Identification of Femoral-Acetabular Symptoms using sEMG Signals during Dynamic Contraction

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Keywords: Discrete Wavelet Transformation, DWT, EMG Signal Analysis, FAI, Hip Muscles, Non-Stationary Signal, Signal Decomposition, Wavelet Decomposition.

Abstract: This paper focuses on development of an algorithm that automatically differentiates a Femoro-Acetabular Impingement (FAI) patient from a healthy control person by comparing their surface electromyography (sEMG) signal recorded from Gluteus Maximus (GMax), Tensor Fasciae Latae (TFL), and Rectus Femoris (RF) muscles in the hip area. A discrete wavelet transform (DWT) method was used to analyse sEMG signals by thirty-eight different wavelet functions (WFs) with 5 decomposition levels of dynamic contractions during the three phases (descending, stationary, and ascending) of a squat task. The Bior3.9 WF was selected as it provided higher amount of energy for most of the subjects and then the wavelet power spectrum was computed for healthy control and FAI groups. The results show that the RF muscle is more active in the ascending phase than the descending phase for FAI subjects, whereas it is more active in the descending phase for healthy control. An independent sample t-test was used to check the activities of muscle in both groups. The results demonstrate no significant difference for GMax (p=0.7477) and TFL (p=0.4997) muscles, while there is a significant difference for RF muscle (p=0.0670).

1 INTRODUCTION

Femoro-Acetabular Impingement (FAI) is a pathological condition in which the femoral head and acetabular socket interact abnormally in the hip joint (Myers, 1999). This abnormality reduces range of motion and ability in patients (Keogh, 2008). In young and active adults with FAI, the pain is usually in the groin area (Samora, 2011). Hip bone abnormalities can damage soft tissue structures and limit the patients' motion. Useful information can be obtained from the muscles and such information has clinical and engineering applications by measuring Electromyography (EMG) signals. EMG is a biomedical signal that provides a great source of information to clinicians and researchers by measuring the electrical currents generated in muscles during contraction (Reaz, 2006). The physiological and anatomical properties of muscles can influence on the nervous system that controls the EMG signal (Ahmed, 2009).

We propose an algorithm to discriminate a FAI patient from a healthy person by comparing their EMG signal recorded from hip muscles. The proposed algorithm will produce a way to diagnose FAI based on muscle activities, which can be a complement to MRI and x-ray methods.

1.1 Background

An EMG signal recorded from muscles requires advanced methods for detection, decomposition, processing, and classification. To use the EMG signal for diagnosis, a feature needs to be extracted before it can be analysed or classified. This is due to the fact that the raw EMG signal includes both useful information and noise. EMG features can be computed in various domains such as time, frequency, time-frequency, and time-scale domains. Analysis of EMG data requires rectification and integration of signals or root mean square values to extract information related to the amplitude of the signal, which deals with the time domain representation. However, the frequency content of EMG is analysed using Fourier Transform (FT) that is a unidimensional technique (Karlsson, 2001). Traditional techniques for analysing surface EMG signal are based on the FT method. The accuracy and

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reliability of this technique depends on the data lengths' and the signal requires to be stationary. Moreover, a signal can be stationary or non-stationary. If a signal is stationary, its properties are statistically invariant over time; however the transient events cannot be predicted in non-stationary signals. The EMG signal is a non-stationary signal. Furthermore, time-frequency methods that are appropriate for non-stationary signal are used instead of frequency methods to improve the EMG analysis (Karlsson, 2001). Thus, for analysing EMG signals in both time and frequency, the short-term Fourier transforms (STFT) or wavelets can be used. The former of the EMG signals usually has three steps: recording the EMG signals, decomposition of signals by signal processing techniques, and classification of signals for diagnostic purpose.

