L. Estrada et al., [30]	Low pass filter	2000	50-300

Electromyography (EMG) is the analytical study of electrical activity produced by skeletal muscles [20]. By applying EMG electrodes to capture the data, it is able to provide detailed muscle's information that involve in musculoskeletal disorder, thus, will help SOCSO to identify the exact problem for their patient. The measurement of muscle signal as electromyography (EMG) is able to assist SOCSO for diagnoses MSDs problems.

## 2. SURFACE EMG SIGNAL ANALYSIS

Digital signal processing or signal processing is concerning the extraction of features and information from measured raw signals. It has been used in many applications such as radar, communication and multimedia, medical imaging, speech generation and recognition, and data compression. EMG signal is acquired from the muscles that required advanced methods for detection, decomposition, processing, and classification of the signal [31]. Time-frequency representation has received considerable attention as a powerful high resolution and precision tool for analysing a variety of bio-signals and system such as ECG, EEG and EMG.

There are several parts of signal processing techniques to analyse the EMG signal. EMG signal is one of the biosignal which are the critical part of biomedical engineering to be processed and classify the signal's information [18]. Surface EMG signals can be processed in three domains, which are time domain, frequency domain and time-frequency domain. The differentiation of the signal will decided what type of domain suitable and efficient to use for the signals. The mathematical functions in the time domain and frequency domain are usually used as a dimensionality reduction method for time-frequency domain features [21].

**2.1. Time domain features**

Time domain information is obtained from raw signal in time representation. The extraction of features is usually quick and easy to be implemented because it involves simple mathematical properties and do not need any transformation based on raw EMG in time information. In has widely used on both medical and engineering research and practices due to their low computational complexity and the low noise environment, however, this method has the major disadvantage of features EMG signal which comes from non-stationary signal with changing in statistical properties over time, but the time domain assumes the data in stationary signal [21], [32]. Table 3 shows the common extracted features for EMG signal analysis in time domain information.

Table 3. Common features extract of EMG signal in time domain

Features	Function	Mathematical Equation
Integrated EMG (IEMG)	<ul style="list-style-type: none"> <li>Normally used as onset detection in EMG non-pattern recognition [32]</li> <li>Fatigue features [35]</li> </ul>	$IEMG = \sum_{n=1}^N  X_n $
Root Mean Square (RMS)	<ul style="list-style-type: none"> <li>It is modelled as amplitude modulated Gaussian random process who is related to content force and non-fatigue contraction.</li> <li>Similar to standard deviation method [35]</li> <li>Fatigue features [21], [36]</li> </ul>	$RMS = \sqrt{\frac{1}{N} \sum_{n=1}^N (X(n)^2)}$
Mean Absolute Value (MAV)	<ul style="list-style-type: none"> <li>Detection of the surface EMG signal for the prosthetic limb control</li> <li>Fatigue features [37]</li> <li>Providing energy information</li> </ul>	$MAV = \frac{1}{N} \sum_{n=1}^N  x(n) $
Zero crossing	<ul style="list-style-type: none"> <li>Measurement of frequency information of EMG</li> <li>Fatigue features [38]</li> </ul>	$ZC = \sum_{n=1}^{N-1} [sgn(X_n \times X_{n+1}) \cap  X_n - X_{n+1}  \geq threshold]$ ; $sgn(X) = \begin{cases} 1, & \text{if } X \geq threshold \\ 0, & \text{otherwise} \end{cases}$
v- Order	<ul style="list-style-type: none"> <li>Implicitly estimates muscle contraction force, <math>m_i</math> [32]</li> <li>Fatigue features [39]</li> </ul>	$X_n = (\gamma m_n^a) x_n$ $V = \left( \frac{1}{N} \sum_{n=1}^N X_n^v \right)^{\frac{1}{v}}$
Log detector	<ul style="list-style-type: none"> <li>Provide an estimate muscle contraction force [32]</li> <li>Fatigue features [40]</li> </ul>	$LOG = e^{\frac{1}{N} \sum_{n=1}^N \log( X_n )}$
Waveform Length (WL)	<ul style="list-style-type: none"> <li>Measure complexity of EMG signal</li> <li>Fatigue features [41]</li> <li>Have less computational complexity</li> </ul>	$WL = \sum_{n=1}^{N-1}  X_{n+1} - X_n $
Willison Amplitude (WAMP)	<ul style="list-style-type: none"> <li>Measurement of frequency information about EMG [32]</li> <li>Fatigue features [42]</li> </ul>	$WAMP = \sum_{n=1}^{N-1} [f( X_n - X_{n+1} )]$ ; $f(x) = \begin{cases} 1, & \text{if } n \geq threshold \\ 0, & \text{otherwise} \end{cases}$
Slope sign change (SSC)	<ul style="list-style-type: none"> <li>To represent frequency information of EMG signal [32]</li> <li>One of fatigue features extract parameters [43]</li> </ul>	$SSC = \sum_{n=2}^{N-1} [f[(X_n - X_{n-1}) \times (X_n - X_{n-1})]]$ ; $f(x) = \begin{cases} 1, & \text{if } n \geq threshold \\ 0, & \text{otherwise} \end{cases}$

