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Predictive sEMG-Driven Assistant for Enhanced Facial Therapy in Paralysis Patients

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Abstract*—Facial paralysis affects motor function, communication, emotional expression, and patient self-esteem, making rehabilitation a complex clinical challenge. This study presents the development of an intelligent therapeutic assistant for facial rehabilitation based on surface electromyography (sEMG). The system processes muscle biopotentials through filtering, normalization, and feature extraction to identify activation patterns that define optimal time windows for therapeutic interventions such as electrical stimulation or massage therapy. A mixed-method design was applied with patients presenting facial motor dysfunction, classified using the House-Brackmann (HB) scale, who participated in rehabilitation sessions supported by the system. A protocol for electrode placement and size was established to ensure signal quality and minimize contamination. Evaluation included algorithm performance metrics, muscle activation records, and clinical observations regarding detection accuracy and practical usefulness. Sessions were conducted in a controlled environment, considering patient comfort and variability in facial movements. Statistical analyses compared muscle activation detection before and after intervention and assessed the system's capacity to support therapeutic decision-making. Preliminary results indicate that the assistant enhances precision and personalization in therapy, reduces therapist uncertainty, and improves intervention effectiveness. This research highlights the potential of sEMG-based intelligent systems in facial rehabilitation and their integration into clinical and telemedicine contexts. Future studies should expand sample size, extend intervention duration, incorporate additional physiological markers, and establish standardized protocols for broader clinical application

***Key Words*– Facial paralysis, Intelligent therapeutic assistant, Predictive systems, Rehabilitation, Surface electromyography**

I. INTRODUCTION

Facial mobility is essential for communication, emotional expression, and social interaction [1]. Impairments in this function can significantly affect patients' quality of life and self-esteem [2]. Such conditions are closely linked to social anxiety, especially in women, where societal perception strongly influences self-image [3]. These consequences are more evident in cases of severe facial disfigurement [4], potentially leading to emotional disorders such as depression, anxiety, and decreased personal self-efficacy [5].

Facial paralysis can stem from central or peripheral origins. Central facial paralysis is related to central nervous system disorders, where lesions in the contralateral cortex may mimic the clinical features of peripheral paralysis [6]. Peripheral facial paralysis, on the other hand, is often caused by infections, trauma, or inflammatory processes [7]. Bell's palsy is the most common form, with an estimated annual incidence of 13 to 34 cases per 100,000 people [7], and is associated with herpes simplex virus reactivation, which can trigger inflammatory swelling of the facial nerve [8].

Treatment of facial paralysis requires extended clinical monitoring and therapies tailored to the degree of neuromuscular impairment [9]. Conventional rehabilitation methods, including facial exercises, electrical stimulation, and manual therapy, heavily rely on precise application and the therapist's expertise. This dependency can limit standardization and, in some cases, reduce the overall effectiveness of treatment [10].

In the last decade, surface electromyography (sEMG) has become a prominent non-invasive method to assess residual muscle activity in patients with neuromotor deficits [11]. This technique offers measurable insights into muscle recruitment and reinnervation patterns [12], making it particularly useful for guiding therapy when voluntary muscle contractions are minimal [13]. Moreover, sEMG is widely applied in rehabilitation, allowing real-time tracking of treatment outcomes and supporting adaptive therapeutic adjustments [14].

sEMG has been utilized in multiple areas, such as prosthetic control, brain–computer interfaces, and biofeedback systems. For instance, studies like [15] have analyzed facial sEMG signals for movement recognition, while others have created high-resolution interfaces to visualize spatial patterns of facial muscle activation [16]. Additionally, combining sEMG-based biofeedback with home exercise programs has been shown to improve facial function [17], correct facial asymmetry, and enhance muscle recovery [18]. These results emphasize the value of sEMG as an aid in neuromuscular rehabilitation.

Despite these advancements, most solutions remain experimental, involve high costs [19], or are not fully integrated into routine clinical practice [20]. Such constraints limit their use in home-based therapy and in settings with fewer resources. Many prototypes also require multiple acquisition channels and complex calibration, making them less practical for patients with limited mobility or without professional supervision [21], [22].

This gap highlights the need for accessible, portable, and user-friendly systems capable of providing reliable real-time information. In this scenario, intelligent sEMG-based therapeutic assistants appear as a promising option, predicting optimal stimulation times based on residual muscle activity. Integrating these systems with accurate classification algorithms and real-time feedback can enable more personalized, objective, and effective therapies [23], [24]. Their potential use in clinical and telemedicine settings could expand access to specialized rehabilitation in resource-limited areas [25], enhancing therapeutic accuracy, reducing clinician uncertainty, and improving the patient experience.

II. METHODOLOGY

This study was conducted under a quantitative experimental approach focused on the design, implementation, and functional validation of a therapeutic assistant based on surface electromyography (sEMG) signals for facial paralysis rehabilitation. The quantitative approach enabled objective measurement of facial muscle activity and the evaluation of system performance through measurable indicators related to muscle activation detection and system response time.