In daily life activities or movements, subjects perform more dynamic contractions instead of isometric contractions. Moreover, in the field of rehabilitation medicine, sports medicine, and etc., tasks similar to daily activities are performed. During dynamic conditions, number of active motor units, active muscle fibres, electrode geometry, muscle fibre lengths, and innervation zone geometry changes. These factors emphasize that the ME signals are non-stationary. Therefore, time-frequency methods have been introduced for the analysis of non-stationary signals. These time-frequency representation methods are: STFT, Wigner-Ville distribution (WVD), Choi-Williams Distribution (CWD), and wavelet transform (WT) that were compared with recent studies for accuracy and precision to analyse the ME signals (Karlsson, 2000 and 2001). A time-frequency analysis based on wavelets (Meyer, 1993), which is introduced recently, is an appropriate tool to overcome the limitations of the traditional time-frequency methods. Karlsson introduced the wavelet transform as a “mathematical microscope” that help observe various parts of the signal by setting the focus (Karlsson, 2000 and 2001). The WT has some advantages over the other time-frequency methods. WT uses short window for high frequencies and long window for low frequencies, although the STFT uses a single analysis window for all frequencies (Rioul, 1991). Furthermore, the WT can be used to analyse both stationary and non-stationary signals in both time and frequency domain. The WT is classified into continuous wavelet transforms (CWT) and discrete wavelet transforms (DWT). The wavelet transform requires the selection of a mother wavelet depending on the application. Wavelets are defined by the scaling function (also called father wavelet) and wavelet function (or the mother wavelet). The scale function in WT determines wavelet dilation and compression of the various wavelets from a mother wavelet. Furthermore, the optimization of the WT is related to the scale function, which is used for a specific signal.

The ability of DWT to extract features from the signal is dependent on choosing an appropriate mother wavelet function. The common standard families of wavelet basis functions are Haar, Daubechies (db1 to db10), Coiflet (coif1 to coif5), Symmlet (sym2 to sym8), Morlet, and Mexican Hat. Although there is not a specific rule for selecting a wavelet basis function, some features of wavelets cause a specific mother wavelet to be more appropriate for a particular application and signal type. According to Santoso et al. (Santoso, 1994) state, for slow transient disturbances db8 and db10 wavelets were the best choice, whereas for short and fast transient disturbances db4 and db6 were more proper. Also, Walker (Walker, 1999) presented general guidelines for selecting a wavelet such that db4 was more appropriate for feature extraction and coiflet6 provided better data compression results. In order to select a more accurate wavelet function, it is significant that the characteristic of signal should be matched with the properties of the wavelet function.

For applying WT to the EMG signal various mother wavelets and scale functions can be used although no agreement has been reached regarding the selection of the mother wavelet and the scale function. For example, Karlsson et al. (Karlsson, 1999) used a Morlet mother wavelet with a linear scale function (Karlsson, 1999, 2000, 2003) and Neto et al. (Neto, 2007) applied Morlet with exponential function. Von Tscharnar (Von Tscharnar, 2000), used Cauchy mother wavelets with polynomial function. Hostens et al. (Hostens, 2004) and Beck et al. (Beck, 2005) applied Daubechies mother wavelets to the EMG signal with different scale functions. Hostens et al. (Hostens, 2004), used a linear scale function while Beck et al. (Beck, 2005) used a dyadic function.

The WT of the EMG signal has been used in several studies related to muscle fatigue, EMG signal processing, and muscle strength. Moreover, Neto et al. (Neto, 2007, 2008), and Von Tscharner et al. (Von Tscharnar, 2000, 2002, 2003, 2006), used the WT for the EMG signals that were recorded during the sports.

Flanders (Flanders, 2002) used DWT to identify the time of occurrence of EMG bursts. They chose wavelet db2 and focused on the coefficient at an intermediate scale (D3) because by plotting the peak-to-peak range of the db2 weighting coefficient values of several muscles, the D3 component had the largest peak weighting coefficients based on their research.

