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Comparative study of detecting of muscle's Fatigue across different Processing Techniques

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***Abstract-** This paper aims to study the problem of muscle fatigue through the analysis of physiological signal "EMG" (Electro Myo Gram). To achieve this we applied different processing techniques based on Matlab. The initial information is a real signal from a physical effort necessary to carry books. The study allowed us to evaluate the different techniques (FFT, STFT and wavelet) and find out the complexity of each method. The performance of each technique will be also extracted from this paper. By comparison the wavelet technique is better to analyse successive efforts in short periods of time but if the effort is continuous all the techniques are good. The different results obtained are in good agreement with literature.*

Keywords: EMG sensor, FFT, muscle fatigue, STFT, wavelet.

1. INTRODUCTION

The contemporary lifestyle and its stress forced the human being to get constantly tired often be it morally or physically. The physical fatigue is regularly equivalent to a lasting muscle strain. This can be either durable (so it is a disease), or temporary (eg muscle cramp).

To study the muscle fatigue technically it is not better than the physiological signal EMG called "Electro Myo Gram» from the applied technique is electromyography [1].

In a simple way, electromyography is the study of muscle function by analyzing the electrical signals generated during muscle contractions. EMG signal detection can be performed either by invasive technique based on the insertion of the needles in the muscle or by non-invasive technique that involves placing electrodes on the muscle surface.

Because the non-invasive technique is less painful and easy to apply, it is often preferred to the needle technique. However, the information carried by the EMG signal is overall the surface, full of redundant signals (noise) and is not directly suitable for certain applications such as the diagnosis of neuromuscular disorders, wherein the drive unit must be studied through its action potential. This is why we must combine this technique of digital processing methods to extract useful information and noise.

2. MATERIALS AND METHODS

Data acquisition- It is an electrical activity record of muscle tissue and in our case is the arm. The electrodes are connected to an electronic platform recording EMG (arduino card) which is linked to a computer [2].

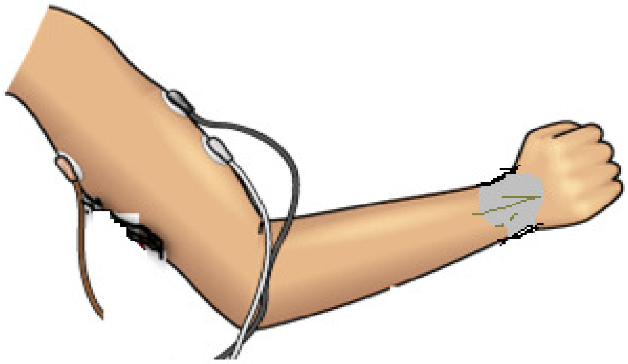

Figure 1 : EMG electrodes and their placement.

Experiment 1 (the subject at rest): The subject is seated and asked to be comfortable: The electrodes collect electrical activity in the form of values; by treating them in MATLAB we get the signal shown in figure 2:

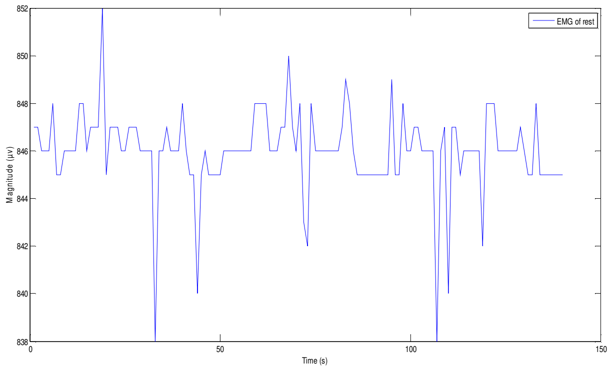

Figure 2: Raw data of rest.

Then we ask the subject to carry books one by one, the collected data from the platform is as follow:

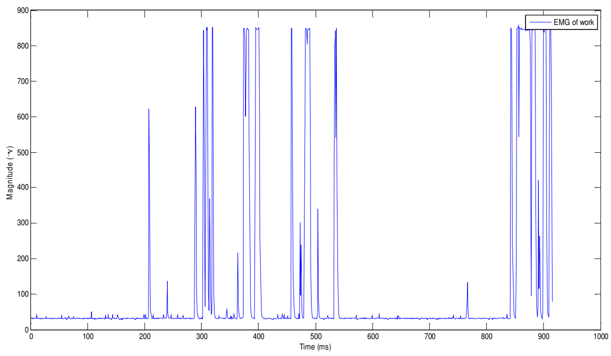

Figure 3: Raw data of work (effort).

