

Calibrating open-source sEMG devices for accurate muscle signal analysis in sports and education

DIEGO PEREZ-RODES¹, BASILIO PUEO^{2*}, JOSE M. JIMENEZ-OLMEDO³

^{1,2,3}Department of General and Specific Didactics, University of Alicante, SPAIN

Published online: June 30, 2025

Accepted for publication: June 15, 2025

DOI:10.7752/jpes.2025.06138

Abstract:

Recent advancements in open-source technologies have considerably increased the appeal of low-cost devices for sports science professionals. However, achieving reliable measurements remains a major challenge. This paper introduces a straightforward yet robust calibration method for an open-source surface electromyography (sEMG) device, designed to balance affordable hardware with the rigorous accuracy requirements of sports science. In a controlled laboratory setting, artificial signals were generated to mimic the amplitude range (0.01–1 mV) and frequency range (up to 300 Hz) of real myoelectric activity. Both the sEMG device and an oscilloscope (serving as a reference gold standard) simultaneously recorded each signal. Regression analyses (ordinary least squares, OLS) coupled with paired t-tests, mean absolute error (MAE), and root mean square error (RMSE) were used to assess and quantify discrepancies across a wide array of amplitudes and frequencies. A strong linear correlation ($R^2 = 0.994$, $p < 0.01$) was found between the sEMG readings and the oscilloscope values. Additionally, the model's predictive accuracy was confirmed with a low mean absolute error (MAE) of 28.1 arbitrary units (a.u.) and a root mean square error (RMSE) of 37.67 a.u. These error metrics showed a high degree of agreement with the reference standard, enabling the derivation of a simple regression equation to convert raw sEMG data into consistent, reliable units. Compared to traditional methods focusing on internal amplifier or ADC calibration alone, this holistic approach calibrates the entire sEMG-ADC chain against a laboratory reference, ensuring that the final digitised signal accurately reflects true muscle activity. These findings demonstrate the true potential of applying open-source sEMG solutions to sports performance monitoring and education, while upholding stringent data quality standards.

Key Words: Surface Electromyography (sEMG), Regression Analysis, Low-Cost Technology, Myoelectric Activity

Introduction:

In recent times, there has been a notable increase in professionals who work directly or indirectly in sports, driven by the growing demand for services related to this sector (Wicker & Breuer, 2014). The reasons behind this increase stem, in part, from the high performance levels demanded of professional athletes in competition, as well as the growing popularity of amateur sports due to the population's rising interest in maintaining a healthy lifestyle through physical activity (Warburton & Bredin, 2017). Furthermore, a significant subgroup of amateur athletes engages in non-professional competitive sports at considerable training intensities, representing a large and scientifically interesting population for performance analysis (Guthold et al., 2018).

Both professional and amateur sports performance have reached very high levels, thanks to the professionalization and technological advancements in the sector (Pfeiffer & Hohmann, 2012). This evolution marks a paradigm shift from traditional, often subjective, coaching methods to a data-driven approach where quantitative metrics are paramount. The techniques and methods employed are scientifically rigorous and are extensively documented in the literature, further enriched by disciplines such as medicine (Baca & Kornfeind, 2006). In this regard, technology has played a fundamental role in the sector's development, enabling the precise measurement and monitoring of athletes and patients (Gabbett et al., 2016; Downey et al., 2018).

As can be seen in the literature, the use of accelerometers, gyroscopes, machine learning algorithms, or computer vision, among other technologies, provides a more precise and detailed perspective on athletic performance. These tools make it possible to quantify movement, load, and physiological response with unprecedented accuracy, enabling the optimization of training, the prevention of injuries, and the improvement of tactical decision-making in sports (McGrath & Scanaill, 2013; Zdravevski et al., 2020; O'Donoghue, 2015).