Thus, Flanders demonstrated that the simplest wavelet such as db2 was suitable for recognizing multiunit EMG bursts. Moreover, Kilby and Gholam Hosseini (Kilby, 2004) also used mother wavelet that had a different set of families to extract detailed features of the sEMG signals. They used mother wavelets that were available in LabVIEW® to decompose the sEMG signals and reconstruct the signal back. The reconstructed signals were subtracted from the original signals in order to calculate the errors to achieve statistical analysis. Based on different errors of the various families of the mother wavelets, they concluded the Daubechies (db5) was the most appropriate mother wavelet for analysing sEMG signals. However, they did not consider several mother wavelets such as Morlet, Meyer, and Mexican Hat because these mother wavelets were not available by the software. Ahmed et al. (Ahmed, 2009) illustrated a comparative study of decomposing sEMG signals by using different types of wavelets. Their goal was to choose a wavelet based on the best possible energy localization in the time-scale plane. In their algorithm, they decomposed a signal using DWT for various wavelets and the energy localization in time-scale plane was calculated. From their results, db4, db5, and db6 were shown to have the best energy localization compare to other wavelets for normal and healthy muscle EMG signal.

2 METHODOLOGY

The EMG data of Gluteus Maximus (GMax), Tensor Fasciae Latae (TFL), and Rectus Femoris (RF) muscles were recorded from 30 subjects during dynamic contraction of a squat task (Fig. 1).

Figure 1: Descending, Stationary, and Ascending Phase of Squat (Lamontagne, 2009).

During the squat, subjects were required to stand with feet shoulder-width apart, parallel to one another. Both arms were anteriorly extended, and heels were in contact with the floor during the entire squat. EMG signals were recorded during squat cycles, thus each recorded signal was divided into three regions based on squat phases (Descending, Stationary, and Ascending phase). Five repetitions of the same movement were executed (Lamontagne, 2009) The recorded sEMG signals formed two groups: control (15 males and 1 female) and FAI (11 males and 3 females). Participant characteristics are indicated in Table 1.

Table 1: Participant characteristics by group.

Group	Gender	Weight (Kg)	Height (cm)
Control (CON)			
1	M	104.591	191.2
2	M	132.009	179
5	M	113.527	176
6	F	97.245	152
7	M	120.189	180.5
10	M	93.078	175.5
11	M	83.666	180.5
12	M	87.466	168
15	M	117.896	177.5
17	M	83.551	178
19	M	83.311	181
20	M	106.529	183
22	M	82.646	177
23	M	147.725	176
24	M	61.129	160.5
25	M	79.526	175.5
FAI (OR)			
3	M	129.012	183.75
4	M	83.035	168
8	M	139.491	186
9	M	133.394	176.5
13	M	126.997	174.2
14	M	101.154	175
16	M	108.719	175
18	M	149.428	176
21	F	97.508	163
26	M	64.312	167
27	M	136.712	167
28	M	120.632	175
29	F	132.507	168.5
30	F	59.766	167

The sampling frequency of the signal was 1000Hz. The DC offset was removed from the raw EMG signals. In order to be able to compare the EMG activity in the same muscle on different subjects, the signals have to be normalized. Normalization of EMG signals were performed by dividing EMG signals during a squat task to a reference EMG value achieved from the same muscle of the same subject. We utilized the Maximum Voluntary Isometric Contraction (MVIC) method for normalization. To measure the MVIC the participants were asked to lie down on a testing bench, which was provided with support beams and adjustable straps to limit the movement of the limbs and hold it in place during isometric contraction. The MVIC data were collected

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for duration of 5 seconds for each muscle. MVICs for GMax and RF muscles were measured when the participants' leg was straight, and they were asked to push upwards against the Hand-Held Dynamometer (HHD). Moreover, MVIC for TFL muscle was collected when the participants were asked to push diagonally against the HHD. After normalization, EMG signals were full-rectified meaning that the absolute value of the signal was used. The rectified signals were passed through a 5th-order low-pass Butterworth filter with cut off frequency of 10Hz. This process provided the linear envelope of signals. Furthermore, the filtered signals were amplitude-normalized to the peak MVIC EMG (nEMG) and then integrated to produce the integrated EMG (IEMG) values.

