International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

# Rate Evaluation of Electromyography Signals for Knee in Gait

[1]Sara W. Almola, [2]Enas T. Shabkhoon

**Submitted**: 15/07/2023 **Revised**: 06/09/2023 **Accepted**: 25/09/2023

**Abstract**: Based on open data from Universidad Militar Nueva Granada, the shape of the electromyogram for gait (Caminar) state is investigated, and the shape leads to the use of Discrete Fourier Transform (DFT) for analysis because it is an AM homologue. Discrete Frequency The spectrum of normal muscle signal has been found based on the polyfit technique for mean values, then the bandwidth of the spectrum is estimated. As a result, even though it has no expected value, it can be described as the imprint stamp of a standard case. The spectrum of muscle signal is covered by five samples, so it can be studied by dwt while the strength of signal is divided into five levels according to normal cases. This division qualifies the strength of abnormal cases.

***Keywords***: *EMG , Caminar , DWT, Am , DFT, SEMG, 3D*

## 1. Introduction:

An electromyogram (EMG) is a biological signal characterized by an electrical potential generated by muscle cells. The amplitude of EMG signals is minimal (0-10 mV) and the frequency is low (0-499Hz). The electromyogram signal's main energy ranges from 50 to 150 Hz[1][2]. Every movement in the body necessitates communication between the brain and the muscle, which is accomplished through the neuromuscular system, whereas Myo-Clinic Center translates the signal of contraction into a graph, sound, or numerical value. In the time of signal variation, engineering can analyze the electrical signal, but they cannot talk about diagnosis.[3] In any application that uses biological signals, feature extraction is a vital step. The required output classes should be maximally separated using the extracted features [4].[5]

Universidad Militar Nueva Granada has shared their professional database with the UCI surface electromyography (SEMG) center for lower limb analysis. The database contains 11 subjects with knee abnormalities and 11 normal. The data were collected using MWX8 Datalog Biometrics electromyography and goniometry equipment. In order to analyze the behavior related to knee muscles, three types of movement were undergone in the database, which are: leg extension from a sitting position movement, gait movement, and flexion of the leg upward. The knee was equipped with four electrodes (semitendinosus, Vastus Medialis, rectus femoris, and biceps femoris) and a goniometer for the acquisition procedure. In this study, 10 cases of the gait movement state for knee muscles are analyzed.[6], [7][8]

## 2. A Graph of the EMG signal:

Accessing data has been done by MATLAB. The point of time variation is defined according to the sampling rate of 1kHz. Plot 3 has been used to put signal variation along the x-axis versus z-axis and separate channels by the y-axis, as it can be seen in fig.(1) and fig.(2) for the sixth case of normal and abnormal, respectively.

[1]*Department of Medical Instrumentation,Techniques Engineering Technical Engineering College*
*Northern Technical University*
*Mosul, Iraq*
*sarah.waleed@ntu.edu.iq*
[2]*Department of Medical Instrumentation, Techniques Engineering Technical Engineering College*
*Northern Technical University*
*Mosul, Iraq*
*eshabkhoon@gmail.com*

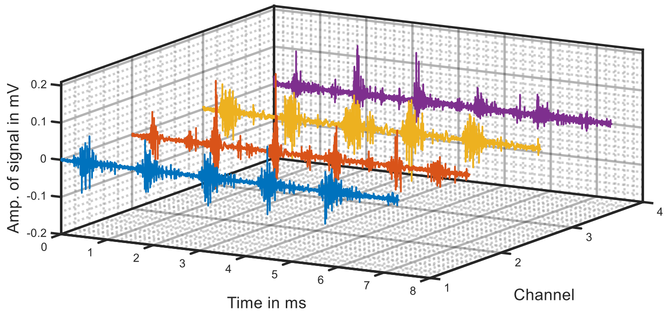


**Fig. (1)** 3D plotting of the electromyograph for normal case 6

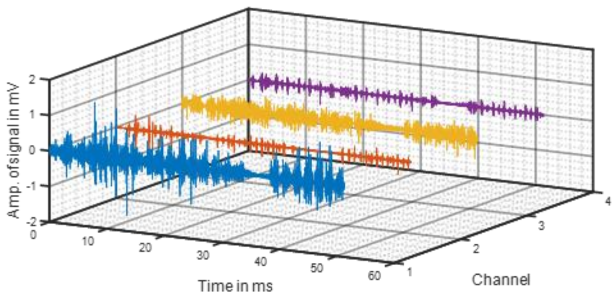


**Fig. (2)** 3D plotting of the electromyograph for abnormal case 6

So many references say that signals like that in fig.(1) are noisy and random as in[1], so it must search for the rating that is embedded in the rhythm of the signal and specify the bandwidth of the spectrum by means of signal processing, as it can be seen in the next section. The shape of the spectrum is important if it can be used to characterize normal cases versus abnormal cases.