**2.2. Frequency domain features**

The raw signal in time domain should undergo Fourier transform to change from time to frequency domain [46]. Power spectral density (PSD) becomes a major analysis in frequency domain [34]. Most of the signals have to change from time to frequency information for the signal being analysed [35]. Fourier analysis is one of the most widely used tools in signal processing [45], [46]. It is mainly used to extract the characteristic of frequency and good in computation and implementation point of view by permission to get

the better results [47], [48]. The Fourier transform is represented in terms of the power spectrum and it is defined as [44]:

$$X(f) = F\{x(t)\} = \int_{-\infty}^{\infty} x(t)e^{-j\pi ft} dt \tag{1}$$

where  $x(t)$  is the time domain signal,  $X(f)$  is the FFT, and  $ft$  is the frequency to analyse. However, there are some of limitation Fourier transform, when have changing in power spectrum that indicate muscle fatigue, the power spectral density (PSD) increases in low component and decreased in high component [21]. Two common and generally features used in PSD is mean frequency (MNF) and median frequency (MDF) to determine muscle fatigue. However, these techniques have the limitation to cater EMG signal behaviour with successfully since it requires a stationary signal for the accurate results [32]. Table 4 indicates the common features proposed in frequency domain information.

Table 4. Common features extract from EMG signal in the frequency domain

Features	Function	Mathematical Equation
Mean Frequency (MNF)	<ul style="list-style-type: none"> <li>It is able to indicate muscle fatigue during cyclic dynamics [21], [32]</li> <li>MNF decrease with increasing force levels</li> <li>Universal indices that can detect both muscle force and muscle fatigue [47], [49]</li> </ul>	$MNF = \frac{\sum_{j=1}^M f_j P_j}{\sum_{j=1}^M P_j}$ <p><math>f_j</math> is frequency of the spectrum at frequency bin <math>j</math>, <math>P_j</math> is the EMG power spectrum at frequency bin <math>j</math>, and <math>M</math> is the length of the frequency bin</p>
Median Frequency (MDF)	<ul style="list-style-type: none"> <li>It is able to indicate muscle fatigue during cyclic dynamics [21], [32]</li> <li>MDF decrease with increasing force levels</li> <li>Universal indices that can detect both muscle force and muscle fatigue [50]</li> <li>Fatigue features [51]</li> </ul>	$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^M P_j = \frac{1}{2} \sum_{j=1}^M P_j$ <p>spectrum is divided into two regions with equal amplitude</p>
Peak Frequency (PKF)	<ul style="list-style-type: none"> <li>Frequency at which the maximum power occurs [32]</li> <li>Fatigue features [52]</li> </ul>	$PKF = \max (P_j), j= 1, \dots, M$
Mean Power (MNP)	<ul style="list-style-type: none"> <li>Average power of EMG power spectrum [32]</li> <li>Fatigue features [52]</li> </ul>	$MNP = \frac{\sum_{j=1}^M P_j}{M}$
Total Power (TTP)	<ul style="list-style-type: none"> <li>Aggregate of the EMG power spectrum [32]</li> <li>Fatigue features [52]</li> </ul>	$TTP = \sum_{j=1}^M P_j = SM0$ <p>where <math>SM0</math> is zero spectral moment</p>
