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Development of a Muscle Fatigue Monitoring Tool Using Myo-Electric Signals and IoT

Marco A. Lopez Oroz, Pedro González-Zamora,
Jesus Pacheco,Víctor H. Benítez

Universidad de Sonora,
Mexico

marco.lopezoroz@gmail.com, {pedro.gonzalez,
jesus.pacheco, victor.benitez}@unison.mx

Abstract. In this project, we develop a system that can monitor the state of a muscle group and estimate muscle fatigue by using EMG sensors and an IoT architecture. The captured data are sent to a remote server for processing and displayed through a web app developed using Node-red. The results are calculated by using previously captured data of bicep EMGs of volunteers. The user interface can display the data being captured in real time as well as the results of previous runs. The purpose of this project is to set up a platform that can be used in the industry for ergonomic purposes, as well as be used in the medical field for monitoring and therapeutic purposes.

Keywords: Myoelectric signals, digital twins, IoT.

1 Introduction

Electromyographic signals (EMGs) are biomedical electric signals emitted by the human body to trigger an organ or muscular tissue to perform an action (tension or contraction).

Since EMG signals are inherently complex and contain a lot of noise (from the measurement equipment, ambient radiation, and even the nervous system itself), using this kind of signal is not simple. There are many ways to “decode” these signals, from statistics to artificial intelligence (AI) algorithms [1].

EMGs have been used to study muscle fatigue in diverse studies [2, 3]. Most of them, use The Median Frequency (MNF), Mean Frequency (MDF), and RMS (Root Main Square) [5–7]as indicators of muscle fatigue.

Thanks to the technological advances related to the measurement of EMG signals, capture devices have become increasingly practical and portable. This allows us to take samples in controlled environments (laboratories) and real-life environments. Data transmission can be performed through the Internet of Things (IoT) architectures, allowing people to analyze and monitor data remotely, and for even better monitoring, technologies such as Digital Twins (DT) can be applied.

A Digital Twin is a virtual representation of an object or the state of an object or process by taking data from sensors and signals. This can help engineers detect problems even before they happen [8]. In this project, a system that can monitor the state of a muscle group in real time by using EMG sensors and an IoT architecture was implemented.

2 Materials and Methods

Based on the Internet of things technology it is possible to give users access to their EMGs data at any time and anywhere. In other words, users can check through a web application the data sets of EMGs that were captured when they were performing an activity.

For this, a commercial capture system was used to measure the EMGs from volunteers, a local server was configured to store and process the EMGs signals, and a remote server placed at the Amazon Web Services facilities[9] was configured to host a database server, mosquito broker[10] and a Web App. The data was processed locally before being sent to the remote server to be less sensitive to the latency of the network.

The stages of development for this project are as follows:

1. Capture system setup,
2. IoT architecture,
3. Data capture,
4. Processing,
5. Analysis results.

2.1 Capture System Setup

The capture system consists of wireless sensors, a base station, and a local server. The architecture of the capture system is shown in Figure 1. The wireless sensors placed at the skin of the volunteer transmit the measured data to a base station.

The base station sent the data to a local server through a USB port and then, the data are processed to extract features that can be used to determine muscle fatigue.

The local server contains a python application that processes the signal. The model of the python application is shown in Figure 2.

The data collected by EMG sensors are captured in the time domain, however in this study was necessary to transform the data to the frequency domain. For this, the python application implements the Fast Fourier Transform [11].

Once the data are in the frequency domain, features such as RMS, MDF, and MNF are extracted and stored in the local server. Subsequently, the stored data are sent to a remote server located in the cloud of Amazon Web Services.

The MNF is obtained following the next steps:

1. The EMG data is transformed into the frequency domain using the Fast Fourier Transform (FT). The FT algorithm used in this work is part of the NumPy library of Python.
2. The Power Spectrum Density (PSD) is calculated by multiplying the previously calculated FT array by its conjugate.

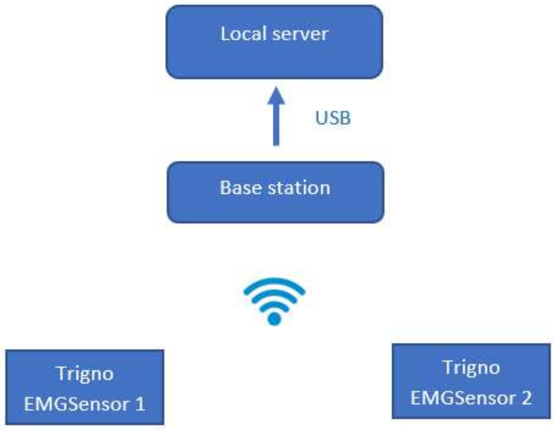


Fig. 1. Capture system setup used in this work. The EMGs signals were measured using wireless sensors that send data to a base station. Then, the base station sends the data to a local server which processes them.

