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Sistema de transmisión de señales EMG bajo esquemas RF
EMG signal transmission system under RF schemes

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Resumen

Con el incremento de patologías en la era post pandemia sobre todo en lo relacionado al manejo de señales biomédicas ha tenido un auge considerable, en este trabajo de investigación se desarrolla un algoritmo auto adaptable para la discretización y empaquetamiento de datos de señales de tipo electromiográficas para órdenes de modulación n-QAM variables, la señal sintética bajo análisis se obtiene del banco de datos PhysioNet, en este caso de implementación el músculo tibial anterior. Se desarrolla una cadena de transmisión basada en el transceptor AD9361, se utiliza un amplificador de potencia para aplicaciones de radio, mediante una frecuencia portadora de 2.45 GHz, asi como su validación espectral, la modulación 16-QAM bajo prueba otorga una precisión de -15.5 (dB) NMSE. Como trabajo futuro se plantea una etapa de adquisición de señales EMG basado en una tarjeta ADC de alta resolución, además de esquemas de n-QAM de mayor orden para mejorar la precisión en la etapa del receptor.

Palabras Clave: EMG, músculo tibial anterior, n-QAM, Transceptor.

Abstract

With the rise in pathological conditions during the post-pandemic era, particularly concerning the management of biomedical signals, a significant surge has been observed. This research endeavors to develop a self-adaptive algorithm for the discretization and data encapsulation of electromyographic (EMG) signals. The synthetic signal used for analysis is acquired from the PhysioNet database, specifically focusing on the implementation of the tibialis anterior muscle. A transmission chain is established utilizing the AD9361 transceiver, while a power amplifier is employed for radio applications, operating at a carrier frequency of 2.45 GHz. The spectral validation of this system reveals that the 16-QAM modulation, yields an accuracy of -15.5 dB NMSE. As a further work, an EMG signal acquisition stage is proposed, based on a high-resolution analog-to-digital converter (ADC) card, alongside the exploration of higher order n-QAM schemes to enhance accuracy in the receiver stage.

Keywords: EMG, tibialis anterior muscle, n-QAM, Transceiver.

1. Introducción

With the exponential increase in pathologies in the post-pandemic era, wireless data management, collection, and transmission systems are required. The need to develop high-precision and transmission systems, as well as applications in the area of Telemedicine, is a current need in the vast majority of countries in America. The utilization of electromyography (EMG) signal analysis has been steadily growing across various domains, including rehabilitation procedures, muscle fatigue assessment, and biomedical investigations (Yousif, 2019). With the extensive development in 5G, efficient n-quadrature amplitude modulation (QAM) modulation schemes have been developed, the increase in demand for high signal rates, various schemes have been used with reference to code division multiple access (CDMA) and Long Term Evolution (LTE) digital multiplexing standards for handling n-schemes QAM (Singya, 2021). N-QAM provides high-data rate for transmission and it is used in many applications such as Digital TV, Wi-Max, orthogonal frequency-division multiplexing (OFDM), and in digital satellite communication system (Sharma, 2015).

Surface electromyography (sEMG) operates on the foundational principle of capturing the electric potential

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generated by muscular contractions. This electrical manifestation is performed to indirect acquisition through the utilization of surface electrodes strategically situated upon skin areas above to the muscle under analysis. The present study embraces this methodological approach due to its non-invasive attributes. sEMG entails the recording and analysis of muscle data and activity, specifically focusing on the storage and acquisition of muscle signals. Parameters such as amplitude and frequency serve as key indicators of the electrical interaction between muscles, as well as aspects such as muscle fatigue, muscle contraction, and torque generation (Naik, 2016). This rise in EMG signal analysis can be attributed to the escalating adoption of mobile devices and remote applications for bio-signals management. In this context, radio frequency (RF) technology has gained significant interest for the monitoring and diagnosis of RF signals, diagnosing issues, and managing large sets of data connected to diseases (Choi, 2018). There has been an increasing interest among users, service providers, and researchers in the precise and cost-effective detection of EMG signals, with the aim of leveraging such data for future processes, diagnostic purposes, classification tasks, or transmission as an alternative to Telemedicine (Yang, 2020).

This research work aims to develop an algorithm that adapts to the number of samples and amplitude levels of the signal being tested. The algorithm is specifically designed to apart the discretization process and packaging the signal based on the desired n-QAM level. In this particular case, the algorithm was validated using a 16-QAM scheme and synthetic signals obtained from the Physionet database. The experimental setup consists of a development kit built based on AD9361 transceiver. The development kit is equipped with a coaxial bandpass filter to restrict the frequency range of the signal and an amplifier under test, which is incorporated with a directional coupler to mitigate line return. Additionally, a spectral analysis technique is employed to validate the transmitted bandwidth.

