

Domotic control by codification of electromyographic signals and network sockets

Control domótico vía codificación de señales electromiograficas y socket de red

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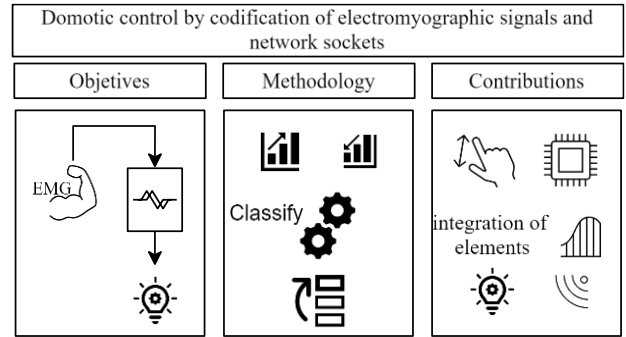
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Abstract

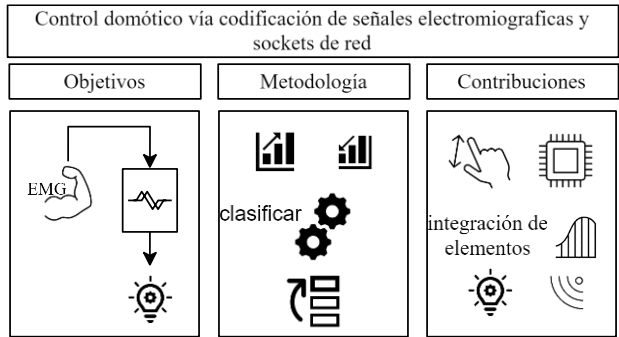
This article presents a system where signals generated by an electromyographic sensor on a person are sent through a client-server network topology. The purpose of these signals is to manipulate home automation devices only with certain arm movements, thus creating a gadget that does not require a keyboard or a touch screen. So that the signal can be interpreted as a control instruction, different patterns of EMG signals were defined that are possible to identify by means of a coefficient evaluation between signals. The use of sockets allows devices to be manipulated on local networks or over the Internet.



Domotic-Control, Electromiography, Socket-Network

Resumen

En este artículo se presenta un sistema donde se envían señales generadas por un sensor electromiografico en una persona a través de una topología de red cliente-servidor. El propósito de estas señales es manipular dispositivos domóticos solo con ciertos movimientos del brazo, creando así un *gadget* que no requiere de un teclado o una pantalla táctil. Para que la señal pueda ser interpretada como instrucción de control, se definen diferentes patrones de señales EMG que son posibles de identificar por medio de un coeficiente de correlación entre señales. El uso de sockets permite que se puedan manipular dispositivos en redes locales o a través de Internet.



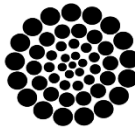
Control-Domótico, Electromiografía, Socket-Red

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## Introduction

The development of technologies such as the Internet of Things (IoT) has led to the creation of network applications, many of them wireless, which achieve task automation and person-to-machine (P2M) and machine-to-machine (M2M) communication (Nathan et al. 2019). Among these applications are those that operate within home networks, known as Home Area Networks (HAN).

Various sensors have been employed in HAN networks with the goal of minimizing human intervention in performing certain tasks. For example, there are solutions ranging from panic alarms via RFID (Widiantari et al. 2022), automatic light control with presence sensors or cameras (Ngoc et al., 2014), to authentication with biometric sensors (Ramli et al, 2013), among others. These solutions tend to use information derived from human characteristics, such as physical traits or body movements, including muscle movements in the arms.

In this context, it can be noted that human muscles exhibit electrical activity when they contract in response to some stimulation. The study of these variations is known as electromyography (EMG). The use of electromyography has expanded from nerve conduction studies to detect certain diseases to hardware control via muscle movements (Minjie & Honghai, 2020) (Kühn et al 2024) (Vujaklija 2024).

To detect these signals, two types of sensors are used: invasive (inserted into a person's skin) and non-invasive (electrodes that only require external contact with the skin covering the muscle). For the latter, models and signal processing techniques have been employed to enhance the information received and generate more and new applications in various fields (Marletti, 2004).

The objective of this paper is to define certain EMG signals that can be produced from a person's arm and encode them into control instructions for a home automation system. For this purpose, a hardware prototype was designed to function as a gadget that does not require a keyboard or touchscreen to send instructions. Unlike other solutions, this eliminates the need to use software applications on smart devices such as mobile phones.