3. Then, the sum of the product of the frequency value of PSD at each frequency bin as well as the sum of the PSD is computed. Finally, the MNF is obtained by dividing the first sum by the second one.

The MDF is the frequency that divides the spectrum into two regions with an equal sum of amplitude. The step 1 and 2 are the same as the ones used to compute the MNF. A more detailed procedure is shown below:

1. The sum of all bins of PSD array is computed and divided by two.
2. The algorithm loop through each frequency bin and sum its PSD value and stop until this sum is equal to half of the total sum of PSD. The frequency where the loop is halted is the median frequency.

The RMS is computed as follows:

1. Given an array of data of length N, each value of the array is squared and then summed.
2. This sum is then divided by N.
3. Finally, the square root of the resulting quotient is computed.

2.2 IoT architecture

The architecture used in this work is based on the 3 layers described in [12]. The setup of the platform implemented in this work is described as follows for each layer.

1. **The perception Layer** refers to the EMGs sensors and the devices used for the captured data. The perception layer represents the capture system setup described

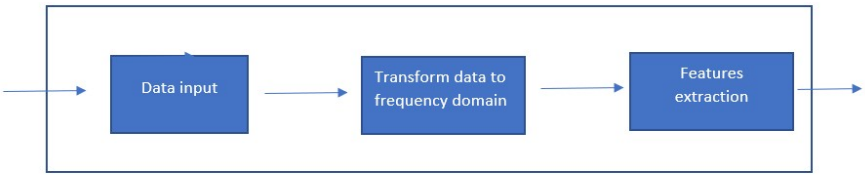


Fig. 2. Data processing using a python application.

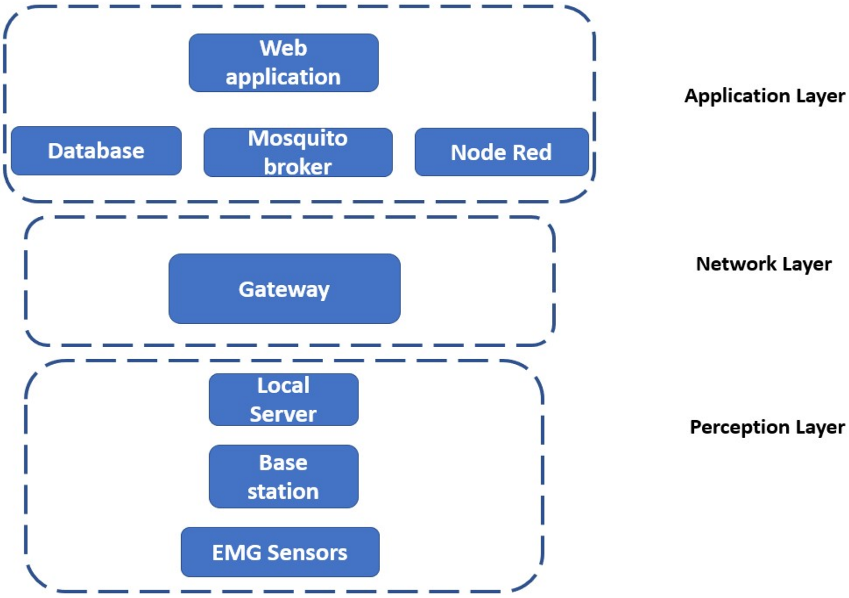


Fig. 3. IoT architecture used in this work.

in the previous section. The EMGs data are captured at frequencies around the 2000 HZ, so that, this will require a high compute performance if the Web App shows in real-time the variables related to muscle fatigue as MNF, RMS, and MDF. For this reason, in this work, only EMG raw data is shown live through the Web App and the muscle fatigue variables are computed offline in a local server located at this layer and sent to the remote server after finishing the data taking.

2. **Network Layer** is the one that describes all the devices that make possible the communication between the Perception Layer and the Application Layer. So, it includes elements such as routers, wireless devices, and the protocols used for the data interchange. The MQTT protocol [10] was used to send the EMGs raw data to the Node-Red platform [1] locate in the cloud. The preprocessed data is sent to the database using the FTP protocol.
3. **Application Layer** is located at the Cloud Server. In this work, Amazon Web Services is used to host a remote no SQL database, a mosquito broker, and a Node Red server. Moreover, the Node Red Server implements a Web App where information related to previous runs of a specific user can be accessed.

Table 1. Body composition of the volunteer that participated in this experiment.

Id	Weight	Body fat	Muscle mass
1	111.3	52.5	21.6
2	59.4	31.6	29.1
3	89.1	47.5	23.5

Fig. 4. Activity performed during data capture.

2.3 Data Apture

Data capture was done using volunteer students from the University of Sonora. A sensor was attached to their bicep and they were asked to perform standing bicep curls (Figure 4) with different weights to analyze the impact of different loads on the myoelectric signals. In this case, 5lb and 10lb dumbbells were used. The body composition of the volunteers is shown in Table 1.