The experimental design is based on the development of a functional prototype and its evaluation through controlled trials involving both healthy volunteers and patients with peripheral facial paralysis. This methodology aims to assess the technical feasibility of the proposed system as a non-invasive clinical support tool, specifically designed to improve temporal coordination between voluntary muscle activation and therapeutic intervention during rehabilitation sessions. All of this is intended to serve as an assistive tool for clinical personnel, reducing the risk of human error when potential movements cannot be visually detected.

A. System Architecture and Signal Processing

The developed prototype consists of a single-channel sEMG acquisition system based on an Arduino Uno microcontroller, selected due to its low cost, ease of implementation, and widespread use in experimental biomedical applications [26], [27]. 1.....The system employs an Arduino Uno R3 connected to a single analog acquisition channel (A0), using its 10-bit ADC with a range from 0 to 1023 counts. It integrates a low-cost sEMG conditioning module, which is one of the few commercially available sensors in the region, configured with an analog gain adjusted for facial signals.

For signal acquisition, reusable adhesive surface electrodes with a diameter of 8 mm were selected, along with short cables to minimize motion artifacts. Smaller electrodes were preferred to reduce the capture of unnecessary residual muscle activity. Due to hardware limitations and the portability objective, the design segments the face into three functional regions (upper, middle, and lower thirds), acquiring one derivation per region,also integrates an sEMG amplification module with basic analog signal conditioning and reusable surface electrodes suitable for repeated non-invasive clinical use.

The sEMG signal was acquired at a sampling frequency of 200 Hz, which is sufficient to capture relevant facial muscle activity, as the primary spectral content of facial sEMG signals lies within low-frequency ranges. Real-time signal processing was implemented and included filtering stages aimed at reducing electrical noise and motion artifacts, which are common in facial electromyography applications.

Subsequently, time-domain feature extraction was performed due to its low computational cost and proven effectiveness in muscle activation detection. The extracted features included Mean Absolute Value (MAV), Root Mean Square (RMS), and Zero Crossing Count (ZC), which are widely used in electromyography-based detection and classification systems [28], [29].

1.. The following features are computed over segmented analysis windows:

- **Mean Absolute Value (MAV):**
$$\mathrm{MAV} = \frac{1}{N}\sum_{i=1}^{N}|x_i|$$
with a 250 ms window length.
- **Root Mean Square (RMS):**
$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2}$$
also computed over a 250 ms window.
- **Zero Crossing (ZC):** count of signal crossings through zero, incorporating a rejection threshold set at 5% of the dynamic range to reduce noise-induced crossings.
- **Energy (EN):** defined as the sum of squared signal values within the analysis window,
$$\mathrm{EN} = \sum_{i=1}^{N}x_i^2$$
- **Weighted slope:** computed over a 20-sample window using linearly increasing weights, and used for predictive activation detection.

MAV and RMS provide direct estimates of muscle activation intensity and exhibit robustness to small amplitude fluctuations. ZC contributes to the discrimination of rhythmic activity patterns, while the weighted slope enables the detection of pre-threshold trends, supporting anticipatory alert generation. These features are selected based on their computational efficiency for microcontroller implementation and their widespread use in facial sEMG literature.

These features allow reliable discrimination between resting and contraction states, even in low-amplitude signals typically observed in patients with neuromuscular impairment.

A baseline calibration stage was performed at the beginning of each therapy session to record resting muscle activity for each subject. Based on this reference, an adaptive thresholding scheme was implemented and experimentally adjusted according to individual responses observed during controlled tests. This approach increases system sensitivity to minimal residual contractions while reducing false detections and improving the identification of clinically relevant predictive muscle events.

B. Design of the System Enclosure

The prototype casing was developed using SolidWorks 2024 with the aim of safeguarding internal electronic components while ensuring portability and suitability for clinical rehabilitation environments. The enclosure features a rectangular shape with external dimensions of 120 × 75 × 35 mm and a uniform wall thickness of 2 mm. This design provides sufficient mechanical strength and structural integrity while keeping the weight low, thereby enabling comfortable handling and potential wearable or portable applications during therapeutic procedures.

To guarantyliable electrical connections and facilitate device integration, a rectangular aperture of 10 × 20 mm was included on one side of the enclosure. This opening allows organized routing of power and signal cables, securing electrode connections and minimizing mechanical stress on the connectors. Furthermore, the design enhances maintenance operations and permits easy assembly and disassembly, which is critical in clinical and experimental scenarios where frequent handling and inspection are necessary.