From these figures (2 and 3) we note that the overall result of the electromyogram is an algebraic summation of much muscle fibers potential, more or less distorted by the respective distances thereof from the electrodes and with the same characteristics thereof.

[0 - 200μv] represents the muscle rest of the amplitude (prior to the first book).

[200-230μv]: the amplitude in this case is to 620 microvolt's and this due to the muscle effort contract once by adding books.

From the 850 ms interval the subject begins to tire and the resulting signal amplitudes fluctuate strongly, not exceeding in any case the amplitude of 1mv.

3. Results and Discussion: Different Techniques for EMG signal analysis

3.1 Fast Fourier Transform

The biomedical signals are stochastic in nature. That means there are not stable in time. This problem is solved using the frequency domain. To translate from the time domain to the frequency domain we normally use the Fourier Transform. The result is called frequency spectrum. The Fourier Transform is described in the next equation [3]:

$$F(\omega) = \int_{-\infty}^{\infty} f(t) \cdot e^{-j \cdot \omega \cdot t} dt \qquad (1)$$

Where: f (t) - the test signal (signal in time domain), ω frequency, $j = \sqrt{-1}$

In order to reduce the time of calculation by reducing the number of operations, especially the number of multiplication was developed the Fast Fourier Transform (FFT). The FFT compute faster by using many different algorithms involving a wide range of mathematics.

By applying the FFT on our data signals (signals of rest and work) considered as raw data, we get the following curves (figures 4 and 5):

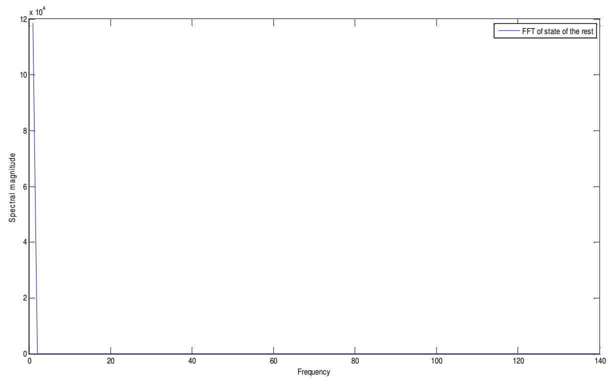

Figure 4: FFT for rest situation.

Note that at the beginning of the graph (figure 4), we obtained mean amplitude which represents the amplitude of rest situation, the other frequencies tends to 0. It means that the muscle is in total rest so it doesn't generate other frequencies.

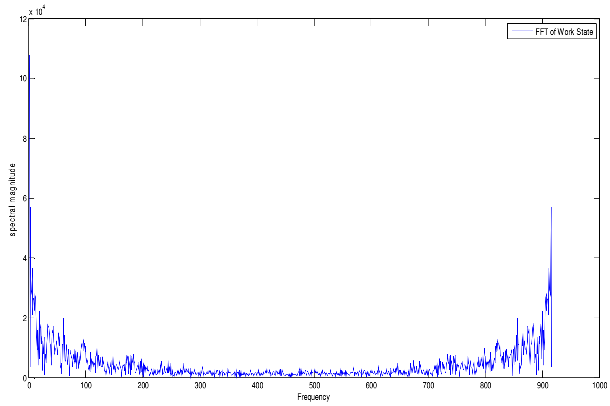

Figure 5: FFT for work situation.

We note that the frequencies in the range of 100 to 700 Hz have the largest energy-demonstrating that the muscle is in action-, and more the frequency increases, the signal strength becomes negligible.

It's seen also that at 800Hz as a frequency the subject becomes tired. If we do the inverse operation of FFT we can calculate the time and see also this threshold of fatigue matches any number of books carried. For this simple case no problems arise but if we consider that the subject perform multiple exercises the situation gets more complicated. It can be seen also that the strength of the signal (amplitude) indicated a relaxation of the muscles as a result of total fatigue but it is diminished and therefore if one repeats physical exercises in short periods the FFT does not show it well.

3.2 SHORT TERM OF FOURIER TRANSFORM (STFT)

This technique allows analysis of non-stationary signals (signals whose statistical characteristics vary with time). Essentially STFT extract several frames of the signal to be analyzed with a window that moves over time. If the time window is narrow enough, each extracted frame may be regarded as stationary so that the Fourier transform can be used. When the window is moving along the time axis, the relationship between the change in frequency and time can be identified. Its square module gives the spectrogram.
Mathematically it is written [4]:

$$STFT(x(t)) = X(\tau, w) = \int_{-\infty}^{+\infty} x(t).w(t-\tau).e^{-jwt}dt \quad (2)$$

Where w is the windowing function called also test window. Comparatively to Fourier transform techniques the STFT allows us to operate not only in frequency but also partly in time.