2.4 Processing

The captured data is saved into .csv files and then the features are extracted. The computed features are Root Mean Square (RMS), Mean Frequency (MNF), and Median Frequency (MDF).

The features were chosen as the literature shows a clear relationship between them and muscle fatigue. As fatigue increases, RMS increases, and frequencies decrease (Figure 5). The RMS, MNF, and MDF can be checked offline through the Web App as it is shown in Figure 6. Users can access their information after the data capture as the data are stored in the remote database. The user only has to log in to the platform and select the data sample.

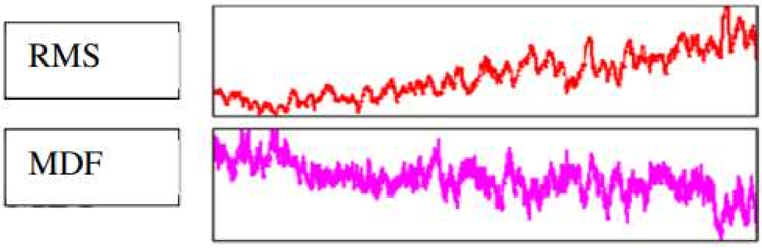


Fig. 5. Expected behavior of RMS and MDF when muscle fatigue is becoming higher [14].

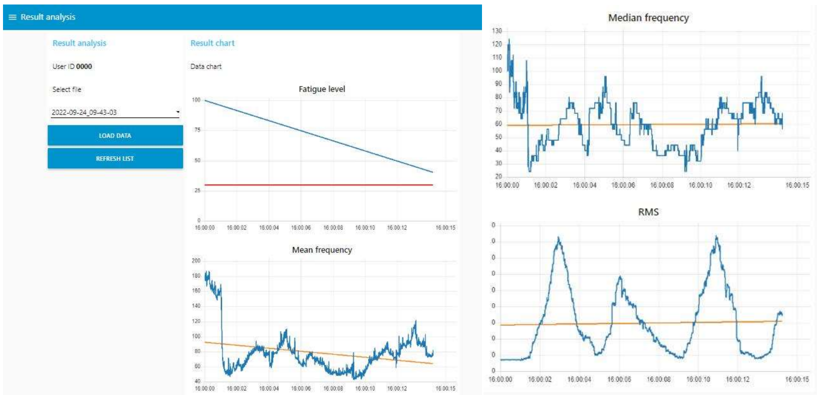


Fig. 6. Web app interface of the platform developed in this work.

3 Results

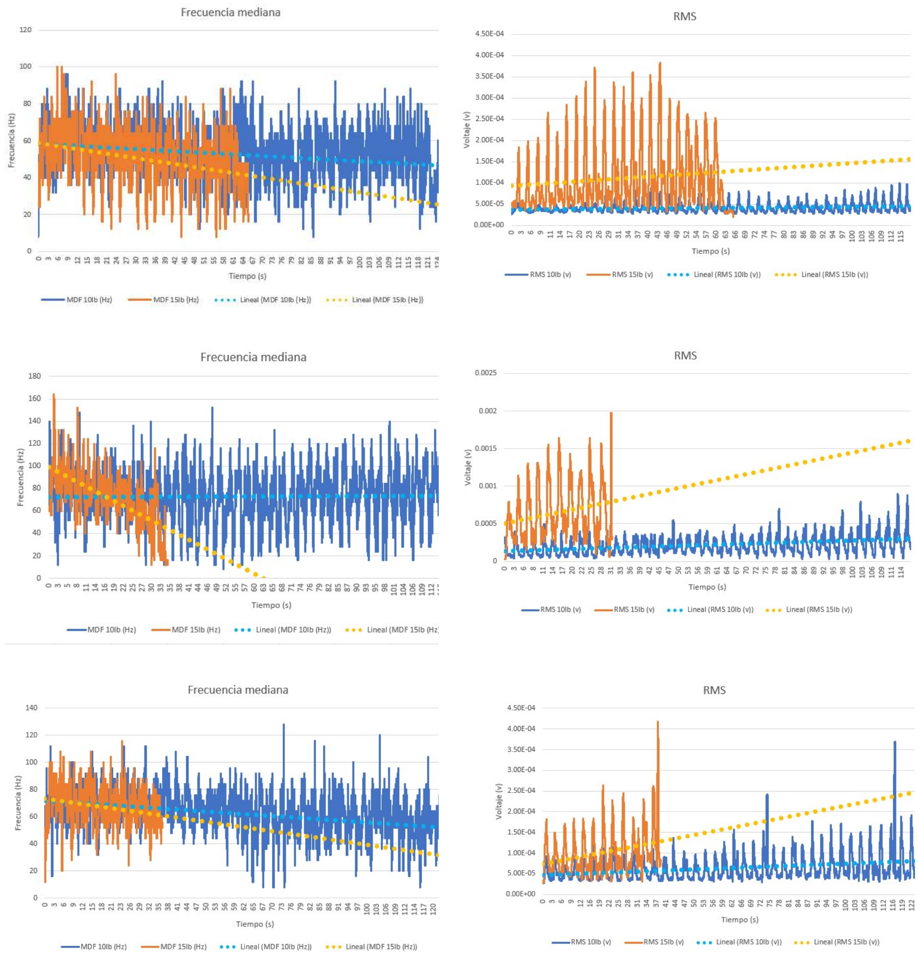
The results obtained (so far) are shown in figure 7. The results shown in Figure 7 follow a similar behavior to the ones shown in Figure 5 as expected. As fatigue increases, RMS increases, and frequency decreases.