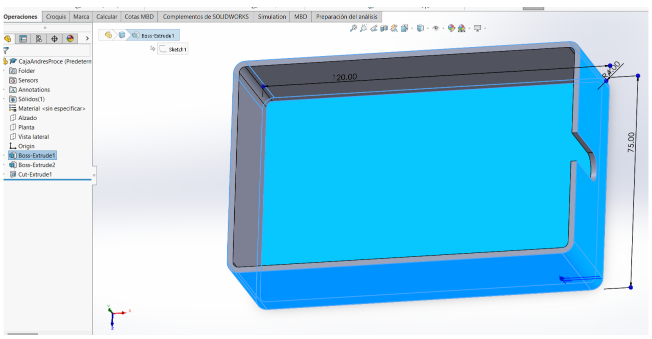

Fig. 1. Prototype enclosure design in SolidWorks

Figure 1 illustrates the preliminary design of the physical prototype, which was subsequently integrated with the electronic components to enable the actual measurement of facial muscle activity

The top cover measures 120 mm × 75 mm with a thickness of 4 mm. A circular opening with a diameter of 35 mm was included to serve a dual purpose: internal ventilation of electronic components and sound output for the buzzer used as an auditory feedback mechanism. Additionally, a 5 mm opening was incorporated for visual access to the system status LED. The enclosure was manufactured using 3D printing technology, enabling rapid and cost-effective prototyping while allowing easy design modifications. This manufacturing approach enhances device reproducibility and adaptability to different clinical contexts.

C. Feedback System for Therapeutic Assistance

The system incorporates a feedback mechanism designed exclusively for therapist assistance during rehabilitation sessions. Feedback is delivered through a visual on-screen interface developed using Visual Studio Code (HTML), complemented by a vibratory alert that serves as an additional sensory cue.

Feedback activation occurs automatically when the system detects a predictive muscle activation event, indicating the optimal moment for the therapist to apply manual or electrical stimulation according to the established therapeutic protocol. This strategy aims to improve temporal alignment between voluntary patient effort and therapeutic intervention, thereby enhancing rehabilitation effectiveness.

The system implements an optimized deterministic rule-based (non-ML) algorithm designed for low latency and clinical interpretability. The processing flow and parameter selection are defined as follows:

- **Initial calibration:** A 2 s automatic resting period is used to estimate the baseline mean; the initial threshold is defined as $T = \mu_{\text{rest}} \times k$ (adjustable).
- **Immediate detection (hysteresis):** Movement onset is detected when $x_f < T_{\text{high}}$; termination occurs when $x_f > T_{\text{low}}$, where $T_{\text{low}} = T+20$. Validation through consecutive readings prevents false activations.
- **Predictive detection:** A weighted slope m is computed over a 20-sample window. If $m < -0.005$ and the estimated time to threshold crossing
$$t_{\text{est}} = \frac{V_s - T}{-m} \cdot \Delta t \tag{1}$$
satisfies $0 < t_{\text{est}} \leq t_{\text{alert}}$ (default: 2000 ms), a predictive alert (visual and vibratory) is triggered to notify the therapist.
- **Additional validation:** The alert is maintained only if the slope condition persists and no confirmed movement is detected (moving = false).

Rationale: A deterministic rule-based approach is selected due to its minimal latency, ease of clinical verification, and the limited pilot sample size. Future work will compare this approach with supervised classifiers trained on an expanded dataset.

Where: V_s is the smoothed signal value, T is the adaptive threshold, m is the slope, and Δt is the sampling interval.

System accuracy was evaluated by measuring the temporal correspondence between detected events and actual voluntary muscle contractions, using therapist clinical judgment and complementary visual recordings as references.

Accurate electrode placement is critical for reliable facial sEMG acquisition. Due to hardware limitations of the acquisition module, which supports only three derivations, the face was divided into three functional regions: upper, middle, and lower thirds. This segmentation allows targeted measurement of muscle activity in specific regions while minimizing interference from adjacent muscles. Small-sized surface electrodes were selected, as larger electrodes increase the likelihood of cross-talk and residual signal capture, particularly in the anatomically complex and densely innervated facial region.

Figure 2 represents the main areas where facial electrical activity is detected, serving as the starting point of the study. In

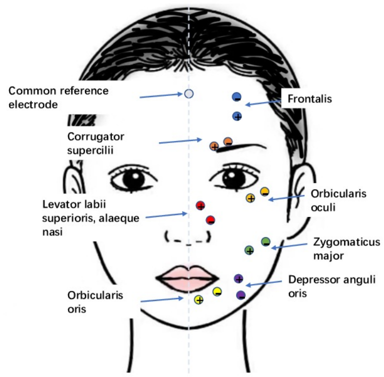

Fig. 2. Facial regions for sEMG electrode placement

addition, it allows the software to classify the principal regions and determine the thresholds for each one.

- In the upper third, electrodes were positioned over the eyebrow region, with the reference electrode placed on the upper forehead to record muscle activity related to eyebrow elevation.
- In the middle third, electrodes were set on the cheek area, aligned with the labial commissure and zygomatic region, using the mastoid as reference, allowing consistent detection of smile-related movements.
- In the lower third, electrodes were located near the upper lip, with the reference on the chin, enabling capture of movements such as lip closure or protrusion.

Skin preparation involved cleaning with alcohol, proper drying, and secure attachment of electrodes to minimize skin–electrode impedance. Short, well-fixed cables were used to limit motion artifacts, and a common ground reference was maintained to guarantee signal stability and consistency.

D. Performance Testing and Functional Validation

Experimental testing was conducted with healthy volunteers and patients diagnosed with peripheral facial paralysis. During testing sessions, the activity of the zygomaticus major muscle was recorded while participants performed controlled tasks, such as smiling, attempting to elevate the labial commissure, or executing voluntary facial movements.