This work is organized as follows, Section 2 discusses traditional wireless EMG signal handling applications, Section 3 describes the EMG transmission stage, and Section 4 discusses the results obtained. Finally, Section 5 describes the conclusions reached.

2. EMG signal extraction and implementation techniques

In a study by (Yag, 2019), a low-cost system was developed that combines EMG sensing with a microcontroller and a WiFi module, resulting in a correlation factor of 0.8 between the sensed signal and the current signal. The developed sEMG system is depicted in Figure 1. sEMG signals contain valuable information for data analysis and autonomous control of actuators (Bruneli, 2015), the acquisition of the low-cost sEMG system involved the placement of electrodes along with a microcontroller-based system. The system also incorporated an analog-to-digital converter (ADC) stage to facilitate the conversion of analog sEMG signals into digital form. Additionally, data transmission was accomplished using Bluetooth (BT) technology, BT is primarily designated for indoor applications, it is pertinent to acknowledge that owing to the substantial magnitude of power it manages, the power density would be considerably affected by distance.

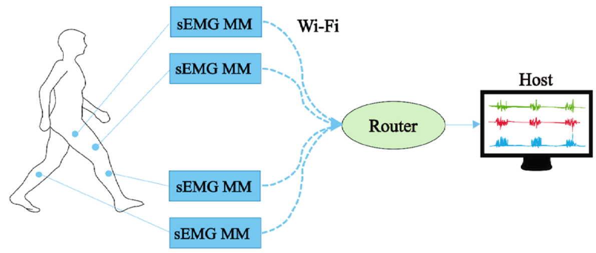

Figure 1: Overview of the proposed sEMG acquisition system (Yang, 2019).

Figure 2 illustrates EMG electronic systems and their application in prosthetics, enabling real-time visualization for future processing. This particular system is based on an ARM Cortex processor and graphical control through a graphical user interface (GUI) (Pancholi, 2018), in this study the patients were evaluated and a classification process was done based on time and frequency domain and a compact EMG data acquisition module for prosthesis application, this type of work is conventionally delimited to intramural contexts and restricted to applications within confined spatial boundaries.

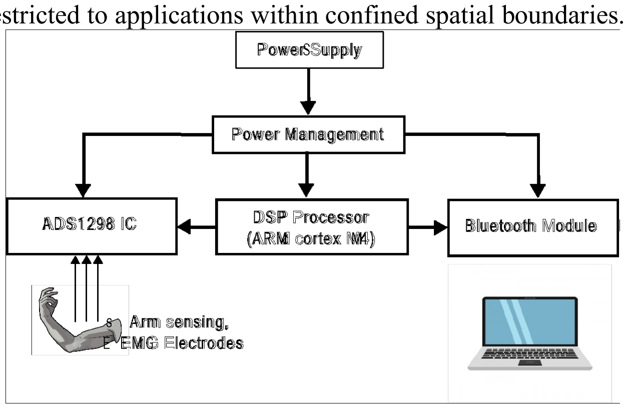

Figure 2: Representation system of the BT-sensing architecture (Pancholi, 2018).

Furthermore, in the work conducted by (Raurale, 2018), a combination of time-domain feature extraction and a multilayer perceptron was employed for classification purposes in prosthesis applications. Figure 3 depicts the schematic representation of an arm-mounted apparatus purposed for the categorization of motion patterns. The illustrated configuration encapsulates a contemporaneous framework tailored for the capture and categorization of EMG signals across a plurality of distinct channels. The classification endeavor is orchestrated through the utilization of a multilayer perceptron (MLP) classifier, and its performance is subjected to comparative analysis vis-à-vis established methodologies, with a specific emphasis on processing velocity., this work is interesting and could be used at a distance to detect pathologies related to the signals under analysis.

Recent advancements in EMG signal processing have led to significant improvements in high-precision signal handling, particularly in the context of facial gestural gestures, achieving an impressive correlation rate of 99.8%, these developments have been made possible through the utilization of the Myoware embedded board, showing remarkable advancements in muscle signal sensing at a low-cost (Gohel, 2020). In the field of rehabilitation therapies, there exists a lack of data regarding the progress of assigned therapies for patients with specific pathologies. Especially in the aftermath of the

COVID-19 pandemic, clinical evaluations have become costly, and both physical space and the availability of hospitals have become limited. Consequently, alternative approaches such as biomedical signal management techniques are imperative for facilitating distance-based tele-rehabilitation and tele-consultation (de Sire, 2022).