2.1 EMG Analysis using Wavelet Transforms

Data analysis was performed using the MATLAB programming language with the signal processing and Wavelet toolboxes (The Math Works, INC.). The EMG values were recorded from GMax, TFL, and RF muscles of the affected sides of the 30 subjects. There were 5 repetitions for every subject with sampling frequency of 1000Hz. The number of samples in each EMG data set was very large, so EMG signals were pre-processed by using the wavelet transform.

The analysis of the data commenced by removing any DC offset in order to be ready for the wavelet families' analysis. The wavelet analysis was performed by a function called mother wavelet. There are different families or set of mother wavelets in the Wavelet method which differ in their mathematical principles named as Haar, Daubechies (db1 to db10), Symlets (sym2 to 8), Coiflets (coif1 to 5), Biorthogonal (bior1.1 to 6.8), Reverse biorthogonal (rbio1.1 to 6.8), Meyer (meyr), Discrete approximation of Meyer (dmey), Gaussian (gaus1 to 8), Mexican hat (mexh), and Morlet (morl). EMG signals were decomposed using DWT with various wavelet functions (WFs). We used discrete wavelet, which allowed us to decompose our EMG signals based on Haar, Daubechies (db1 to db10), Symlets (sym2 to 8), Coiflets (coif1 to 5), Biorthogonal (bior1.1 to 6.8), and discrete approximation of Meyer (dmey) mother wavelets. Moreover, MATLAB code was written to apply a DWT to the EMG signals. The WT decomposes a signal into several multi-resolution (levels) components based on basis functions or WFs. These WFs are achieved by dilation, contraction, and shifts of a unique function. Decomposition of the signal into basis of wavelet functions implies the computation of the inner products between the signal and the basis function, leading to a set of coefficients called wavelet coefficients.

The maximum level to apply the wavelet transform depends on how many data points are contained within our data set, while there is a down-sampling by 2 operations from one level to the next level. We used 5 levels of decomposition. Thirty eight different wavelet functions exerted at decomposition level 1 to 5. The wavelet coefficients from each wavelet function were used to calculate the energy of the sEMG signals for each subject in each phase.

2.2 Wavelet Selection based on Energy Calculation

The wavelet energy was computed for approximation (Ea) and detail (Ed) coefficients. Ea is the percentage of energy corresponding to the approximation and Ed is the vector containing the percentage of energy corresponding to the details. Ed for each sEMG signal was collected after using 38 wavelet functions and the highest five energies were highlighted for each subject in three phases. Then, the highest repetition wavelet function was chosen as our wavelet function. This procedure is indicated in Fig 2.

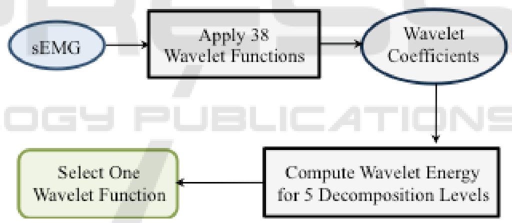

Figure 2: Procedure of Selecting a WF.

2.3 Wavelet Power Spectrum

The wavelet power spectrum is a way to determine the distribution of energy along the sEMG signal. Wavelet coefficients of the selected wavelet function were computed and the power spectrum was measured during 5 levels of decomposition. The distribution of power for each muscle during descending, stationary, and ascending phase for both CON and OR groups was determined. Fig. 3 shows the block diagram for computing power and discriminating two groups based on their power spectrum.

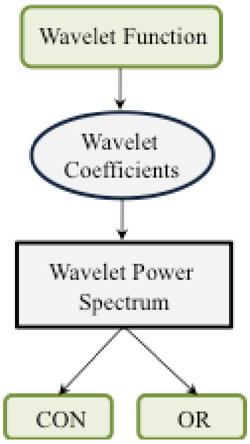

Figure 3: Block Diagram for Computing Power Spectrum.

3 RESULTS

The algorithm developed in this study evaluated for its performance by discriminating the CON and OR group from one another.