Despite the evident popularity of sports-related technologies—which have become affordable for professionals and users alike (e.g., heart rate monitors or pulse oximeters)—many devices used in research remain inaccessible to a wide range of professionals in the field. This inaccessibility creates a significant "scientific divide. In education, grassroots sports, or general sports services focused on amateur athletes, the economic factor can be a significant barrier to accessing certain technologies. Consequently, evidence-based practices that are standard in

elite sports cannot be implemented in these settings, limiting the potential for talent development, injury prevention, and optimized health outcomes for the broader population.

Many devices potentially usable for sports research are derived from the medical sector, which requires stringent certification for commercialization—often substantially increasing product costs. Moreover, specialized or custom-developed technological solutions from established manufacturers tend to come at a high cost as well, placing them beyond the budgets of smaller clubs, public schools, and independent practitioners.

The application of open-source technologies in the realm of sports science opens new horizons for professionals in this sector. Such technologies offer a broad range of solutions that can not only replace many commercial devices used in this setting but also be adapted as specialized solutions for specific modalities or athletic needs, thanks to their flexibility and diversity (Gómez-López et al., 2014). Built upon accessible platforms like Arduino or Raspberry Pi, open-source hardware empowers users to build and modify their own tools, fostering innovation and democratizing access to technology.

From this perspective, open-source options represent an affordable solution for sports procedures and studies. Nonetheless, their adoption is not without challenges. These technologies require advanced technical knowledge for configuration and customization, which may hinder their use by professionals lacking specific training. Additionally, the lack of formal technical support and potential compatibility issues with proprietary systems could pose operational challenges (Prat & Camerino, 2012). Further considerations include data security and privacy risks, as well as the absence of certifications or standards that constrain their acceptance in professional contexts where data integrity and reliability are paramount. Finally, reliance on the community for updates and any hidden costs associated with customization and maintenance are also important factors.

Surface electromyography (sEMG) is a noninvasive technique used to measure muscle activity, with diverse applications in sports science and education. As a cornerstone of biomechanical and physiological assessment, sEMG is used to monitor performance, facilitating evaluations of neuromuscular function, analysis of force production, and tracking of muscle activity changes in response to training (Felici & Del Vecchio, 2020; Xu, 2023; Ergeneci et al., 2022; Massó et al., 2010). It is also employed for injury prevention and rehabilitation, enabling the detection of muscle imbalances and asymmetries that may predispose individuals to injury, as well as for monitoring recovery and functional readaptation following an injury (Ergeneci et al., 2022; Spanu et al., 2021). Additionally, the integration of portable sEMG-based technology, such as flexible textile electrodes, allows data collection under real-world sports practice conditions, providing real-time feedback to adjust and optimize training load (Spanu et al., 2021).

The high utility of sEMG is counterbalanced by the high cost of certified, research-grade commercial systems, which restricts its application primarily to well-funded laboratories and elite sports organizations. While low-cost, open-source sEMG alternatives have emerged, their widespread adoption is hindered by a critical concern: a lack of documented evidence regarding their measurement reliability and validity. Without a standardized method to verify that these devices produce accurate and repeatable data, sports professionals cannot confidently use them for making critical decisions about training, injury risk, or rehabilitation. This creates a clear research gap: a need for a robust, accessible calibration methodology that can bridge the gap between affordable technology and scientifically rigorous application.

This study proposes and validates a calibration method for a low-cost, open-source surface electromyograph (sEMG) to ensure the reliable use of this technology by sports professionals. The core of the problem lies in the fact that an sEMG device's role is to amplify weak myoelectric signals (on the order of microvolts to millivolts) and bring them to a measurable level (usually in volts). Our objective is to establish a precise mathematical relationship—a calibration function—that correlates the device's output signal with its known input signal across a range of relevant frequencies.

To achieve this, our methodology involves feeding the open-source sEMG device with artificial electrical signals of known amplitude and frequency, generated in a controlled laboratory environment to emulate muscle activity. We simultaneously record the resulting output signal using two systems: the native software associated with the low-cost sEMG device and a high-precision digital oscilloscope. The oscilloscope provides readings in volts and serves as our "gold standard" reference measurement. In contrast, the initial data from the sEMG software are in undefined physical units (i.e., "raw" or arbitrary units). By modeling the relationship between the raw output and the gold-standard voltage input, we aim to derive a calibration that ensures the data recorded by the low-cost device are reliable, valid, and comparable to those obtained using more costly reference equipment.