This solution considers other users who have communication difficulties, such as with writing or speaking, where touchscreens or speaking systems like Alexa are required.

To identify EMG signals, linear correlation of variables is used to compare the similarity between a generated signal and a predefined signal.

Additionally, the use of a client-server architecture, where communication is established via network sockets, allows for local or Internet-based control.

The work in this paper is organized as follows:

Section 1, "Related Work," presents a brief investigation of other IoT solutions where EMG signals have been used for control and communication. It also mentions some works related to network sockets for client-server solutions with TCP/IP standards.

Section 2, "Development," describes the methodology used, as well as the implementation of hardware and logic system. It includes the interaction of devices through the flow programming software known as Node-RED and the creation of sockets and communication within it.

Section 3 discusses the results obtained in the previous sections, emphasizing those aspects that help to achieve the objectives of this work.

Section 4, "Conclusions," provides a general analysis of the system's operation and mentions potential future work.

Finally, Section 5, "References," lists the bibliography consulted for the development and theoretical foundations of this work.

## 1 Related Work

Sensors on the human body are becoming increasingly common as sources of information for IoT applications, with desirable characteristics including low energy consumption and wireless connectivity (Harshitha et al., 2018). Among these sensors are those that send EMG-type signals, which have gained significant attention due to their use in fields such as robotics.

For example, Ibarra-Fuentes and Morales-Sanchez (2022) propose controlling a mobile robot using EMG signals emitted by a commercial armband known as the Myo Armband, which has 8 electrodes and 9- inertial measurements axis with its own processor. As a classification method, the authors apply the K-Nearest Neighbors (KNN) algorithm.

Another example of EMG sensor uses, applied to issues beyond health monitoring is presented by Gu et al. (2019). In this work, the authors represent 26 Morse code symbols through EMG signals from a human arm.

Using statistical techniques such as the mean absolute value, they filter the signals and then employ the Constant False Alarm Rate (CFAR) adaptive algorithm for signal encoding.

In this context, signals from sensors need to be transmitted over a data network, requiring a set of communication protocols such as TCP/IP. TCP/IP standards have been used in various control fields, as described by Juhasova et al. (2017).

Here, the authors described the design of a communication channel cell between processes (sockets) that control robotic arms by evaluating sensed variable conditions and programmed logic.

The security provided by a TCP-based socket has been used in device monitoring solutions in IoT architectures (Nathi & Sutar, 2019). To implement these sockets, graphical flow control tools like Node-RED can be used. This tool has been employed in some works for node communication under the publish/subscribe model, commonly used in IoT with the MQTT protocol (Kodali & Anjum, 2018).

Using each of these previously described tools, this work proposes a communication system based on sockets that can control home automation devices through EMG signals.

## 2 Development

The first objective is to determine the behavior of EMG signals in a person’s arm during natural movements, and then propose different signals for home automation control.

To achieve this, an experimental methodology was employed, where conditions were established, and the type of hardware required for measurements was defined to understand the behavior of the signal under study.

### 2.1. Behavior of EMG Signals in the Arm

EMG signals from the left flexor carpi radialis (FCR) muscle of 20 individuals (10 men and 10 women) were analyzed, with the characteristics described in Table 1, using the following testing software and hardware.

Box 1

Table 1

Physical Characteristics of Individuals Using the OYMotion Sensor

Age	weight	height
Range [18, 56]	Range (kg) [60, 90]	Range (m) [1.6, 1.8]
Avg 32.65	Avg 72.8	Avg 1.69

Source: Own elaboration

#### Hardware and Software Used:

- OYMotion EMG Sensor with electrode connector PJ-342, module connector PH2.0-3P, voltage output 0-3.0V, and detection range of +/- 1.5 mV.
- ESP8266MOD Microcontroller, 32-bit CPU 160 MHz, 802.11b/g/n
- Card Manager Module for Arduino Esp8266, version 3.0.2
- Adafruit ESP8266, version 1.1.2
- Arduino IDE Development Software, version 1.8.19

#### 2.1.1 Tests Conducted

The OYMotion sensor features an elastic band capable of securing the electrodes on each person's flexor muscle. Once the sensor is in place, each person performed the following actions to define three types of signals:

*Rest:* Arm stationary to avoid generating any tension in the muscle.