## 3. Analysis of Signals

EMG signal analysis provides an efficient and effective way of understanding the nature of the signal. Once suitable EMG signal analysis techniques and methodologies are easily accessible, the nature and features of the signal may be adequately understood, and hardware designs for different EMG signal application fields can be built[9],[10].

To explore the frequency domain behavior and to define the frequency components of EMG signals, it is necessary to get the harmonic frequencies of the EMG spectrum of EMG signals[11] . It depended at first on the fast Fourier transform technique to get the harmonic frequencies of the EMG spectrum.

Traditionally, FFT has been taken for discrete signals in the time and frequency domain depending on the sampling rate. The data were collected at a sampling rate of 1000Hz. For analysis, 10000 points for each channel were taken. The average of the signals was measured in the frequency domain and the result is shown in Fig.(3.a,b).

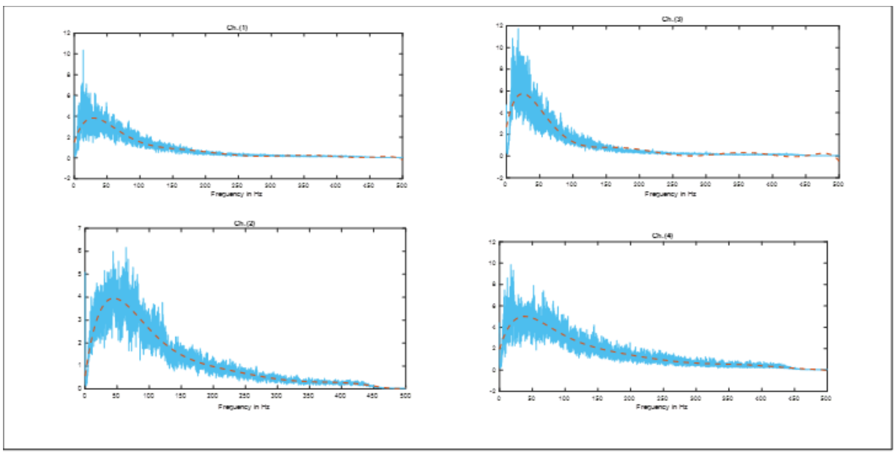

**Fig (3.a).** Average of Normal EMG spectrum and it's mean

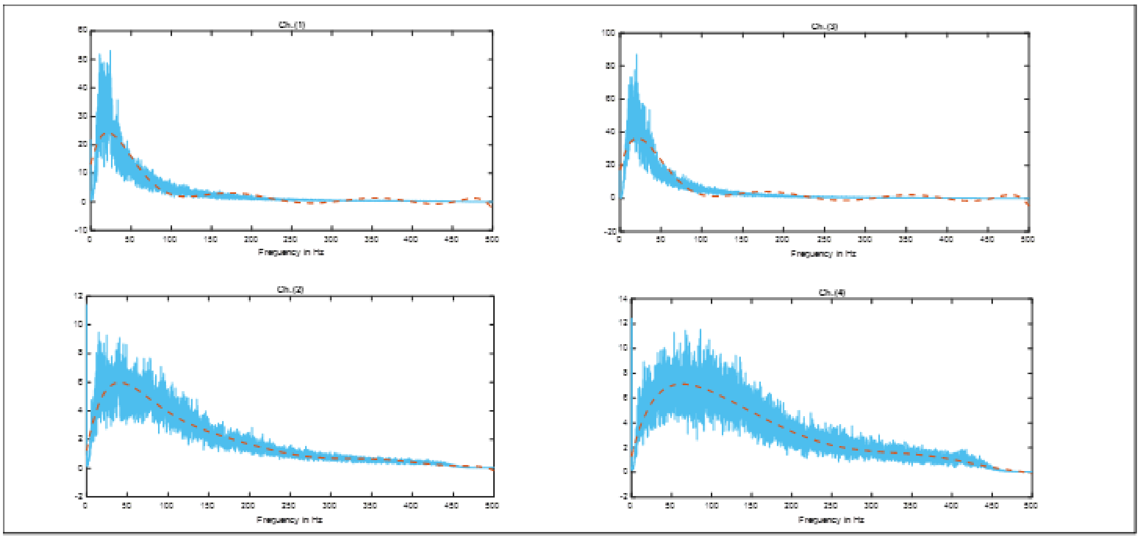


**Fig (3.b).** Average of Abnormal EMG spectrum and it's mean

Half power bandwidth

The half power bandwidth of each channel (normal and abnormal cases) has been measured and calculated by calculating the difference between the minimum and the maximum half power frequency points. Fig. 4 (a,b). table 1 (a,b).