System performance was evaluated based on its ability to detect muscle activation, the response time from contraction onset, and the clarity of feedback provided to the therapist. Performance metrics included detection rate, accuracy, and response time, enabling a comprehensive assessment of the prototype.

The obtained results were qualitatively contrasted with visual video recordings and the therapist's clinical perception, strengthening the functional validation of the proposed system.

E. Subject Inclusion Criteria

Initially,participants of varying ages were included, provided they had no degenerative muscular diseases or associated neuromuscular disorders. For patients with facial paralysis, inclusion required an active rehabilitation phase and completion of at least two weeks of prior therapy to ensure measurable sEMG activity.

Additionally, only patients classified up to grade III on the House–Brackmann (HB) scale were included, as this level still allows for observable residual muscle activity both clinically and electromyographically.

The procedure developed to evaluate system functionality is defined as follows:

- **Subject instructions:** Participants perform between 10 and 20 repetitions of the target action (e.g., voluntary smile, cheek inflation, or eyebrow elevation), maintaining the contraction for 2–3 s and relaxing for 8–10 s between repetitions.
- **Video synchronization:** All sessions are recorded. Contraction onset is manually annotated, including frame-by-frame inspection to identify facial gestures at specific time points and verify temporal correspondence with system detections.
- **Control conditions:** Testing includes healthy subjects for baseline calibration and simulated low-activation conditions to evaluate sensitivity under low-amplitude signals.
- **Repeatability:** Each test, in both healthy participants and patients with the condition, is repeated across different days or weeks to assess consistency and potential variations in system sensitivity.

III. Discussion and Results

The proposed system represents a specialized device for facial paralysis rehabilitation, emphasizing accessibility, portability, and ease of use. Unlike invasive techniques such as needle electromyography, the system employs surface electrodes (sEMG), providing a safe, non-painful, and patient-friendly solution. The device is designed to operate with low-amplitude signals and controlled frequency ranges, ensuring user comfort and safety throughout therapy sessions. By focusing specifically on facial rehabilitation, the system offers improved clinical relevance compared to high-cost generic electromyography equipment.

Through the use of an Arduino microcontroller and a graphical interface developed in Visual Studio Code (HTML), the resulting prototype is low-cost, easily replicable, and simple to maintain. The value proposition lies in delivering an affordable, portable, and highly specialized solution that complements conventional rehabilitation therapies through real-time feedback, particularly suited for clinics and rehabilitation centers with limited resources.

The sEMG signal processing pipeline begins with digital signal conditioning, employing a sequence of filters to improve signal quality and reliability. A median filter is first applied to reduce impulsive noise and signal spikes. Subsequently, a high-pass filter is used to suppress the DC component, followed by a low-pass filter to smooth rapid fluctuations, thereby forming a digital band-pass range of 10–500 Hz. In addition, a notch filter is implemented to attenuate power line interference at 50 Hz, and a moving average filter is applied to further stabilize the signal.

To prevent false activations, a hysteresis-based logic was implemented using two detection thresholds combined with validation through three consecutive readings. This strategy improves robustness against transient noise. Furthermore, the signal is normalized, and relevant features such as mean, variance, slope, energy, and RMS are extracted to facilitate reliable comparison and contraction detection.

This processing approach ensures stable and clinically usable sEMG signals, suitable for rehabilitation and therapeutic assistance applications.

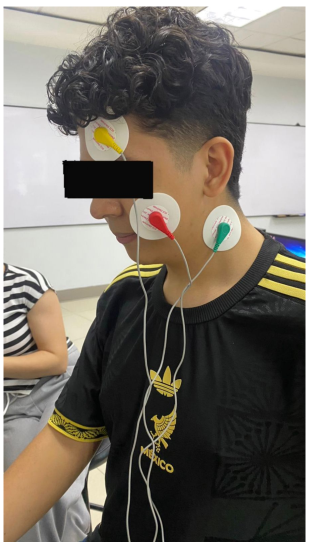

Fig. 3. Initial experimental testing

Figure 3 represents the initial tests conducted on a healthy subject, serving as a preliminary calibration step and as a starting point to improve the code before ultimately testing it on subjects with the condition.

The sEMG-based facial movement detection system presents inherent limitations when signal amplitudes do not exceed the predefined detection thresholds. This condition may result in false detections or failure to identify subtle facial movements, such as *cheek elevation* or *eyebrow activation*. These challenges are particularly common in low-intensity gestures or in patients affected by facial paralysis.

Individual calibration plays a critical role in improving detection accuracy, as sEMG signal amplitude varies significantly across users. Inadequate calibration may compromise the system's reliability and robustness, leading to underestimation or overestimation of facial muscle activity.

Personalized adjustment of detection thresholds during the initial calibration phase significantly enhances the system's ability to identify facial movements of varying intensity, thereby improving performance in assistive and interactive rehabilitation applications.

The system response time is defined as the interval between the execution of a facial movement by the user and the correct detection of that movement by the system. This parameter is essential to ensure smooth interaction and minimize latency in facial movement interpretation.