*Normal Movements:* Lifting and lowering the arm, moving the fingers, lifting an object with the hand, writing.

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*Control:* Clenching the fist for one second with maximum force and repeating this action 3 times with one-second intervals.

The aim of these three actions is to identify if there are significant changes between the EMG signals, considering that the *Control* signal (point c) involves intentional movement.

To read the values of each EMG signal from these movements, a code was implemented using the Arduino IDE tool with the mentioned libraries and modules. For visualizing samples of these signals, a moving average filter with a window of 10 samples was implemented in the same code. The formula is given in equation [1].

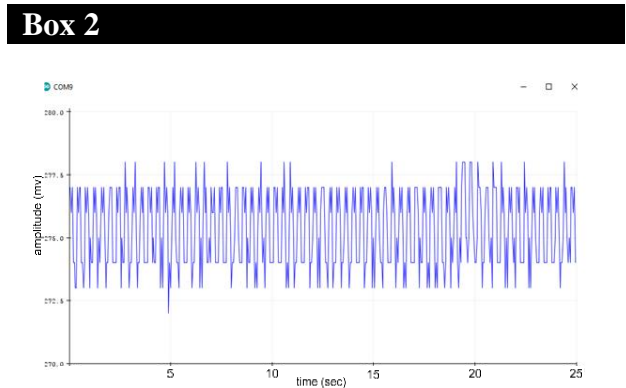
$$\dot{X} = \frac{1}{w} \sum_{k=1}^w X_k \tag{1}$$

Where:

$\dot{X}$  is the average value of w samples of EMG signals.

W: is the number of samples to average.

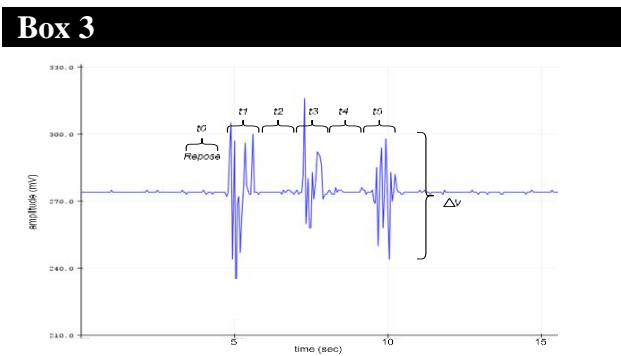
This procedure aimed to smooth the obtained signal by removing noise that may appear with maximum and minimum values. The average behavior of a Rest-type signal is shown in Figure 1. It can be observed that the EMG signal exhibits a uniform behavior, with small amplitude variations (+/- 2 mV). In this figure, it was necessary to reduce the scale on the y-axis to appreciate these variations; otherwise, the signal would appear as a continuous line, as described in the following case.



**Figure 1**  
EMG Signal of the FCR with Muscle at Rest  
*Source: Own elaboration*

For item c (*Control* signal), its graph is shown in Figure 2. From this, the following characteristics can be defined:

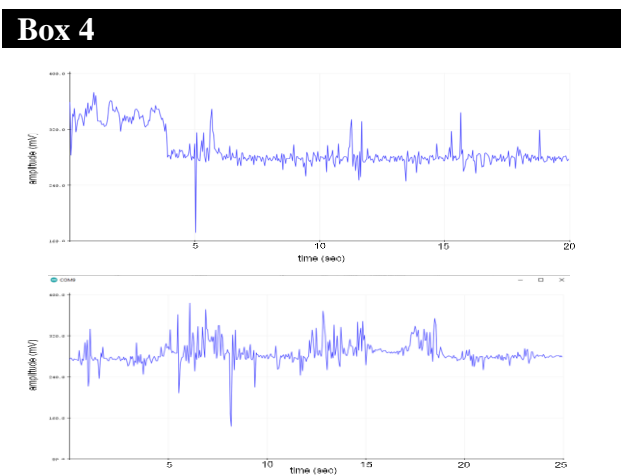
There is a *Rest* signal that shows modifications at the times marked as *t1*, *t3*, and *t5*, where a change ( $\Delta v$ ) in its amplitude is observed. These abrupt changes occur when the fist is clenched, and the times *t2* and *t4* are the intervals when the hand is open and the muscle tension is minimal.



**Figure 2**  
EMG Signal of the FCR after Clenching the Fist 3 Times with 1-Second Intervals  
*Source: Own elaboratio*

For item b (*Normal Movements*), there are studies in the literature that investigate the kinematics and dynamics of the human arm in daily activities.