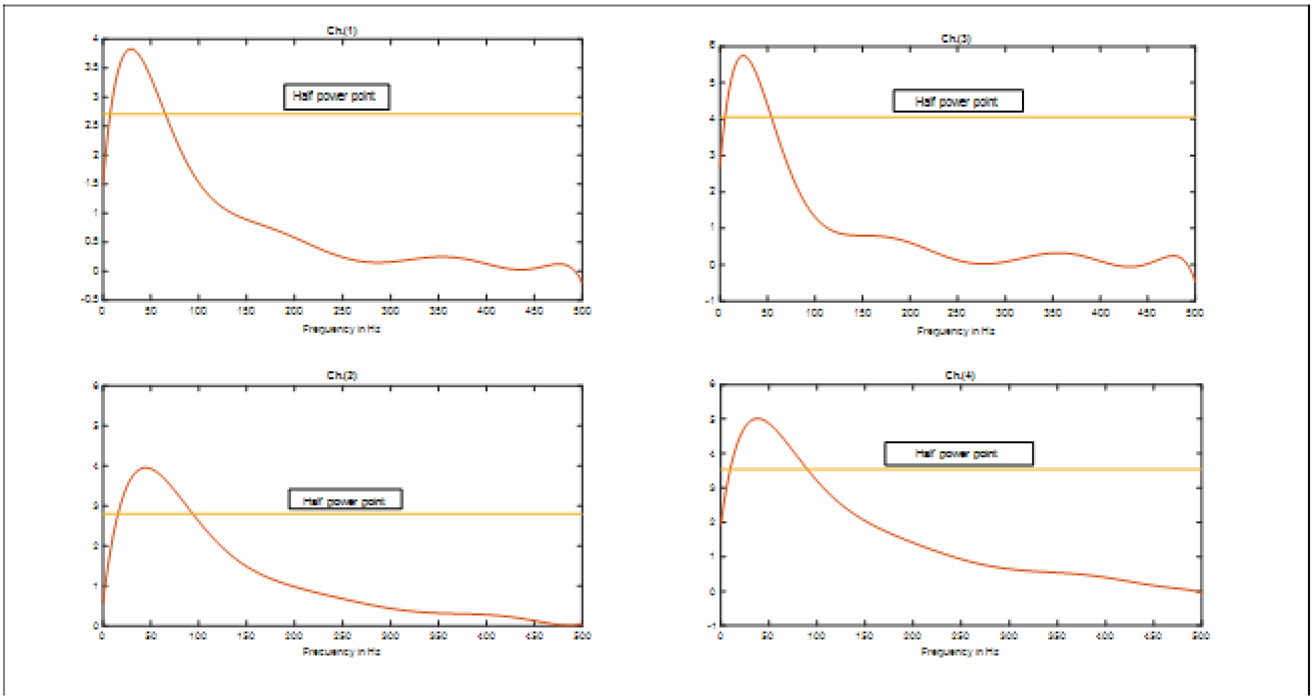


**Fig. (4.a)** Mean of EMG spectrum and its half power points for Normal cases (CH.1,2,3,4)

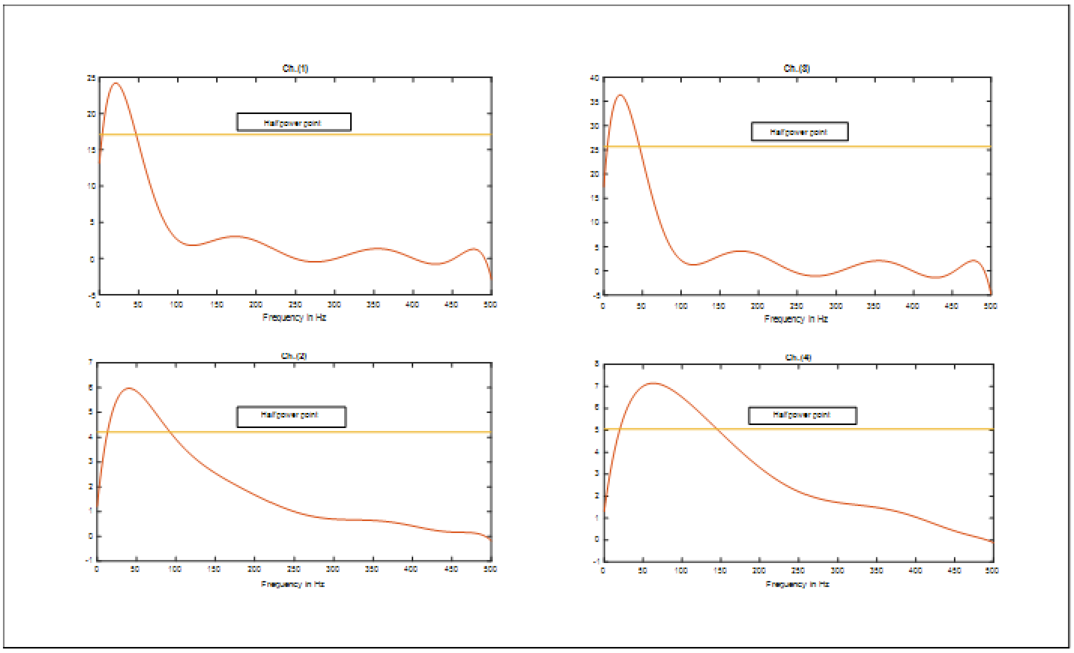


**Fig. (4.b)** Mean of EMG spectrum and its half power points for Abnormal cases (CH.1,2,3,4)

**Table (1.a):** Maximum and half power points (normal cases)

| Channel number | Maximum points | | | Half power points | | | Bandwidth |
|---|---|---|---|---|---|---|---|
| | X axis | Y axis | | X axis | | Y axis | |
| | | | | Min X | Max X | | |
| 1 | 29.35 | 3.827 | | 7.701 | 65.31 | 2.706 | 57.609 |
| 2 | 44.7 | 3.949 | | 15.75 | 94.11 | 2.792 | 78.86 |
| 3 | 24.35 | 5.743 | | 5.451 | 54.16 | 4.06 | 48.709 |
| 4 | 38.1 | 5.012 | | 9.801 | 89.96 | 3.544 | 80.159 |

**Table (1.b):** Maximum and half power points (Abnormal cases)

| Channel number | Maximum point | | Half power point | | | Bandwidth |
|---|---|---|---|---|---|---|
| | X axis | Y axis | X axis | | Y axis | |
| | | | Min X | Max X | | |
| 1 | 20.8 | 24.2 | 3.6 | 46.9 | 17.11 | 43.3 |
| 2 | 40.45 | 5.97 | 13.1 | 92.81 | 4.2 | 79.7 |
| 3 | 21.35 | 36.34 | 4.65 | 46.15 | 25.696 | 41.46 |
| 4 | 63.16 | 7.142 | 20.2 | 145.2 | 5.05 | 125 |

**Signal Recovery**

The objective of signal recovery is to obtain a pattern of normal and abnormal EMG cases, which can be achieved by the mean of spectrum (mean of absolute values and phase shift) from the fast Fourier transform. Fig. 4.a,b).

Typically, linear phase shift variation can lead to a pattern even if there is a time delay, but here the phase shift is completely random, and it must return to the description of. Therefore, each case must be recovered by its recorded values (Fig.5a,b,c,d). In fact, recovery of signal by a linear phase shift has failed, which leads to considering that phase shift as a stamp of signal.