Experimental tests were conducted with six users performing movements targeting different facial regions: cheek, eyebrow, and maintenance of a neutral facial expression. The obtained results are summarized below:

TABLE I
SAMPLE CHARACTERISTICS AND PARTICIPANT DISTRIBUTION

Description	Value
Total number of participants	[6]
Participants with facial paralysis	[2]
Healthy control participants	[4]
Mean age (years)	[28]
Sex (M/F)	[2]/[4]
House-Brackmann distribution	HB II: [1]; HB III: [1];
Repetitions per task (per subject)	[4]

Once the pilot tests are completed, a statistical analysis is conducted to estimate system response times according to the facial region under study. These measurements are computed individually for each participant, and a mean value is obtained for each of the three facial regions (upper, middle, and lower thirds). Subsequently, an overall average is calculated across the three regions to determine the system's global response time. This metric reflects the latency between the detection of muscle activation, the capture of participant movement, and the activation of the user interface, including both visual and vibratory feedback.

TABLE II
RESPONSE TIME OF THE FACIAL MOVEMENT DETECTION SYSTEM USING sEMG

Facial Movement	Alert Time (s)	Average Response Time (s)
Cheek	2.0	1.33
Eyebrow	1.0	1.33
Neutral expression	1.0	1.33

The average response time was calculated using the following expression:

$$T_{\text{avg}} = \frac{\sum_{i=1}^{n} T_i}{n} = \frac{2.0 + 1.0 + 1.0}{3} = 1.33 \text{ s}$$

Where:

- T_{avg} represents the average system response time.
- T_i corresponds to the response time recorded for each facial movement.
- n is the number of measurements (3: cheek, eyebrow, and neutral state).

The results indicate that the system achieves an average alert time of 1.33 seconds, which is suitable for interactive applications such as facial gesture-based communication interfaces.

It should be noted that factors such as EMG signal processing speed, individual user calibration, and measurement stability may influence response time. When significant delays are observed, optimization of digital filters or adjustment of detection thresholds can further reduce latency and improve system responsiveness.

Electromyographic signal analysis is essential for evaluating muscle activity. This section presents the sEMG signal analysis in the time domain, addressing three key aspects: temporal signal behavior, signal inversion to highlight muscle activation, and root mean square (RMS) calculation.

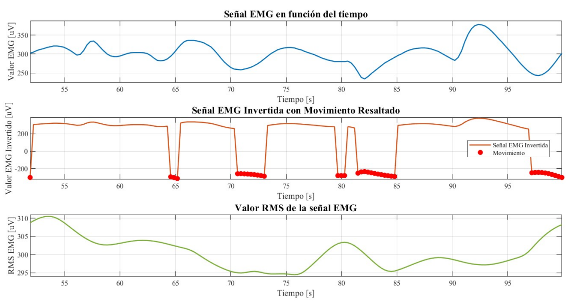

Fig. 4. Processed sEMG signals in MATLAB

In Figure 4, the first graph shows the inverted sEMG signal, where peaks or abrupt changes throughout the recording have been highlighted with red circles. This inversion makes the moments of increased muscular activity more visible, allowing an easier identification of events associated with facial movements or specific muscle contractions. By displaying the signal in this way, sudden variations in amplitude can be observed more clearly than in the raw waveform, where these responses may appear less evident within the natural irregularity of the biological signal. These highlighted points correspond to instants in which the subject generates a measurable myoelectrical response captured by the surface electrodes.

Similarly, the second graph again presents the inverted signal with the peaks marked in red, confirming the presence of significant muscular activity and allowing the recognition of contractions or relevant events within the recording. This repeated visualization helps validate that the detected changes are not random fluctuations, but rather muscular responses that maintain a clear temporal relationship with the performed movement. In addition, these marked points serve as reference indicators of the moments in which the muscle exhibits greater activation.

Finally, the last graph includes in its lower subplot the RMS value calculated according to the studies conducted, which reflects the energy of the signal and serves as a more stable and precise indicator of muscular activity intensity, since it is less susceptible to non-physiological fluctuations. Unlike the raw signal, the RMS provides a continuous quantitative representation of muscular effort over time, making it possible to observe not only isolated activation peaks but also the general energetic trend of the recording. The variability of the RMS therefore represents changes in contraction intensity, complementing the interpretation of the previous graphs and providing a more reliable understanding of the subject's muscular response during the analyzed session.

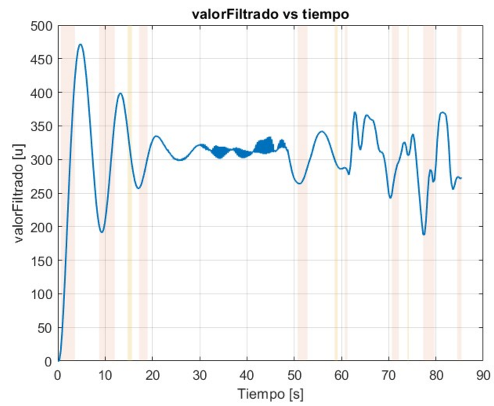

Fig. 5. Time-domain representation of the sEMG signal

Figure 5 shows the sEMG signal in the time domain, illustrating the behavior of the filtered value over approximately 90 seconds. The blue line highlights variations in muscle activity, with peaks and troughs corresponding to moments of contraction and relaxation. The vertical bands in red and orange mark specific intervals of interest, which are directly associated with muscle activations,in other words, they capture the signal precisely at the moments when the muscle becomes active.