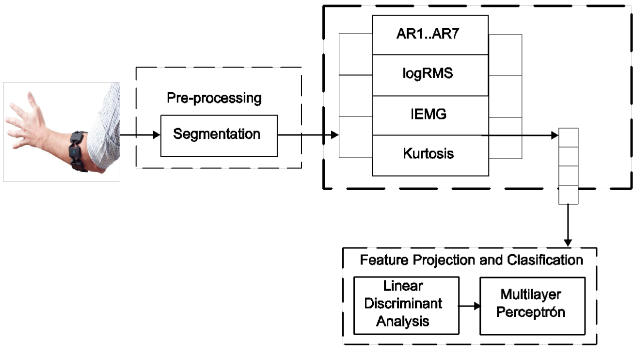

Figure 3: Proposed EMG motion recognition system (**Raurale, 2018**).

A real-time system is introduced for acquiring and classifying EMG signals across multiple channels as shown in Figure 4. The classification task is performed using the MLP classifier (Cárdenas, 2020). The system's performance in terms of processing speed is compared to state-of-the-art approaches. The authors acknowledge the importance of high precision in the classification processes for future diagnostic purposes, particularly in the context of identifying pathologies, here was developed a Python-based classifier was developed and implemented on an embedded (b) ECG/EMG platform. Additionally, in (c) a wireless transmission using the XBEE protocol in the 2 GHz band was established, aiming to contribute to the field of Telemedicine, this experiment was applied for a flexor digitorum profundus muscle, as is depicted in (a).

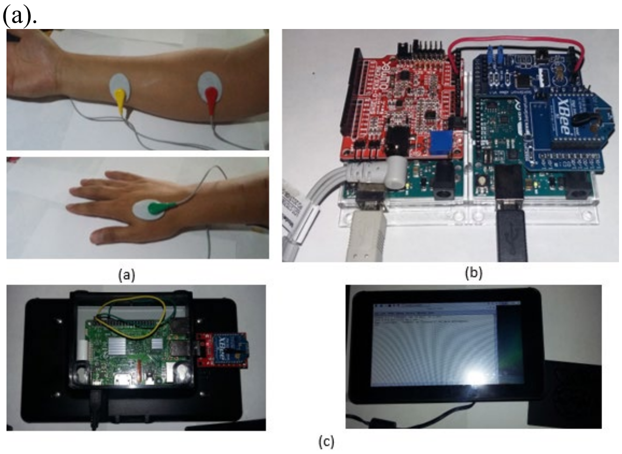

Figure 4. Acquisition and classification system for the flexor digitorum profundus muscle through a Raspberry Pi3 board.

3. EMG transmission stage

The proposed system utilizes a flexible digital modulation technique known as n-QAM. For the purpose of implementation, a 16-QAM scheme was employed to modulate synthetic EMG signals, with reference to PhysioNet data bank (Goldberger, 2000). An n-QAM system is composed of two channels, I(t) and Q(t) are combined to form the transmitted signal. In this particular case, these signals are designed to be separated from each other by 90 degrees, effectively forming the bandwidth during transmission. The resulting n-QAM signal can be mathematically expressed using equation (1).

$$\begin{aligned} s(t) &= I(t)\cos\cos(2\pi f_0 t) + Q(t) \\ &\qquad \cos\cos(2\pi f_0 t - 90^o) \\ &= I(t)\cos\cos(2\pi f_0 t) + Q(t)\sin\sin(2\pi f_0 t). \end{aligned} \tag{1}$$

where f_0 represents the fundamental frequency, specifically set at 2.45 GHz in this case, the complex signal can be expressed by the equation (2).

$$\tilde{s}(t) = s_I(t) + js_Q(t), \tag{2}$$

Equation (3) represents the signal emitted from the transceiver after up-conversion in frequency.$s_I(t)$ y $s_Q(t)$ denote the respective in-phase and quadrature signals of the components within the n-QAM system, where ω_0 is the fundamental angular frequency of the complex signal.

$$\begin{aligned} s(t) &= R\{\tilde{s}(t)e^{-j\omega_0 t}\} \\ &= s_I(t)\cos\cos(\omega_0 t) - s_Q(t)\sin\sin(\omega_0 t) \end{aligned} \tag{3}$$