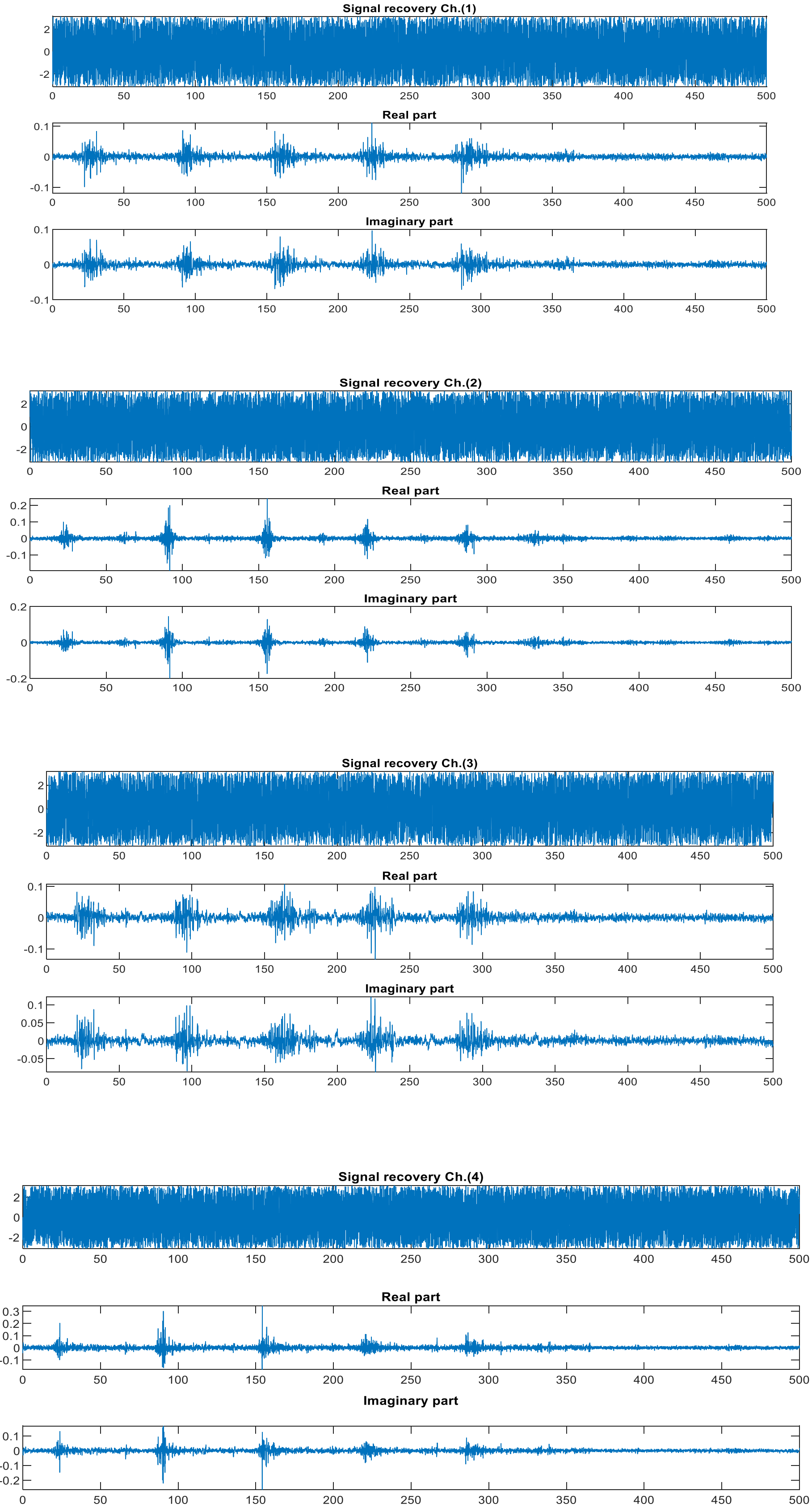


**Fig. 5.** (a,b,c,d)

## 4. Match Filter of Signal

The match filter is required to purify the signal, but there is a redundant noise even more. I have been searching here for an optimum model for the filter by fitting the average, but the fit and nearest do not match analog models for filters. As can be seen in fig. (5), the image filter covers the whole spectrum of signal by five samples. For that type of filtration, it can be compatible with DWT later. Refer to the reference for more details. For those reasons, digital filter and accumulation must give a good result in case recognition[12] [13]

## 5. Rate of Signals

In this paper, a scattering graph is used for analyzing the relationship between the features that are extracted from the muscle channels and the knee movement for evaluating the normal and abnormal case characteristics. The graph indicates that there is a significant overlap between the values when the muscle is actually used for the knee bending movement, the signal

has a higher force in abnormal cases compared to normal cases. The scatter refers to that; channel one has 50% abnormal cases over the maximum strength of normal cases and channel three has 40% abnormal cases over the normal cases, while channel two and channel four are overlapped completely as in the scattering graph, dig (6). Below half point is referred to as a low level L, while below quadratic point is a very low level O, above half point and below maximum for medium level M, above maximum and below 125% of maximum for high level H, and finally above 125% of maximum is very high V. Table (3) shows the distribution of levels.