The 1st, 2nd, and 3rd Spectral moments	<ul style="list-style-type: none"> <li>Spectral moment is an alternative statistical analysis way to extract features from the EMG power spectrum [32]</li> <li>Fatigue features [53]</li> </ul>	<p>First three moment- most important spectral moment</p> $SM 1 = \sum_{j=1}^M P_j f_j$ $SM 2 = \sum_{j=1}^M P_j f_j^2$ $SM 3 = \sum_{j=1}^M P_j f_j^3$
Frequency Ratio (FR)	<ul style="list-style-type: none"> <li>Distinguish between contraction and relaxation (between the low frequency components and the high frequency components of) [32]</li> </ul>	$FR = \frac{\sum_{j=LLC}^{ULC} P_j}{\sum_{j=LHC}^{UHC} P_j}$ <p>ULC and LLC are upper- and lower-cutoff of low frequency band UHC and LHC are upper- and lower-cutoff of high frequency band</p>
Power spectrum ratio (PSR)	<ul style="list-style-type: none"> <li>Ratio between the energy <math>P_0</math> (nearby the maximum value of EMG power spectrum and the energy <math>P</math> is the whole energy of the EMG power spectrum [32]</li> </ul>	$PSR = \frac{P_0}{P} = \frac{\sum_{j=f_0-n}^{f_0+n} P_j}{\sum_{j=-\infty}^{\infty} P_j}$ <p><math>f_0</math> is a feature value of the PKF and <math>n</math> is the integral limit</p>
Variance of central frequency (VCF)	<ul style="list-style-type: none"> <li>One of an important characteristic of the PSD [32]</li> </ul>	$VCF = \frac{1}{SM0} \sum_{j=1}^M P_j (f_j - f_c)^2 = \frac{SM2}{SM0} - \left(\frac{SM1}{SM0}\right)^2$

**2.3. Time-frequency domain**

In signal processing, time-frequency distributions are powerful and accurate techniques that represent a signal in jointly time and frequency representation [32], [55]. In an analysis of the signals, TFR is widely used in modifying and synthesizing of non-stationary signals because it provides time and frequency information for the signals. For that reason, the time-frequency distributions (TFDs) are appropriate to analyse EMG signals that consist of non-stationary and multi-frequency components signal [32]. TFDs are broadly classified into two categories which are linear and bilinear TFD. Table 5 shows the several of mathematical equation for time-frequency analysis method from linear and bilinear TFD.

Table 5. Time-frequency signal processing method

Method	Mathematical Equation
Gabor	$C(n, k) = \int_{-\infty}^{\infty} x(\tau)h * (n, k) d\tau$
Spectrogram	$S_x(t, f) = \left  \int_{-\infty}^{\infty} h(\tau)w(\tau - t)e^{-j2\pi f\tau} d\tau \right ^2$
Wavelet	$CWT(t, a) = \int_{-\infty}^{\infty} x(\tau) \frac{1}{\sqrt{ a }} \Psi * \left( \frac{\tau - t}{a} \right) d\tau$
S-Transform	$S(\tau, f) = \int_{-\infty}^{\infty} h(t) \frac{ f }{\sqrt{2\pi}} e^{-(\tau-t)^2 f^2 / 2} e^{-j2\pi f t} dt$
Wigner-Ville distribution (WVD)	$WVD_x(t, f) = \frac{1}{2\pi} \int x\left(t + \frac{\tau}{2}\right) x^*\left(t - \frac{\tau}{2}\right) e^{-2\pi f \tau} d\tau$
Choi-Williams distribution (CWD)	$CWD_x(t, f) = \iint \frac{1}{\sqrt{\frac{4\pi\tau^2}{\sigma}}} e^{\left(-\frac{(\mu - t)}{4\tau^2}\right)} x\left(\mu + \frac{\tau}{2}\right) x^*\left(\mu + \frac{\tau}{2}\right) e^{-2\pi f t} dt$