EMG signals, which were collected from three muscles, were analysed by 38 wavelet functions with 5 levels of decomposition for three phases of dynamic contraction during squat task. The five wavelet functions that represented the highest amount of energy for each subject were highlighted. The same scenario was repeated for all subjects by analysing EMG signals from all three muscles for each descending (D), stationary (S), and ascending (A) phase separately. The highest five energies occurred in various levels for different subjects and muscles. The five WFs that indicated the highest percentage of energy were selected for each subject. The total number of repetitions for the wavelet functions between CON and OR group during three phases was computed for each muscle separately. Bior3.9 wavelet function indicated the highest number of repetitions between subjects for each muscle during three phases except for muscle 1 of OR group which Bior3.7 worked best (Table 2). As the difference between Bior3.7 and Bior3.9 was not significant in muscle 1 of OR group, Bior3.9 wavelet function was used for further analyses.

Table 2: Selection of a WF with Highest Repetition of Energy.

Subject	Muscle	Wavelet Function	D	S	A	Total
CON	1 (GMax)	bior3.9	12	6	7	25
OR	1 (GMax)	bior3.7	6	6	4	16
CON	2 (TFL)	bior3.9	8	8	4	20
OR	2 (TFL)	bior3.9	9	7	9	25
CON	3 (RF)	bior3.9	7	8	13	28
OR	3 (RF)	bior3.9	7	10	6	23

3.1 Wavelet Power Spectrum

The WT converts the data array, which is stored from the EMG recorded signal, into a series of wavelet coefficients. Each of these coefficients represents the amplitude of the wavelet function at a specific location in the array. The best way to specify the distribution of energy within the data is to compute the wavelet power. The power, which is the squared absolute value of the wavelet coefficients, calculated. The wavelet power spectrum for each muscle during descending, stationary, and ascending phases was computed by using Bior3.9 WF. This scenario was repeated for all subjects from both groups. The subjects were categorized based on calculated power of each phase in Table 3. OR and CON groups were divided into three categories based on the squat phases. All 16 subjects in the CON group used their muscle 1 in the ascending phase whereas; most of them used muscle 2 and muscle 3 in their descending phase. In OR group, muscle 1 was used in ascending the same as CON group. However, muscle 2 was used in ascending and muscle 3 in both descending and ascending phases.

Table 3: Muscles used by CON and OR During Squat Cycle.

	Descending	Stationary	Ascending	Total
CON				
Muscle 1	0	0	16	16
Muscle 2	10	2	4	16
Muscle 3	14	2	0	16
OR				
Muscle 1	2	0	10	12
Muscle 2	4	0	8	12
Muscle 3	5	2	5	12

Moreover, after calculating the power of the DWT coefficients at various levels, the power was then compared for the sEMG for OR and CON group of three muscles (GMax, TFL, RF). Fig. 4 and Fig. 5 show the results of each muscle for both groups.

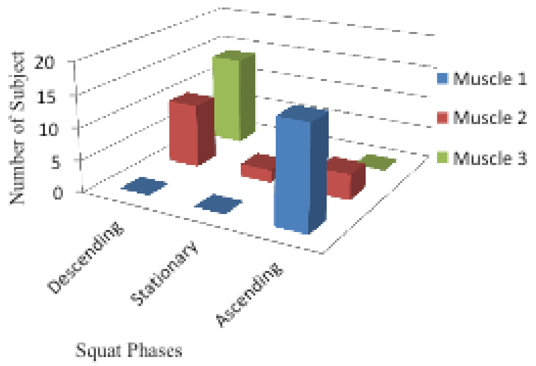

Figure 4: Muscles Power for CON Group.

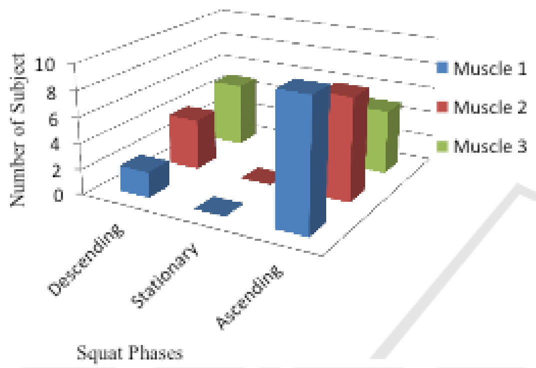

Figure 5: Muscles Power for OR Group.