Figure 5 displays the developed platform for transmitting the EMG signal, the experimental stage involves synthetic EMG signals that were acquired from the data-bank Physionet. Specifically, data from the tibialis anterior muscle of adult subjects aged 40-50 years were recorded at a sampling rate of 50 KHz and subsequently down sampled to 4 KHz. The ZX60-5916MA+ power amplifier served as the device under test (DUT), operating within its linear region with the intention of not adding short-term memory effects to the system. Additionally, a ZFBP-2400-S+ low-pass filter, suitable for base radio applications, was utilized in the setup, the directional coupler ZADC-15-252+ ideal for wideband, 850 to 2500 MHz provides return protection of the signal transmitted to the transceiver. The transmitted signal is shown in the spectrum analyzer for bandwidth monitoring. In Figure 6, the EMG signal obtained from the tibialis anterior muscle is depicted. Two analog filters were employed: a high-pass filter with a cutoff frequency of 20 Hz and a low-pass filter with a cutoff frequency of 5 KHz (Goldberger, 2000),

Figure 5 shows, in the first instance, ARRadio + SoCKit as a platform, a software-defined radio (SDR), which replaces the traditional and expensive signal vector analyzer (SVG). Additionally, there is the ARRadio transceiver compatible through the FMC port. which is an integrated processing and programmability based on FPGA, the system has two transmission channels in this case one is used and the ZX60-5916MA+ amplifier used as device under test, a 2.3-2.5 GHz coaxial bandpass filter is used to guarantee the transmission bandwidth and a coaxial bandpass filter with attenuation return of 20 dB for card protection. Finally, the spectral validation of the SIGLENT SSA3032X spectrum analyzer is evaluated in hardware.

In Algorithm 1, we present the segmentation stage for digital data packets of order n-QAM. It is important to note that prior to this stage, an offline process of signal discretization is necessary. The algorithm then proceeds to package the signal based on the required number of bits specified by the n-QAM system. Furthermore, the algorithm is adapted to accommodate the variables analyzed in this research product. To validate its effectiveness, a synthetic healthy EMG signal was used. However, the ultimate goal is to transition to real-time acquisition systems utilizing high-speed analog-to-digital converters (ADCs) and the establishment of a comprehensive database for classification processes aiming to diagnose muscular pathologies and even ECG-type signals.

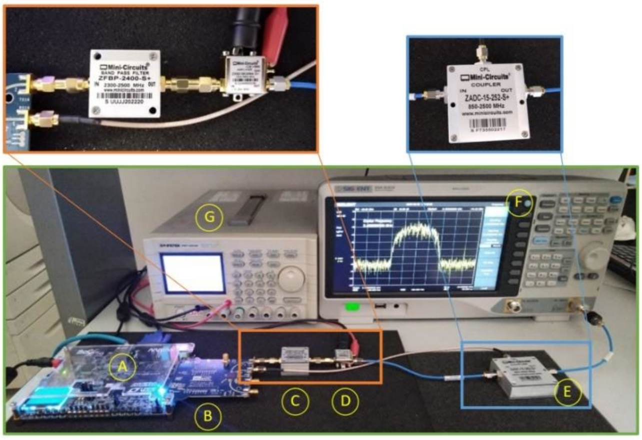

Figure 5: Overview of the developed platform. (A) Cyclone V FPGA SoC-Kit. (B) AD9361 RF Agile Transceiver. (C) Coaxial Bandpass Filter 2.3-2.5 GHz. (D) ZX60-5916MA+ Amplifier. (E) ZADC-15-252+ Directional Coupler. (F) Spectrum Analyzer SIGLENT SSA3032X. (G) Power Supply GW Instek PST-3202.

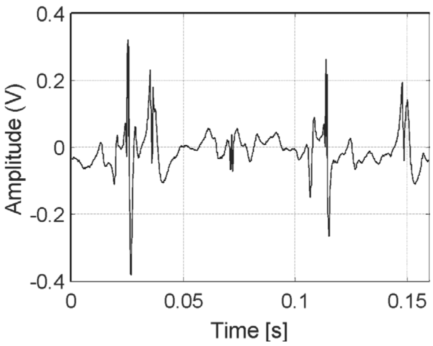

Figure 6: Synthetic Healty EMG signal from the Tibialis anterior muscle (Goldberger, 2000).