**2.3.1 Linear Time-Frequency Distribution (TFD)**

Linear TFD is more basic form compared to bilinear TFD. The common techniques used are Gabor, Short-time Fourier Transform (STFT), Spectrogram, wavelet transform (WT) and S-Transform [32].

a) Gabor

Dennis Gabor, a British physicist, suggested expanding a signal into a set of functions that are concentrated in both the time and frequency domains, and then use the coefficients as the description of the signal’s local property [56] Gabor transform is defined as:

$$C(n, k) = \int_{-\infty}^{\infty} x(\tau)h * (n, k) d\tau \tag{2}$$

where  $x(t)$  is the signal under analysis and  $h(n,k)$  is the set of elementary function and is defined as:

$$h(n, k) = w(\tau - nT_w)e^{-j2\pi k f_0 \tau} \tag{3}$$

where  $w(t)$  is the observation window.  $T_w$  and  $f_0$  are the time and frequency sampling interval that must satisfy the Heisenberg uncertainty relation [55], [56].

$$T_w f_0 \geq \frac{1}{4\pi} \tag{4}$$

b) Spectrogram

Spectrogram provides a distribution of energy signal in time-frequency distribution (TFR) which is represented in three-dimensional of the signal energy with respect to time and frequency [57]. The optimum frequency is useful for extracting features of any signals for further analysis, including Electromyography (EMG) signals [58]. This technique is roughly reflected how frequency content changes over the time. Smaller size window produces better time resolution, but reduces frequency resolution [59]-[61]. The chosen window width has been maintained and gives fixed frequency and time resolution for all frequencies [44].

The equation of spectrogram is as Equation 5.

$$S_x(t, f) = \left| \int_{-\infty}^{\infty} h(\tau) w(\tau - t) e^{-j2\pi f \tau} d\tau \right|^2 \quad (5)$$

where  $h(\tau)$  is the input signal and  $w(t)$  is the window observation window. In this study, Hanning window is selected because of its lower peak side slope which is narrow effect to provide higher accuracy on other frequencies around fundamental value and other frequency components.

#### c) Wavelet Transform (WT)

Wavelet transform (WT) is one of the efficient mathematical tools for local analysis of non-stationary and fast-transient signals. WT is another linear TFD technique that was explored widely in various researches as an alternative to STFT [62]. This method has improved to reveal the information that the signal contains both in time and in frequency to analyse the non-stationary signals [59]. WT functions by shifting and spreading the mother wavelet [63]. The WT offers high time resolution for high frequency component and high frequency resolution for low frequency component such as transient [64], [65]. The estimation provided by WT is better accuracy and precision of simulated data set [32]. However, WT is incapable to give an accurate result under noise condition [66]. This technique successful to use for EMG, but it is not capable to give the information with effectively. This is because EMG signal acquire noise while travelling through different tissue in the human body [31]. But, it is different with continuous wavelet transform (CWT) that able to show better performing in extracting indices in time-frequency domain [32]. In analysis, it's able to give comparable fatigue estimates in isometrics and dynamic contractions.

$$CWT(t, a) = \int_{-\infty}^{\infty} x(\tau) \frac{1}{\sqrt{|a|}} \Psi * \left( \frac{\tau-t}{a} \right) d\tau \quad (6)$$

where  $t$  is translation,  $a$  as scale parameter and  $\Psi$  is the mother wavelet.

#### d) S-transform

S-transform is a TFR that known for its local spectral phase properties where it is an extension ideas of WT and STFT [66]. In S-transform techniques, the frequency-dependent window allows for a frequency-dependent resolution with narrower windows at higher frequencies and wider windows at lower frequencies [67]. It uniquely combines a frequency-dependent resolution that simultaneously localizes the real and imaginary spectra.