As indicated in above graphs, subjects from both groups used higher power in descending and ascending phases. In order to indicate whether there is a significant difference between these two groups in using their muscles during ascending and descending phases, the actual A/D ratio for CON and OR was computed.

By calculating the ratio, we can still see which phase was the most active; however, we are also able to see the extent of activity. Therefore, we calculated the ratio of A/D for every subject in CON and OR groups and then calculated the average. The resulting average for each muscle is provided in Table 4 with the standard deviation for each group.

Table 4: Average Ratio with Standard Deviation Values for Each Muscle in CON and OR Groups.

	CON	OR
Muscle 1 (GMax)	13.38 ± 1.902	11.319 ±1.921
Muscle 2 (TFL)	1.33 ± 0.150	1.829 ± 0.205
Muscle 3 (RF)	0.613 ± 0.090	1.975 ± 0.260

The muscles power is plotted and shown in Fig. 6 for CON and OR group. In CON group muscle 1 and 2 were active in ascending phase whereas, muscle 3 was active in descending phase. Moreover, in the OR group all three muscles were active in the ascending phase.

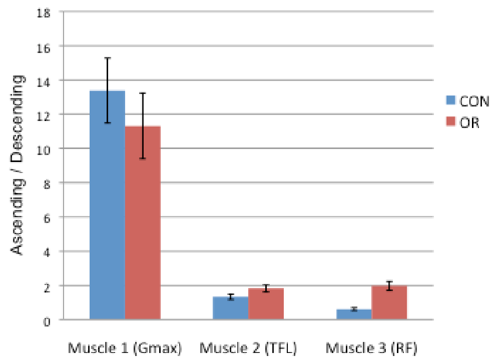

Figure 6: Average Ratio Muscle Power for CON and OR.

In general, the described algorithm can be summarized as follows:

The raw EMG signals are collected from a participant for GMax, TFL, RF muscles during descending, stationary, and ascending phases of squat task. Then, the collected EMG signals are normalized. The Bior3.9 wavelet function is applied to normalized EMG signals and the wavelet coefficients are computed. Based on wavelet coefficients the wavelet power spectrum is calculated. In addition, the ratio power which is the ratio of ascending power over descending power is computed in order to identify whether the subject has FAI or not. If the ratio value for RF muscle is less than zero, it means the participant used his/her RF muscle in descending phase and he/she belongs to CON group. Whereas, if the ratio value is greater than zero, it means he/she used his/her muscle in ascending phase and the subject belongs to FAI group.

3.2 Statistical Analysis

In this study an independent samples t-test was used to check if the two means (averages) from CON and OR groups are reliably different from one another. Each t-value has a p-value that is the probability that the pattern of data in the sample could be produced by random data. The 2-tail t-test was applied to check the activities of muscles for CON and OR groups. Table 5 illustrates no significant difference was found for GMax and TFL; whereas RF shows a significant difference between CON and OR groups (p= 0.0670) although the threshold (p=0.05) was not reached. This can be due to the fact that the sample size in this study was small and we require more samples for more reliable results.

Table 5: P-value for GMax, TFL, and RF Muscle.

	P-value
Muscle 1 (GMax)	0.7477
Muscle 2 (TFL)	0.4997
Muscle 3 (RF)	0.067

4 DISCUSSION

Spectral properties of EMG signals have been defined by their power spectra. The shape of the power spectrum can be changed when the EMG signals are generated from different types of Motor Unit (MU) (Moritani, 1985; Gerdle, 1998; Elert 1992).