After doing the STFT operation on the raw signal we get the curves bellow (figure 6):

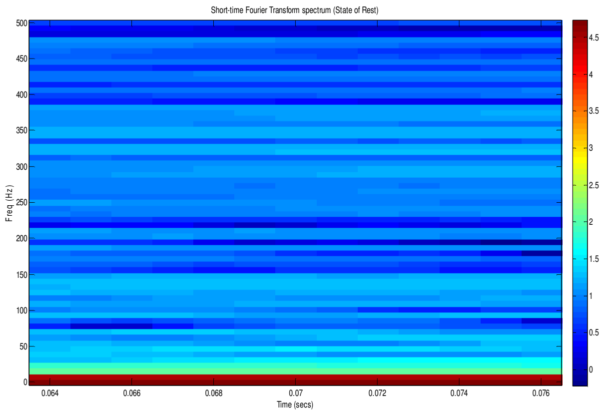

Figure 6: STFT for rest situation.

As illustrated in the graph, the subject is at rest and it appears in the blue graph because there is no force exerted. Recalling that the blue color as it shows in the bar represents the lowest intensity.

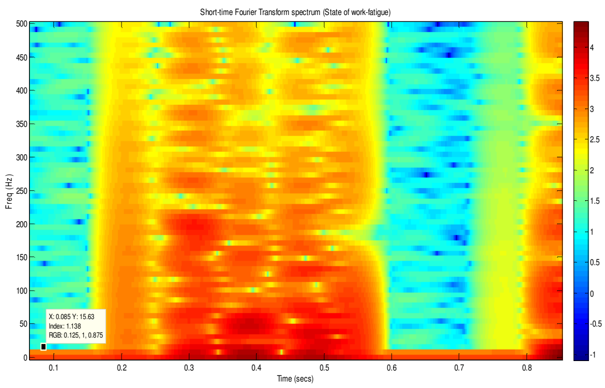

Figure7: STFT for work situation.

From the graph representing the subject at work, we can see:

[0 -0.15ms]: The subject has not yet begun to exert a force, because the muscle is at permanent rest. [1.5-0.6ms]: the red color begins to appear indicating that the muscle makes an effort.

[0.6-0.7ms]: the subject relaxes and takes his rest. [0.7- 0.8ms]: The subject begins to weary.

After a moment of rest the muscle returns to work. It is shown that the STFT method is more effective for detecting the muscle fatigue that the FFT method.

Through a simple logic one can see that if one has a sequence of fast efforts, the STFT shows consequently an amalgam of colors and it becomes difficult to distinguish the starting point of fatigue.

3.3 Wavelet transform

Among the types of signal processing tools for describing signals in both of time and frequency domains we have the famous wavelet technique. It allows us to capture two information: time and frequency.

Recall that wavelet is a wave-like oscillation with amplitude that begins at zero, increases, and then decreases back to zero; we have several analyzing wavelet called mother wavelets (figure 08) [5].

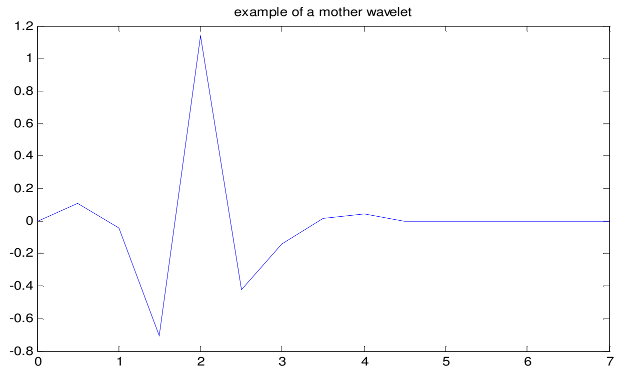

Figure 8: Wavelet function.

Discrete wavelet transform (DWT) are based on the harmonic analysis and use discrete-time filter banks which are called the wavelet and scaling coefficients. The DWT of a signal χ is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response g resulting in a convolution of the two:

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k] \qquad (3)$$

The signal is also decomposed simultaneously using a high-pass filter h.

Then, we can construct the original signal by doing the inverse DWT.