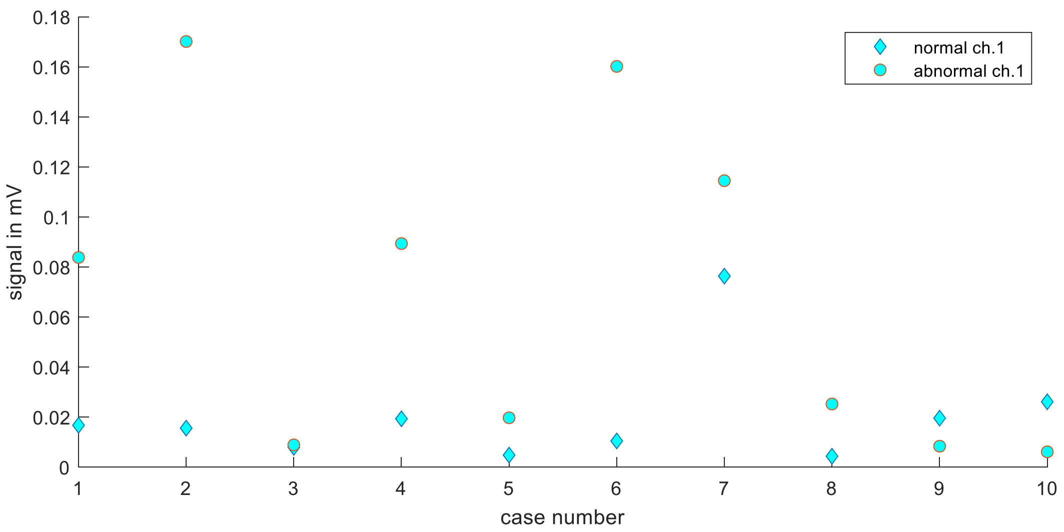


**Fig. (6.a)** Scatter graphs of normal and abnormal cases (ch.1)

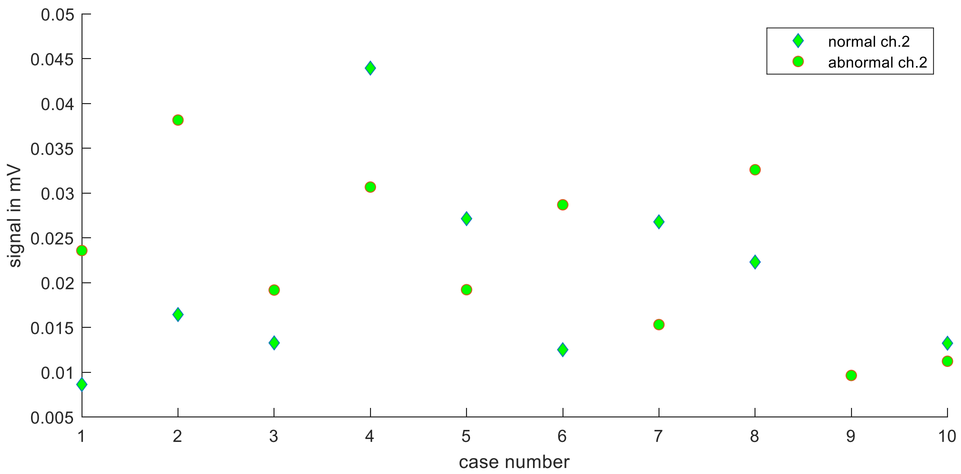


**Fig. (6.b)** Scatter graphs of normal and abnormal cases (ch.2)

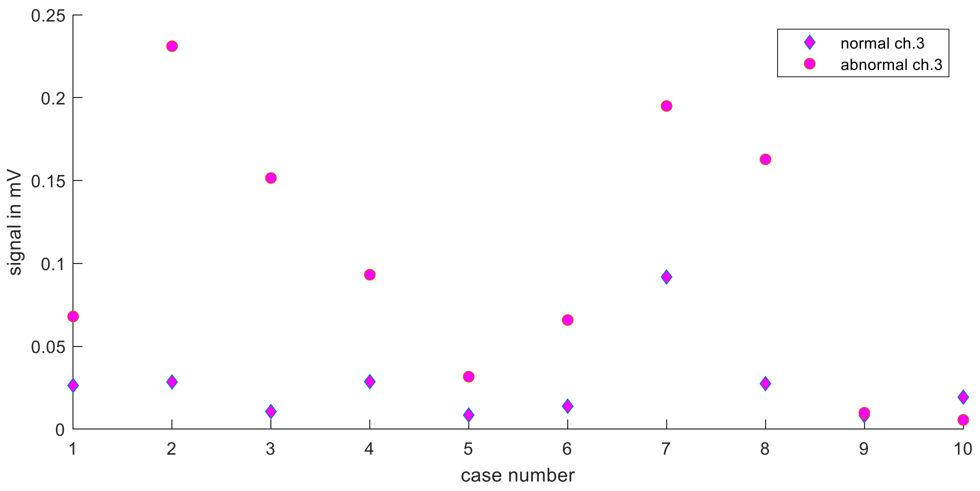


**Fig. (6.c)** Scatter graphs of normal and abnormal cases (ch.3)

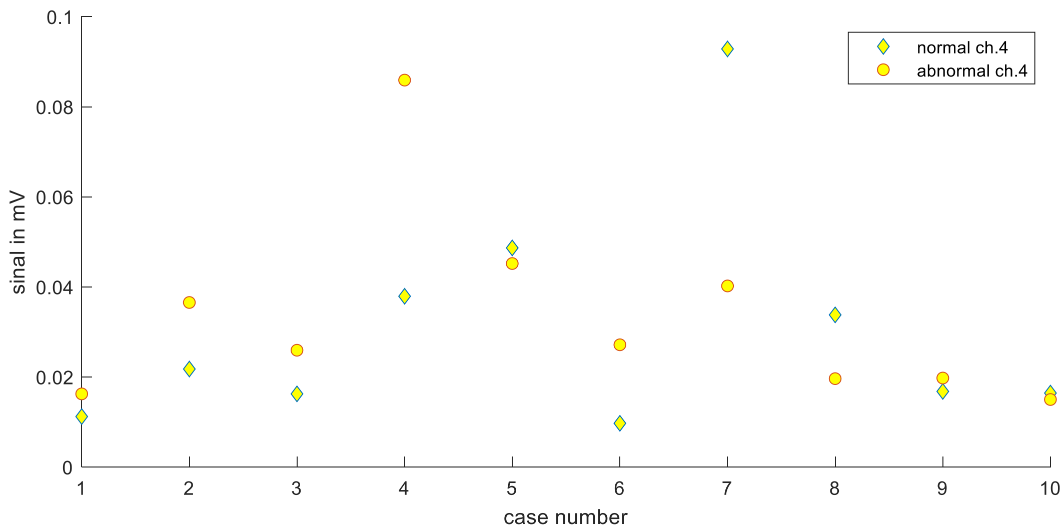


**Fig. (6.d)** Scatter graphs of normal and abnormal cases (ch.4)

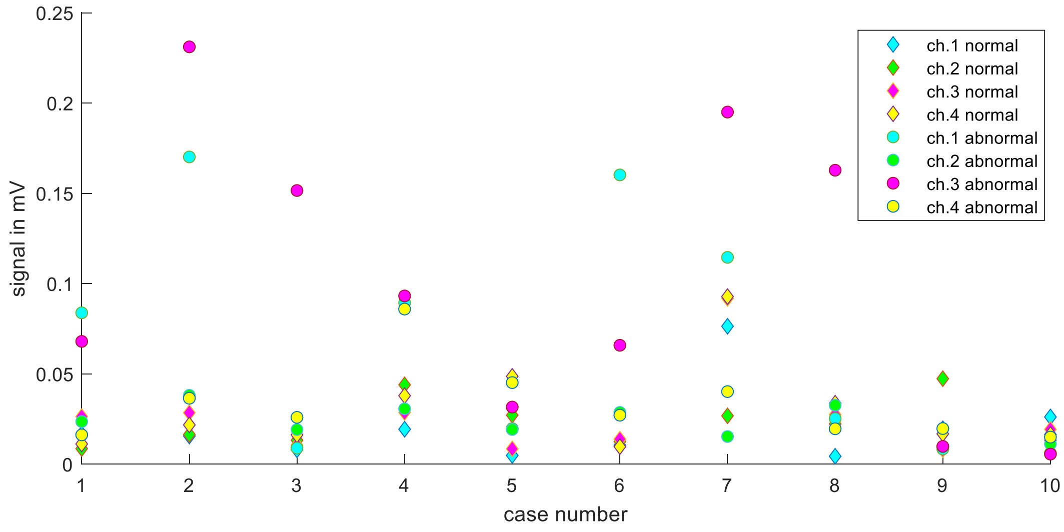


**Fig. (7)** Scatter graphs of normal and abnormal cases (all channels)

**Table (2)** rate of the muscle channels

| Case | Ch (1) | | | | | Ch (2) | | | | | Ch (3) | | | | | Ch (4) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| number | O | L | M | H | V | O | L | M | H | V | O | L | M | H | V | O | L | M | H | V |
| 1 | | | | * | | | * | | | | | | * | | | * | | | | |
| 2 | | | | | * | | | * | | | | | | | * | | * | | | |
| 3 | * | | | | | | * | | | | | | | | * | | * | | | |
| 4 | | | | * | | | | * | | | | | | * | | | | * | | |
| 5 | | * | | | | | * | | | | | * | | | | | * | | | |
| 6 | | | | | * | | | * | | | | | * | | | | * | | | |
| 7 | | | | | * | | * | | | | | | | | * | | * | | | |
| 8 | | * | | | | | | * | | | | | | | * | * | | | | |
| 9 | * | | | | | * | | | | | * | | | | | * | | | | |
| 10 | * | | | | | * | | | | | * | | | | | * | | | | |

## 6. Discussion and Conclusion

In this study, EMG signals of 10 normal and abnormal cases were taken from the available database. Four electrodes were used to collect the data from the knee muscles. All of these EMG signals were graphed by MATLAB. It was clear from the graph that all the signals were random and noisy (Fig. 1,2).

The next step was to utilize the fast Fourier transform to determine the frequency component of EMG signals. The result shows that the average of abnormal cases spectrum has more power than the normal cases spectrum. That means... (the maximum half power point for normal cases was in channel three, reaching almost 5.8 while it reached almost 35.2 in channel three of abnormal cases) fig (4.a,b), table (1.a,b).

Then the signals of EMG were recovered to obtain the pattern of normal and abnormal EMG cases. After signal recovery by the IDFT, it can consider the mean spectrum of muscle as a general stamp of solders' walking but the phase shift phase as an imprint stamp for individual solders. Both real and imaginary parts were equal in fig. (5.a,b,c,d). Now if the abnormal signal is recovered by the abnormal spectrum and by its individual phase, what does it mean? For what purpose can it be attained? It is just a question now, but it falls in the physiology domain.