The S-transform technique was used in many applications such as Geophysics, Biomedical Engineering, power transformer protection, power quality analysis, oceanography, atmospheric physics, medicine, hydrogeology and mechanical engineering [68]. The advantages of S-transform are scalability and very low sensitivity to noise levels [69]. The features extracted from the S-transform are simple and very effective [68], [79]. Moreover, this technique provides multiresolution analysis while retaining the absolute phase of each frequency [68], [71]. In addition, the S-transform has other disadvantages such as its accuracy depends on the chosen size of the windows, sensitivity to noise and it requires higher complexity computation [72]. The mathematical formula for S-Transform is expressed as follows:

$$S(\tau, f) = \int_{-\infty}^{\infty} h(t) \frac{|f|}{\sqrt{2\pi}} e^{-(\tau-t)^2 f^2 / 2} e^{-j2\pi f t} dt \quad (7)$$

where  $h(t)$  is the signal and  $g(\tau)$  is a window function. Windows function is a modulated Gaussian function expressed by:

$$g(\tau) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(t^2 j2\pi f t)} dt, \quad \sigma = \frac{1}{|f|} \quad (8)$$

### 2.3.2 Bilinear Time-Frequency Distribution (TFD)

Unlike linear time-frequency transforms, the signal appears twice in bilinear time-frequency transforms, so called bilinear transform. Bilinear TFD could perform better than the linear TFD due to the fact that it does not suffer for the smearing effects cause by windowing function. However, bilinear TFD suffers the cross term effects or artifacts which present in the midway between the actual frequency components of multicomponent signals [22], [73]. Wigner-Ville distribution (WVD), and Choi-Williams distribution (CWD) are some of the time-frequency approaches from bilinear TFD that is used for EMG signal processing [31]. That is the reason this paper is the focus of this type's of bilinear method

## a) Wigner-Ville distribution (WVD)

Wigner-Ville distribution (WVD) has attracted much attention from other bilinear TFD because of its several desirable mathematical properties such as preserving time and frequency marginals and shifts. It offers a high frequency resolution, but still creates spurious frequency information or cross-terms interferences when it is applied to multi-component signals [74]. The joint density spectrum produced by WVD able to display very good localization properties. It generally concentrated around the instantaneous frequency of the signal, but it is very noisy [31]. Furthermore, it also has the disadvantage which is not a precise representation of the changing of frequency components with fatigue. Equation (9) shows the formula for WVD as follows.

$$WVD_x(t, f) = \frac{1}{2\pi} \int x\left(t + \frac{\tau}{2}\right) x^*\left(t - \frac{\tau}{2}\right) e^{-2\pi f\tau} d\tau \quad (9)$$

where  $\int x\left(t + \frac{\tau}{2}\right) x^*\left(t - \frac{\tau}{2}\right)$  is the instantaneous autocorrelation function and  $*$  is the conjugate operation.

## b) Choi-Williams distribution (CWD)

Choi-Williams distribution (CWD) is time-frequency spectrum of a discrete time signal which is sampled at sampling frequency that can obtained by the square modulus of its short-time Fourier transform with the time window [76], [77]. This technique is able to avoid one of the main problems of WVD which is reducing interference [18] and it is said as the most accurately show the frequency compression [74]. CWD does not suffer from this problem, but it creates lower resolution and an increase in the computational resources [78]. Besides that, it is not satisfying all the desired properties for a time frequency distribution [31]. The formula for CWD is definitely as Equation (10).

$$CWD_x(t, f) = \iint \frac{1}{\sqrt{\frac{4\pi\tau^2}{\sigma}}} e^{\left(-\frac{(\mu-t)}{\frac{4\tau^2}{\sigma}}\right)} x\left(\mu + \frac{\tau}{2}\right) x^*\left(\mu - \frac{\tau}{2}\right) e^{-2\pi f\tau} dt \quad (10)$$

where  $x$  is the input signal value,  $x^*$  is the complex conjugate of  $x$ .

### 3. CONCLUSION

The review of the relation function of EMG on musculoskeletal disorder (MSDs) is shown and the used of surface EMG to access the features and characteristic of the signal was reviewed. The purpose of this paper is to provide the details of information of surface Electromyography for the analysis of MSDs on the methodologies used for detecting and processing the EMG signal. In an analysis of EMG signals, one of the most important processes is to extract the suitable features that will affect the developed application of the chosen technique. There are some other techniques have been used in the analysis, however, the common techniques of analysis is selected to be explored and the features of time domain, frequency domain and time-frequency domain have been extracted from the analysis of EMG signal in order to diagnose and localise the exact problem of the muscles that will contribute to MSDs problems.

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