We have applied the different wavelet transforms on the two raw EMG signals. For the first situation (rest), we found the following:

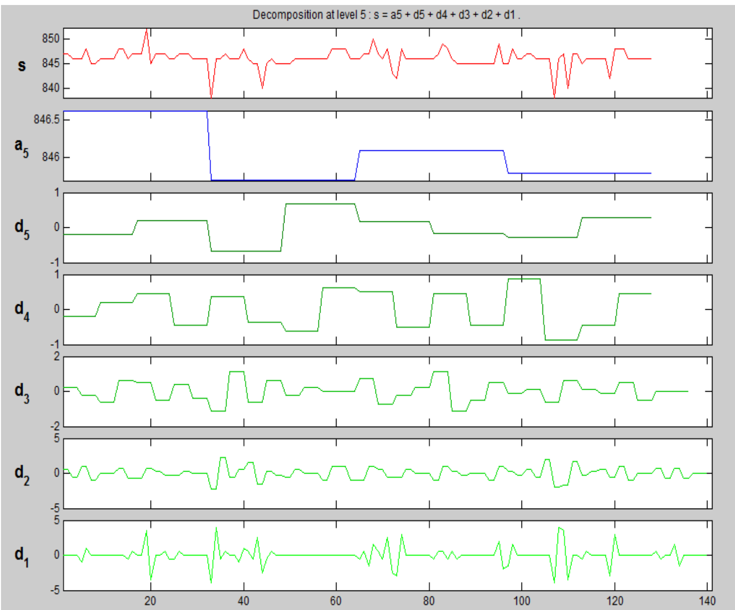

Figure 9: Wavelet decomposition of rest case.

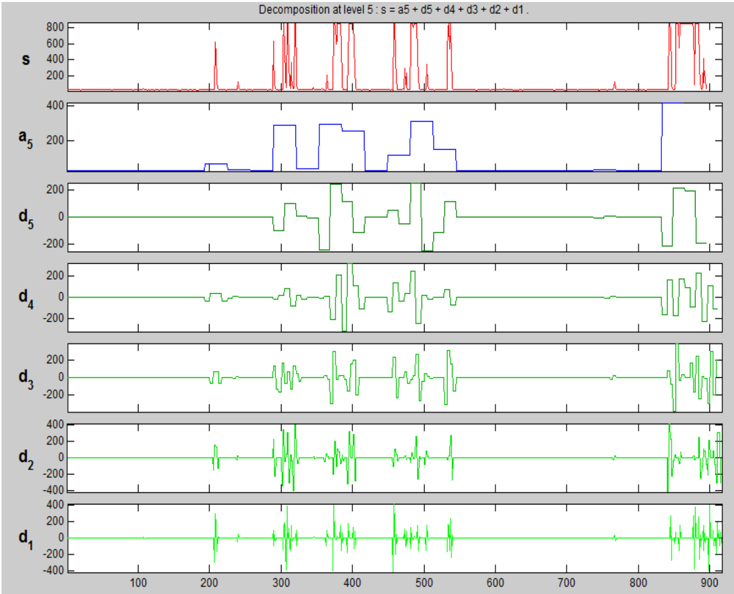

Figure 10:Wavelet decomposition of work case.

We have chosen the Daubechies wavelets [6] because it depends on the type of the original signal (EMG raw signal which look like noise with a strong asymmetry). There are other reasons for this choice of Daubechies, among them, their belonging to the family of orthogonal wavelets which characterize the discrete wavelets [7] and also for the reason of having minimal coefficients to calculate with respect to other types of wavelets excepted Haar wavelet but it gives better results [8] [9]. We note that we can use developed wavelet to analyze our raw data such as thresholding [10] but for us it's sufficient. In the figures, 09 and 10 are shown the waveforms of wavelet components (a5, d1, d2, d3, d4, d5) - after the application of wavelet transform DWT "DB1 wavelet". Numbering waveforms is the degree of decomposition-.the signal "s" is the reconstructed signal, obtained by the inverse application 'idwt'. We can say that the signal "s" is our raw signal but filtered. From the figures 09 and 10, we see that the d1 is interesting for us because it reflects the EMG phenomenon and it has a high frequency. By analyzing the d1 signal we can say that at 900 Hz the subject get tired. So we can detect the time the fatigue settles. We can deduct also that the physical efforts had multiplied the scale of magnitude of the result signal (100 to 800 max) and of the wavelet coefficients (the variation range of d1 was enlarged from [-5 to+5] to [-400 to +400]).

4. CONCLUSIONS

In this paper, the phenomenon of muscle fatigue was studied by analyzing physiological signal "EMG" (at rest and work), the analysis was done by using signal processing techniques generated by Matlab such as FFT, STFT and wavelet. These techniques have allowed us to detect the precise time of the onset of muscle fatigue as a result of doing some physical exercises. Wavelet signal transform, FFT and STFT were compared to each other. Unlike the FFT, the STFT and wavelet also determine the degree of fatigue (amount). The results obtained can also be considered as a learning pedagogical tool for biomedical engineering students.

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