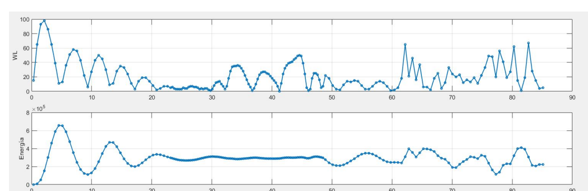

Fig. 6. Energy representation of the sEMG signal

Figure 6 represents the signal, or more specifically the intensity of muscle activation, when a response is generated by the subject during the performed movement. Unlike the previous processed representations, this signal does not display isolated peaks, but instead reflects the continuous relationship of muscular activity throughout the recording period. In this way, it provides a more stable visualization of how the muscle effort evolves over time, allowing the observation of increases or decreases in activation intensity without focusing only on abrupt events. This continuous behavior makes the graph useful for understanding the general energetic pattern of the muscular response,

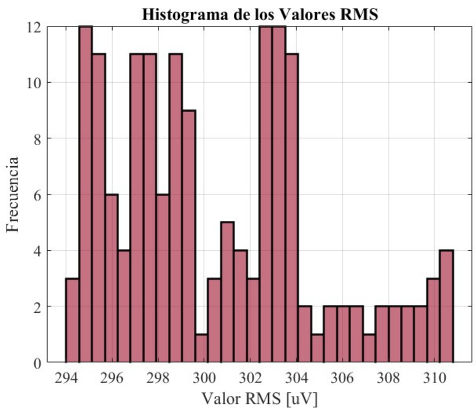

Fig. 7. Processed sEMG signals in MATLAB

Figure 7 presents a histogram of the RMS values obtained from the initial tests performed during various facial movements, along with an analysis of the concentrated values, which reveals a relatively consistent level of muscular intensity.The graph shows that values below 290 µV correspond to facial movements. These movements, including micro-expressions or blinking, produce low-amplitude signals. The results demonstrate that facial movements generally exhibit lower intensity compared to other muscular activities, which is essential for distinguishing between high- and low-intensity contractions in diagnostic and rehabilitation contexts.

In typical physiological conditions, electromyographic (EMG) activity associated with voluntary movement shows higher amplitudes than at rest. However, in patients with facial paralysis, voluntary activation may be severely reduced, while the resting state may present residual activity, background noise, or involuntary micro-contractions, which can lead to an apparent inversion of absolute magnitude between both states. Nevertheless, the methodological objective of the system is not to compare absolute values, but to evaluate the separability between the rest and movement distributions.

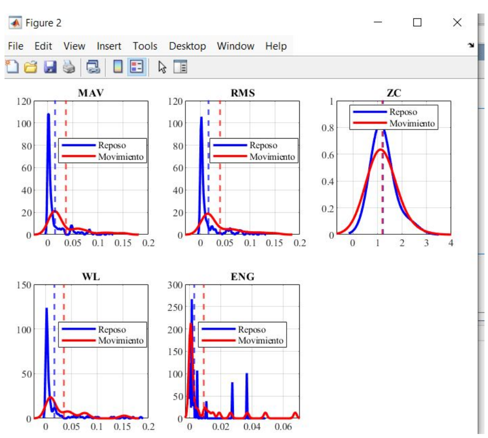

Fig. 8. Stadistics Results

In Figure 8, MATLAB software was used for the development and extraction of several statistical metrics from a session conducted on a patient with a pathological condition. For this reason, the resting activity appears higher than the movement activity. This behavior is attributed both to the system configuration implemented during programming and to the physiological condition of the patient, in which voluntary movement activity is significantly reduced or appears inverted.

Furthermore, the selection of the parameters is justified as follows:

- **MAV (Mean Absolute Value).** The MAV quantifies the average intensity of the electromyographic signal. In the figure, it shows a more concentrated blue curve (rest) compared to a more dispersed red curve (movement), with clearly separated mean values represented by dashed lines. This configuration indicates that the system discriminates between rest and movement states. However, in patients with facial paralysis, this relationship may be inverted because voluntary activation during attempted movement is reduced, while noise and involuntary micro-activations may appear during rest. Therefore, MAV demonstrates a clear separation between states and confirms the system's ability to detect muscular activity even under low activation conditions.
- **RMS (Root Mean Square).** The RMS measures the signal's energy and provides a more sensitive estimate of its amplitude variations than MAV. In the graph, it shows a behavior similar to MAV, with a clear distinction between rest and movement distributions, confirming changes in signal energy between states. Consequently, RMS validates muscle activity detection and reinforces system robustness against amplitude variations.
- **ZC (Zero Crossings).** Zero crossings quantify the number of times the signal changes sign, reflecting neuromuscular activation dynamics. In the figure, a noticeable separation between rest and movement is observed, indicating high sensitivity to changes in activity. Therefore, the zero crossing rate is an effective metric for distinguishing states and provides complementary information about the temporal structure of muscle activation.
- **WL (Waveform Length).** Waveform length quantifies signal complexity and variability. In the graphical representation, the movement state shows greater dispersion, while rest appears more stable, indicating that muscle activity increases the temporal complexity of the signal. Consequently, WL captures variations in muscle activity and provides evidence of morphological changes in the EMG signal during activation.
- **ENG (Energy).** Energy summarizes the total amount of recorded activity and is particularly sensitive to peaks and transients. The figure shows differences between states, with a stronger response during movement, complementing the other metrics by providing a global measure of signal intensity. Therefore, energy allows state discrimination and contributes to a comprehensive characterization of the EMG signal.