It is found that the mean strength of abnormal signals is greater than the mean of normal cases within the pass band.

The next point in the study was the scattering graph. It indicated that there is a notable overlap between the normal and abnormal case values. Five levels indicate the degree of strength.

## References


[1] M. B. I. Reaz, M. S. Hussain, and F. Mohd-Yasin, "Techniques of EMG signal analysis: Detection, processing, classification and applications," *Biol. Proced. Online*, vol. 8, no. 1, pp. 11–35, 2006, doi: 10.1251/bpo115.

[2] J. Wang, L. Tang, and J. E Bronlund, "Surface EMG Signal Amplification and Filtering," *Int. J. Comput. Appl.*, vol. 82, no. 1, pp. 15–22, 2013, doi: 10.5120/14079-2073.

[3] R. Hippenstiel, "Introduction to Signal Processing," *Detection Theory*. pp. 37–62, 2001. doi: 10.1201/9781420042047.ch3.

[4] Z. Taghizadeh, S. Rashidi, and A. Shalbaf, "Finger movements classification based on fractional Fourier transform coefficients extracted from surface EMG signals," *Biomed. Signal Process. Control*, vol. 68, no. February, p. 102573, 2021, doi: 10.1016/j.bspc.2021.102573.

[5] N. Rabin, M. Kahlon, S. Malayev, and A. Ratnovsky, "Classification of human hand movements based on EMG signals using nonlinear dimensionality reduction and data fusion techniques," *Expert Syst. Appl.*, vol. 149, p. 113281, 2020, doi: 10.1016/j.eswa.2020.113281.

[6] N. Alexander and H. Schwameder, "Effect of sloped walking on lower limb muscle forces," *Gait Posture*, vol. 47, pp. 62–67, 2016, doi: 10.1016/j.gaitpost.2016.03.022.

[7] M. Akhtaruzzaman, A. A. Shafie, and M. R. Khan,

"GAIT ANALYSIS: SYSTEMS, TECHNOLOGIES, and IMPORTANCE," *J. Mech. Med. Biol.*, vol. 16, no. 7, 2016, doi: 10.1142/S0219519416300039.

[8] S. J. Preece and W. Alghamdi, "The effect of increasing trunk flexion during normal walking," *Gait Posture*, vol. 83, no. February 2020, pp. 250–255, 2021, doi: 10.1016/j.gaitpost.2020.10.021.

[9] S. R. Devasahayam, "Signals and systems in biomedical engineering: Physiological systems modeling and signal processing: Third edition," *Signals and Systems in Biomedical Engineering: Physiological Systems Modeling and Signal Processing: Third Edition*. pp. 1–468, 2019. doi: 10.1007/978-981-13-3531-0.

[10] A. Del Vecchio, A. Holobar, D. Falla, F. Felici, R. M. Enoka, and D. Farina, "Tutorial: Analysis of motor unit discharge characteristics from high-density surface EMG signals," *J. Electromyogr. Kinesiol.*, vol. 53, p. 102426, 2020, doi: 10.1016/j.jelekin.2020.102426.

[11] U. Frisch and D. Sornette, "Extreme Deviations and Applications," *J. Phys. II*, vol. 7, no. 9, pp. 1155–1171, 1997, doi: 10.1051/jp1:1997114.

[12] U. Ozkaya, O. Coskun, and S. Comlekci, "Frequency analysis of EMG signals with Matlab sptool," *9th WSEAS Int. Conf. Signal Process. SIP '10*, no. May 2010, pp. 83–88, 2010.

[13] Q. N. Warren, "Production Engineering," Oil Gas Eng. Non-Engineers, pp. 61–67, 2022, doi: 10.1201/9781003100461-6.

[14] Ms. Ritika Dhabalia, Ms. Kritika Dhabalia. (2012). An Intelligent Auto-Tracking Vehicle. International Journal of New Practices in Management and Engineering, 1(02), 08 - 13. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/5

[15] Kuna, S. L. ., & Prasad, A. K. . (2023). Deep Learning Empowered Diabetic Retinopathy Detection and Classification using Retinal Fundus Images. International Journal on Recent and Innovation Trends in Computing and Communication, 11(1), 117–127. https://doi.org/10.17762/ijritcc.v11i1.6058

[16] Anand, R., Ahamad, S., Veeraiah, V., Janardan, S.K., Dhabliya, D., Sindhwani, N., Gupta, A. Optimizing 6G wireless network security for effective communication (2023) Innovative Smart Materials Used in Wireless Communication Technology, pp. 1-20.