This research aims to enable the replication of a person's arm movements by a robotic arm (Rosen et al., 2005). These studies indicate that, naturally, an arm typically exhibits shoulder and elbow flexion movements, rotational movements, and object lifting. For these reasons, the experimental movements mentioned earlier were defined. Examples of these signals are shown in Figure 3, where it is not possible to determine a consistent pattern of behavior.



**Figure 3**  
EMG Signals During Normal Arm Movements  
*Source: Own elaboration*



2.1.2 Signal Encoding

The amplitude values of each sample during the time intervals from  $t1$  to  $t5$ , shown in Figure 2, are stored in a vector  $\hat{c}$ , creating a discrete and finite signal. Considering that each interval contains 100 samples, the resulting vector will be segmented according to equation [2], and represents a control signal of three events, with an event being when a person clenches their first for one second.

$$ti = \hat{c} [n], \hat{c} [n+1], \dots \hat{c} [n+99] \tag{2}$$

Where:

$n$ : is the index of the vector  $\hat{c}$  that identifies each position.  
 $i$ : is the time interval number (1-5).

According to [2], the values of  $n$  for each interval and the amplitude values of the signal must match the data shown in Table 2.

Box 5  
Table 2

Pattern of Values Defining a Control Signal		
Time Interval	Value of n according to [2]	Expected Amplitude Value $\Delta v$
i=1 (t1)	0	275±30mV
i=2 (t2)	100	275± 2mV
i=3 (t3)	200	275±30mV
i=4 (t4)	300	275± 2mV
i=5 (t5)	400	275±30mV

For a *Control* signal to be identified, the following two conditions must be met:

- i. *Synchronization Signal.* As shown in Figure 2, a *Control* signal must be preceded by an interval  $t0$ , which represents a *Rest* signal.
- ii. *Change Patterns.* When a *Rest* signal is disrupted by sensing values different from  $275 \pm 2$  mV, the next 500 values of the signal will be stored in a new vector  $\bar{a}$ . These values must follow the pattern defined in Table 2, which requires comparing vectors  $\hat{c}$  and  $\bar{a}$ .

By using the variable correlation formula, the vectors  $\hat{c}$  and  $\bar{a}$  are compared to determine the percentage of similarity between them, in order to ascertain whether the signal is a *Control* signal or not.

The formula adapted for this work is shown below.

$$r_{ti} = \frac{\sum_{n=0}^{n+99} [\hat{c}[n] - \bar{X}] [\bar{a}[n] - \bar{Y}]}{\sqrt{\sum_{n=0}^{n+99} (\hat{c}[n] - \bar{X})^2 \sum_{n=0}^{n+99} (\bar{a}[n] - \bar{Y})^2}} \tag{3}$$

Where:

$r_{ti}$ : is the correlation coefficient for the time interval  $ti$ .  
 $n$ : is the index value of each vector according to

Table 2

$\bar{X}$  is the mean value of all the values in the vector  $\hat{c}$ .  
 $\bar{Y}$  is the mean value of all the values in the vector  $\bar{a}$

In this way, the  $r_{ti}$  for each time interval is calculated, expecting that their average meets the condition  $0.9 \leq r_{ti}$  to ensure similarity between signals.

2.2 Network Architecture

The Control signals identified in section 2.1.2 must be sent through a network system to control home automation devices. For this purpose, the following network architecture shown in Figure 4 is proposed.

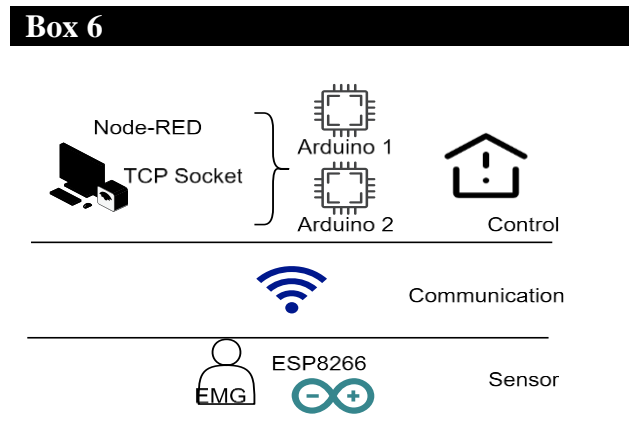


Figure 4  
Network Architecture for a Home Automation System with EMG Signals and Sockets