The obtained results demonstrate that the predictive sEMG-based system is effective in detecting facial muscle activity patterns, particularly in key muscles such as the zygomaticus major and the orbicularis oris. These findings are consistent with previous studies reporting residual muscle activation in patients with peripheral facial paralysis [30].

Compared to traditional methods such as clinical observation or static visual biofeedback, the proposed assistant offers significant advantages by enabling real-time dynamic visualization and quantifying muscle intensity through parameters such as RMS and MAV. This provides therapists with continuous and objective information to determine the optimal timing for therapeutic intervention.

Experimental tests conducted on healthy subjects and simulations of low muscle activation allowed the identification of characteristic amplitude ranges for each facial region. These values were critical for establishing detection thresholds capable of distinguishing between rest, voluntary contraction, and low-force activation attempts. Threshold calibration, supported by prior sEMG classification studies [31], improved system accuracy and reduced misinterpretations caused by noise or artifacts.The integration of these thresholds into real-time predictive processing represents a key contribution of this project. The results support the hypothesis that sEMG-based systems can serve as effective tools to assist therapists in facial rehabilitation. However, broader clinical validation, including patients with higher severity levels, is required to strengthen applicability and generalization.

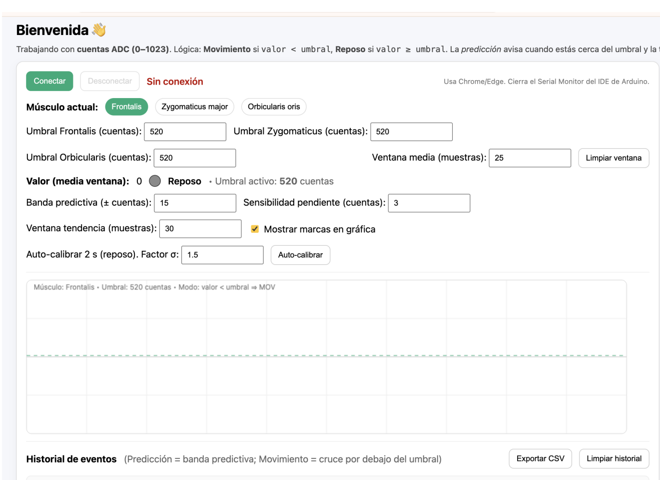

Fig. 9. Graphical User Interface (GUI) software

Figure 9 represents the final interface designed in HTML, which connects to the microcontroller port,in this case, the Arduino. This interface allows the user to visualize facial activity in real time and provides alerts whenever the patient performs a movement. Additionally, it includes self-calibration parameters that enable the system to be customized for each user and situation, allowing specific thresholds to be adjusted according to the patient's needs.

The interface designed in HTML is easily shareable and includes a highly valuable feature; all real time activity can be exported as a CSV file. This functionality allows the data to be analyzed in any software environment and has been used to perform mathematical analyzes in MATLAB. At the bottom of the interface, this section is referred to as the "event history," which facilitates the exchange of information among specialists regarding any study subject, whether in clinical practice or academic research.

TABLE III
MATERIAL COST BREAKDOWN

Material	**Cost (USD.)**
EMG Module	18.00
Arduino Mega	30.00
Disposable electrodes (50 units)	5.00
830-point breadboard	6.00
LED diodes (10 units)	2.00
Buzzer	2.00
Jumper wires (40 units)	8.00
3D printing	12.00
Manufacturing labor	36.00
Total	**119.00**

The table cost breakdown presents the detailed distribution of expenses associated with the development of the prototype. It includes the main electronic components, such as the Arduino Mega and the EMG module, as well as the supplies required for measurement, including disposable electrodes and the breadboard used during the initial tests. Output elements such as LED diodes and the buzzer are also considered, together with jumper wires for internal connections. In addition, the cost of 3D printing for the fabrication of the casing and the manufacturing labor required for device assembly is incorporated.Which demonstrates the economic feasibility of the prototype and reinforces its role as an accessible solution compared to high-cost commercial electromyography equipment.