Algorithm 1 EMG signal segmentation and n-QAM digital packets
Require: $n \geq 1$
Ensure: $EMG_{stream/n} = EMG_{QAM}$
  while $N \neq 0$ and $N \leq length(EMG_{adq})$ **do**
    if N is integer **then**
      $EMG_{offset} = EMG_{adq} - min(EMG_{adq})$
      $EMG_{norm} = EMG_{offset}/max(EMG_{adq})$
      $EMG_{stream} = Dec2Bin(EMG_{norm})$
    end if
    StoreDigitalizedSignal ← EMG_{stream}
end while=0

The implemented approach based on Algorithm 1 outlines the procedure for segmenting of the EMG signal. This segmentation step is performed as a preprocessing task before the signal is introduced into the transceiver chain.

3.1. *Segmentation and discretization n-QAM algorithm*

Figure 7 illustrates the preprocessed signal, which undergoes further processing before being introduced into the AD9361 toolkit. The SOCKit development card is utilized, and it is connected through a static internet protocol (IP), enabling remote monitoring of the implementation. The key components of the implementation include a variable modulator employing n-QAM and a raised cosine filter. The filter characteristic used for the filter stage is Span in symbols 40, output samples per symbol of 16 based on the m-ary 16-QAM, and a linear gain of one for a normalization transmission, the linear amplitude filter gain of one is used and two gain blocks of 2^14 based for the maximum amplitude resolution of 14 bits.

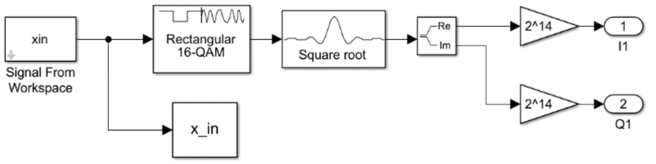

Figure 7: The input stage of the system based on Algorithm 1, before proceeding to the modulation and finite impulse response (FIR)-type filter stages.

The raised cosine receive filter is employed in the system to facilitate matched filtering for the transmitted waveform. In this implementation, the filter is configured with a rolloff factor of 0.5. The carrier frequency utilized is 2.4 GHz, and the system operates with a bandwidth of 18 MHz. Figure 8 illustrates the adjustment of the transmission parameters in the system.

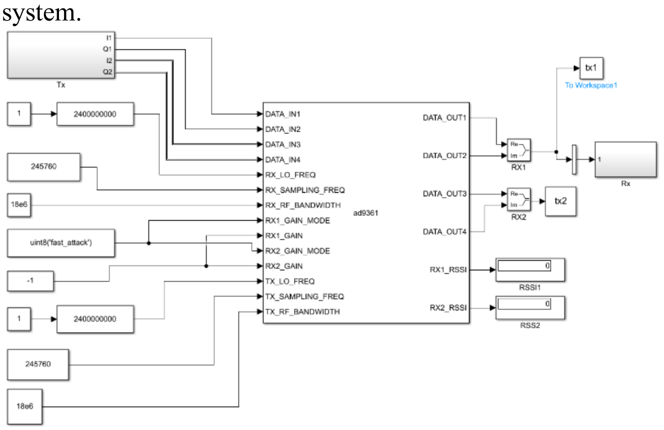

Figure 8: Toolkit AD9361 RF front-end, with the involved transmission variables of the system.

4. Results

During the measurement stage, a power level of -24.5 dBm is recorded within the system's bandwidth. It is important to note that a 10 dB attenuator is placed at the input port of the spectrum analyzer as part of the system's protection methodology. The power amplifier ZX60-5916MA+ operates with a gain of 17.21 dB, resulting in an output signal power of -41.71 dBm at the ZFBP-2400-S+ filter. The filter introduces a negligible loss, close to 0 dB. Consequently, the transmitted signal from the AD9361 RF Agile transceiver is relatively low in power, approximately 100 nW. Figure 9 shows the bandwidth in the frequency domain with a power of -34.49 dBm, considering that the input port has a 10 dB protection attenuator, an average power of -24.49 dBm is obtained, this signal is the transmitted signal with a carrier of 2.4 GHz.

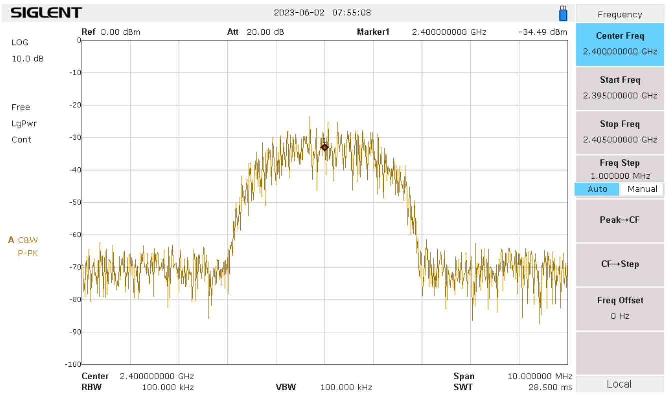

Figure 9: Transmitted EMG signal with bandwidth power of -34.5 dBm operating at 2.40 GHz carrier frequency.