Source: Own elaboration

The following operation can be described from this figure:

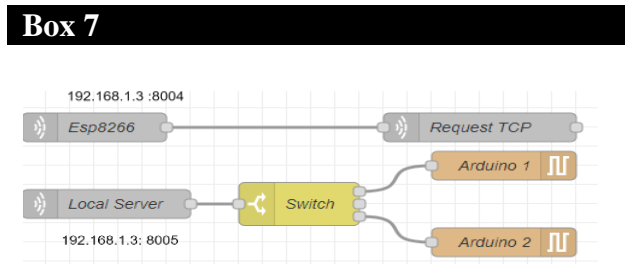
A user employs an EMG sensor via to a wristband to generate *Control* signals. It is assumed that the sensor circuit is connected to the ESP8266 via a wired connection.

This microcontroller connects to a local computer equipped with Node-RED software through a Wi-Fi connection. The software is used to establish socket connections between the EMG user (ESP8266) and the devices to be controlled (Arduino 1 and 2).

With Node-RED, multiple simultaneous connections to various microcontrollers such as Arduino can be established. The data flow diagram and device connection through Node-RED are shown in Figure 5.

In this figure, the socket labeled as ESP8266 listens on port 8004, waiting for a connection from the microcontroller with the EMG sensor. Once communication is established, the encoded control signals are sent to a “Request” method that connects to the server named “Local Server.”

This server listens on port 8005 and forwards the control signals to a “switch” node, which acts as a selector between the two controlling devices, Arduino 1 and 2. Registered port numbers were chosen for the sockets because it is a local network, and similarly, the server address is assigned as 192.168.1.3 because it is a private device.



**Figure 5**  
Node-RED Connectivity Diagram Allowing Socket Connections Between Different Nodes in a Home Automation System  
*Source: Own elaboration*

The Arduino devices in the proposed network architecture are examples of controllers connected to home automation devices such as a light, fan, or automatic door, and they wait for a signal to operate.

### 3 Results

From Section 1, it can be found that electromyography has been applied to fields beyond health, such as robotics and communications.

Although there are various applications of EMG signals, no cases were found where the implementation area focuses on everyday activities like home automation and where device control is achieved without the use of a keyboard or touch panels.

In Section 2, during experimental tests with EMG signals, it was observed that different amplitude values can be obtained between individuals performing the same arm movements.

However, significant patterns can be identified that allow for the establishment of different signal types. Specifically, a *Rest* signal has minimal variation from an initial reference value, while a *Control* signal can be generally defined by its values and ranges as seen in Table 2, also starting from a reference value.

The use of formula [3] aids in the identification of Control signals. In addition, a similarity condition helps to exclude or include signals with similar patterns but different values.

The proposed logical connectivity structure, illustrated in Figures 4 and 5, allows a server socket listening on port 8004 to receive control signals, such as those coming from the ESP8266. A second server can then send these instructions to multiple home automation devices.

The idea of presenting two servers is to demonstrate that it is possible to create multiple connections within a single device and interconnect them through Node-RED.

### 4 Conclusions

Signals from biometric sensors often require filtering and amplification methods for better analysis. Future work will consider the use of other processing techniques and sensors to eliminate potential sources of uncertainty.

During the use of the EMG muscle sensor, it was observed that individuals can exhibit various distinct patterns, such as the force with which they clench their fist or the speed at which they move their fingers. These behaviors are known as behavioral biometrics and could be used in future work for user recognition.

The use of client-server systems implemented with tools like Node-RED facilitates the control of flow and connectivity between devices. Unlike other systems, it is possible to integrate nodes and protocols that create solutions with various features such as storage, monitoring, and control.

Author contribution

*González-Silva, Marco Antonio:* Contributed to the project idea, literature review, methodology development, and article writing.

*Hernández-Pérez, Faride:* Contributed to defining the solution to the problem, conducting experimental tests, interpreting results, and writing the article.

Abbreviations

CFAR	Constant False Alarm Rate
EMG	Electromyography
FCR	Flexor Carpi Radialis
HAN	Home Area Network
IoT	Internet of Things
KNN	K-Nearest Neighbor
M2M	Machine to Machine
MQTT	MQ Telemetry Transport
P2M	Person to Machine
RFID	Radio Frequency Identification

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