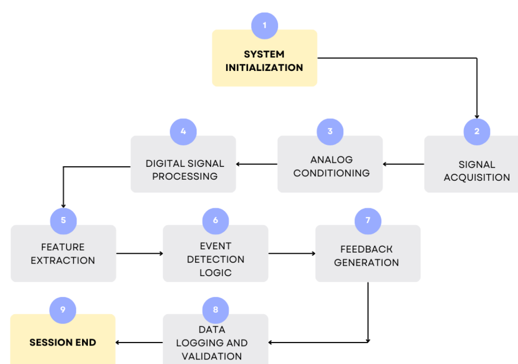

Fig. 10. Flowchart of clinical trial operations

The figure 10 illustrates the operational diagram of the system's clinical trials. It shows how sEMG signals are acquired from the facial muscles. These signals are processed through amplification and filtering, followed by the implementation of the predictive algorithm, which analyzes residual muscle activity to determine the optimal moments for therapeutic intervention. Finally, the diagram depicts the feedback provided to both the patient and the therapist, either through visual biofeedback, closing the cycle of monitoring and continuous improvement during clinical sessions.

Facial rehabilitation presents high inter- and intra-subject variability due to muscular asymmetry, etiology, and degree of denervation. In the pilot study, detection sensitivity is lower in patients with House–Brackmann scale grades close to III compared with healthy controls, due to lower signal amplitudes and higher background noise. However, the adaptive thresholding logic and validation through consecutive readings improve the detection of micro-contractions to a meaningful extent.

In the comparative context and proposed approach,commercial multichannel systems provide higher spatial resolution, advanced processing algorithms, and extensive analytical capabilities. However, their high cost, calibration complexity, and requirement for specialized personnel limit their adoption in public healthcare settings and rural telemedicine environments. In addition, the proposed system arises from a contextual need in Honduras, where healthcare infrastructure is constrained by limited investment and restricted budgets for specialized rehabilitation technologies.

Traditional therapeutic approaches rely heavily on visual observation and clinician experience, which introduces variability in both timing and dosage of interventions, as muscle effort cannot be objectively quantified through visual assessment alone.

The designed device emphasizes portability and low cost, incorporating adaptive thresholding and a predictive detection band to synchronize therapeutic intervention with voluntary patient effort. It also includes a therapist-oriented graphical user interface (GUI) that enables data recording and export, supporting longitudinal monitoring and teleconsultation scenarios. These characteristics position the system as a complementary tool for healthcare professionals, providing objective support and improving upon visual assessment alone, particularly in resource-constrained environments.

Therefore, the system is not intended to replace clinical judgment; rather, its function is to augment and standardize the objective information available to the therapist by providing temporal alerts that can be accepted, ignored, or used to support decisions such as electrical stimulation or manual therapy. In clinical practice, it is recommended that the therapist use the interface to adjust thresholds on a per-session basis and combine the sEMG signal with functional assessment and direct observation.

IV. Study Limitations and Suggested Improvements

The project presents several limitations that should be addressed in future developments. From a technical perspective, the limited number of acquisition channels constrained the ability to record multiple facial muscles simultaneously, reducing spatial resolution. Electrode placement proved to be critical, as even minor variations in positioning or skin preparation had a significant impact on signal quality. Additionally, the sEMG module showed limitations in amplification and filtering, which prevented complete elimination of interference and affected data fidelity. Persistent motion artifacts and electrical noise also challenged the stability of the signals.

From a methodological standpoint, the small sample size restricted validation in patients with severe facial paralysis. Furthermore, algorithms trained on preliminary datasets may carry inherent bias, emphasizing the need to expand and diversify the clinical database.

Despite these constraints, the project provides a solid foundation for future improvements aimed at enhancing both the technical performance and clinical applicability of the system.

Recommendations for future work include upgrading certain electronic components and processors to improve therapy quality. Additionally, integrating a predictive system trained with artificial intelligence could offer significant benefits. Due to the limited sample size, it was not feasible to train a fully robust algorithm; instead, a slope-drop mathematical model was implemented. Although this model demonstrated efficiency, it still leaves room for optimization. Another suggested enhancement is to enable the system to provide electrical stimulation directly to the patient—referred to as electrostimulation—which would further enhance the effectiveness of the proposed technology.

V. Conclusions

The surface electromyography (sEMG)-based therapeutic assistant demonstrated strong potential as a clinical support tool for facial paralysis rehabilitation by accurately detecting facial muscle activity patterns and enhancing decision-making beyond traditional visual observation methods. The system successfully identified muscle activation in critical regions such as the forehead, eyebrows, blinking muscles, mouth, and smile, facilitating optimal intervention timing and improving therapeutic effectiveness.

The integration of the system into therapeutic workflows provided immediate and interpretable feedback on muscle activity, enabling real-time personalization of interventions and improved clinical efficiency. Experimental evaluations validated the prototype as a complementary technological solution capable of delivering objective and quantifiable data, thereby enriching conventional rehabilitation approaches. These findings indicate that the proposed assistant represents a promising innovation for optimizing treatment outcomes and diagnostic precision. Nevertheless, larger-scale clinical studies and further system integration in real-world settings are required to fully maximize their therapeutic impact.

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