The results also show that the average slope is more critical when a higher load is applied to the muscle group. The above results were stored for each user in the created platform and each user can.

4 Conclusions and Future Work

A platform to capture and process EMGs data was developed in this work. The system can measure myoelectric signals from users and store them in a remote server after being processed. This brings the capability to the system to extract features related to muscle fatigue. Moreover, the platform architecture is based on an IoT architecture to give continuous access to users to check the data anytime and anywhere.

The tool can be used in the industry to monitor the status of muscle fatigue of their employees and it can be also used in the field o medicine.



(a) (b)

Fig. 7. Typical MNF (a) and RMS (b) behavior of 3 volunteers.

The future work is to use the variables related to muscle fatigue as RMS, MNF, and MDF to give valuable information that allows people to make strategies to create better working environments.

References

1. Yousif, H. A., Zakaria, A., Rahim, N. A., Salleh, A. F. Bin, S., Mahmood, M., Alfarhan, K. A., Kamarudin, L. M., Mamduh, S. M., Hasan, A. M., Hussain, M. K.: Assessment of muscles fatigue based on surface EMG signals using machine learning and statistical approaches: A review. In: IOP Conference Series: Materials Science and Engineering vol. 705, no. 012010 (2019) doi: 10.1088/1757-899X/705/1/012010

2. Cifrek, M., Medved, V., Tonković, S., Ostojić, S.: Surface EMG based muscle fatigue evaluation in biomechanics. Clinical Biomechanics, vol. 24, no. 4, pp. 327–340 (2009) doi: 10.1016/j.clinbiomech.2009.01.010
3. Reaz, M. B., Hussain, M. S., Mohd-Yasin, F.: Techniques of EMG signal analysis: Detection, processing, classification and applications. Biological Procedures Online, vol. 8, pp. 11–35 (2006) doi: 10.1251/bpo115
4. Phinyomark, A., Thongpanja, S., Hu, H., Phukpattaranont, P., Limsakul, C.: The usefulness of mean and median frequencies in electromyography analysis. Computational Intelligence in Electromyography Analysis, A Perspective on Current Applications and Future Challenges (2012) doi: 10.5772/50639
5. Wang, L., Wang, Y., Ma, A., Ma, G., Ye, Y., Li, R., Lu, T.: A comparative study of EMG indices in muscle fatigue evaluation based on grey relational analysis during all-out cycling exercise. BioMed Research Internatinal, pp. 1–8 (2018) doi: 10.1155/2018/9341215
6. Zhang, G., Morin, E., Zhang, Y., Etemad, S. A.: Non-invasive detection of low-level muscle fatigue using surface EMG with wavelet decomposition. In: 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) pp. 5648–5651 (2018) doi: 10.1109/EMBC.2018.8513588
7. Fuller, A., Fan, Z., Day, C., Barlow, C.: Digital twin: Enabling technologies, challenges and open research. IEEE Access, vol. 8, pp. 108952–108971, (2020) doi: 10.1109/ACCESS.2020.2998358
8. Amazon web services: Overview of Amazon web services AWS whitepaper (2022)
9. Shahri, E., Pedreiras, P., Almeida, L.: Extending MQTT with real-time communication services based on SDN. Sensors, vol. 22, no. 9 (2022) doi: 10.3390/s22093162
10. Brigham, E. O., Morrow, R. E.: The fast Fourier transform. IEEE Spectrum, vol. 4, pp. 63–70 (1967) doi: 10.1109/MSPEC.1967.5217220
11. Lombardi, M., Pascale, F., Santaniello, D.: Internet of things: A general overview between architectures, protocols and applications. Information, vol. 12, no. 2 (2021) doi: 10.3390/info12020087
12. Lekic, M., Gardasevic, G.: IoT sensor integration to Node-RED platform. In: 2018 17th International Symposium, INFOTEH, pp. 1–5 (2018). doi: 10.1109/INFOTEH.2018.8345544