In Figure 10, the constellation diagram of the QAM modulation is presented, along with the relative error vector magnitude (EVM). The primary objective of this work is to develop an adaptive algorithm capable of accommodating various n-QAM modulation schemes. In future research, comprehensive validation will be conducted to assess the performance of different n-QAM schemes and evaluate their EVM spectral purity.

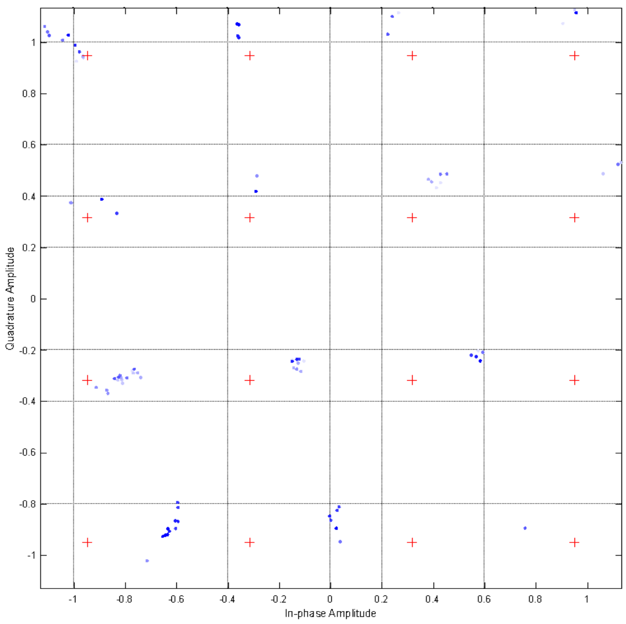

Figure 10: 16-QAM constellation of the transmitted signal.

Figure 11 presents the recovered signal of the healthy EMG, which undergoes a low-order discretization using 16-QAM. This discretization involves dividing the signal into 16 segments during each period. The normalized signal then becomes part of the post-processing stage in the receiver of the AD9361 RF board. The performance of the system is evaluated by calculating the normalized mean square error (NMSE). For the specific case of 16-QAM, an NMSE of -15.5 dB is achieved. In subsequent stages of the signal processing, filters are proposed to mitigate errors in the frequency domain. Additionally, a peak detector processing technique is employed to eliminate high voltage levels that may arise during signal demodulation in the receiver.

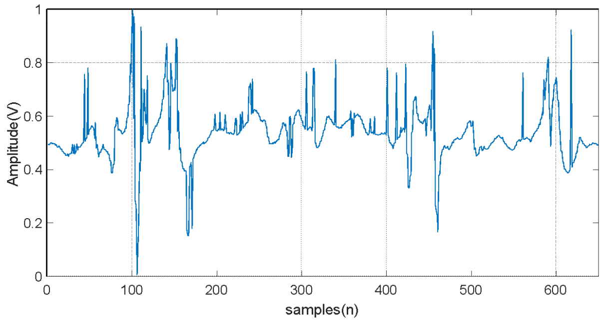

Figure 11 Recovered EMG healthy signal after 16-QAM demodulation process.

5. Conclusions

This research focuses on the development of an adaptable algorithm capable of accommodating various n-QAM modulation schemes. Initially was developed a transmission platform based on AD9361 RF Agile Transceiver, protected with a directional coupler and a spectral analysis of the implementation. The process of signal normalization enables the analysis of EMG signals with varying voltage and frequency levels. Synthetic signals obtained from (Goldberger, 2020) were used in this particular study, but the algorithm is flexible and can be extended to incorporate signal acquisition stages with embedded cards within the transceiver chain. The ZX60-5916MA+ amplifier, serving as the device under test (DUT), is operated below the P1dB point to minimize the introduction of non-linearities into the power system. The primary aim of this work is to propose a remote monitoring approach for biomedical signals, with potential for expansion to encompass various types of biosignals. The proposed methodology presents an alternative and cost-effective solution for precise monitoring in the post-pandemic era.

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