This study has indicated that the wavelet transform method can be used to quantify features of the muscle activity for dynamic contraction. The fundamental properties of EMG spectra are conserved across dynamic contraction, therefore the WT will be a useful tool for studying EMG signals. The wavelet power spectrum of OR and CON groups was analysed for GMax, TFL, and RF muscles in the hip area by using the Bior3.9 wavelet function in order to discriminate the two groups. The power was calculated for each muscle and an independent sample t-test was used to check the activity of three muscles in hip area to discriminate an OR patient from a healthy person. The p-value for GMax, TFL, and RF muscles is 0.7477, 0.4997, and 0.0670 respectively for 2-tail test. Therefore, RF muscle is statistically significant although the threshold (p=0.05) was not reached due to small sample size. As a result, RF muscle is more active in ascending than descending phase for OR people, whereas it is more active in descending phase for CON people.

Muscle contraction is produced by a sequence of electrical and chemical events, which start with an action potential, which is created at the neuromuscular junction. Individual muscle fibres are classified into three primary muscle fibre types named type I, type IIA, and type IIB based on their contractile and metabolic properties. Type I is referred to slow twitch oxidative, type IIA is fast twitch oxidative and type IIB is fast twitch glycolytic (Ethier, 2007). These three types of muscle fibres have very different functional characteristics. Type I fibre is characterized by low force, power, speed production and high endurance. Type IIB has high force, power, speed production and low endurance, while type IIA indicates feature between the two other types. The MU consists of a single motoneuron and the group of muscle fibre it innervates. All muscle fibres in a single MU contain the same muscle fibre type. Three types of MUs (slow, fast fatigue-resistant, and fast fatigable) are categorized on the basis of their twitch speed and fatigability. The slow twitch MU is small and can produce less force compare to fast twitch MU. Type I muscle MUs contract slower, and they reach to peak power slower and highly resistant to fatigue compare to type II fast twitch MUs. Type IIA and IIB are capable of the same amount of peak force, however type IIA fibres take longer to reach their peak power compare to type IIB. Therefore, the total peak power by type IIB is higher than type IIA. In other words, type I has low intensity, lower frequency, and low power compare to type II.
The average ratio (ascending over descending phase) power for GMax, TFL, and RF muscles, as indicated in Table 4, presents the power of RF muscle is higher in OR group than CON group. The faster motor units generate higher frequencies in their power spectra (Wakeling, 2004). Thus, the larger numbers of MUs are recruitment in RF muscle for OR than CON. Therefore, type II (fast twitch) MUs are active in OR group, while in CON group type I (slow twitch) MUs are used.

5 CONCLUSION & FUTURE WORK

The algorithm developed in this study aimed to automatically discriminate CON and OR groups based on sEMG recorded from three hip muscles (GMax, TFL, and RF) during dynamic contraction. The program was capable of identifying OR from healthy people by analysing the activity of hip muscles.

The novel method developed in this study was used to analyse EMG signals recorded from GMax, TFL, and RF muscles for 16 CON and 14 OR subjects during squat cycles. In this study the DWT was selected and various wavelet functions from this WT method were applied to EMG signals from three muscles in order to select the best possible energy localization in the time-frequency plane. This analysis showed the Bior3.9 wavelet function provided higher amount of energy for most of our subjects. By selecting Bior3.9 the wavelet power spectrum was computed for CON and OR during 5 levels of decomposition. The result indicated the RF muscle (muscle 3) is more active in the ascending phase than the descending phase for OR, while it is more active in descending phase for CON.

During dynamic contraction there is a progressive recruitment of faster MUs in OR group during ascending phase. EMG activity at higher frequencies correlated with higher contractile force, and with the progressively faster types of MU, which can be assumed to be recruited. Thus, during dynamic contraction the higher wavelet power in RF muscle of OR group demonstrates that faster MUs were active, while lower power in CON group related to the fact that slower MUs were active.

This research work showed that the proposed algorithm can find a good solution for pre-screening problem. Nevertheless, some more improvements could be achieved. In this algorithm, only the three muscles of hip area were considered, this might be different if we consider all the muscles in the hip area. Another limitation is that the physical activity and age parameters of subjects were not available. Therefore, research should be conducted in a wider range, parameters like physical activity, age, and gender could be considered.

Some future work from this thesis may consist of considering a larger sample size for more accurate and reliable values. The goal can be developing a software application, which can assist doctors and physicians to diagnose FAI faster and easier.

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