Material & methods

Instrumentation

This study utilized an FG-100 DDS function generator to emit controlled electrical signals that simulate muscle activity, an open-source EMG board (SHIELD-EKG-EMG, Olimex, Plovdiv, Bulgaria) with an integrated voltage divider—representing the low-cost device whose performance is to be calibrated—a personal computer equipped with data acquisition software for recording and analyzing signals, an open-source development board (Olimexino- 328, Olimex, Plovdiv, Bulgaria) for data management and transmission, and

an oscilloscope (TDS 3012, Tektronik, Tokyo, Japan), used as the reference instrument (“Gold Standard”) to obtain precise signal measurements and validate the EMG device readings. Figure 1 displays the experimental setup.

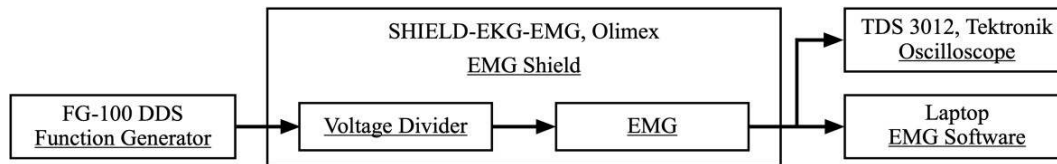


Figure 1. Schematic representation of the experimental setup.

The oscilloscope, as the measuring tool, is connected to both the function generator output and the EMG board output. Measuring the function generator output is intended to confirm the amplitude and frequency of the signal generated. This setup enables a parallel reading of the electromyographic signal from the EMG board through its software as well as via the oscilloscope.

Procedure

In the experiment, the oscilloscope serves as the Gold Standard; thus, its measurements are used as references to scale the data obtained by the computer software. A set of 129 artificial signals is generated and conditioned, covering amplitude and frequency ranges typical of natural surface electromyographic signals acquired on the skin (0.01–1 mV in amplitude and 0–300 Hz in frequency). Signals are generated at 43 frequencies spanning 1 Hz to 300 Hz (1, 3, 5, 7, 9, 11, 13, 15, 17, 19, 23, 25, 27, 29, 31, 33, 35, 40, 45, 50, 55, 60, 65, 70, 80, 90, 100, 110, 120, 130, 140, 150, 160, 170, 180, 190, 200, 220, 240, 260, 280, and 300 Hz), approximating a logarithmic distribution.

Each frequency is generated at three amplitudes (2.5 V, 5 V, and 10 V), which are divided by 20,000 using the voltage divider (yielding 0.125 mV, 0.25 mV, and 0.5 mV, respectively) before entering the EMG board. This extensive set of signals (3 amplitudes $\times$ 43 frequencies = 129 conditions) was designed to ensure robust calibration validity under a wide range of conditions, simulating various patterns of muscle activity. For each generated signal, 30 measurements are recorded simultaneously using the software developed and the oscilloscope. Measurements from both the oscilloscope (OSC) and the software (EMG) must be manually logged by the operator. A total of 3,870 measurements were acquired on each reading device (EMG and OSC).

Statistical Analysis

In this validation study, we aimed to assess the agreement between the oscilloscope (OSC), regarded as the gold standard, and Electromyography (EMG), a practical tool, across input voltages of 2.5, 5, and 10 V and frequencies of 5–200 Hz. Descriptive statistics, including mean and standard deviation (SD) as well as minimum values, were calculated for each combination of (OSC, EMG), frequency (5 to 200 Hz), and voltage (2.5, 5, 10 V). Outliers were identified using the Interquartile Range (IQR) method, corrected based on known input values where applicable, or removed if the source of deviation was unknown. To evaluate normality, the Shapiro-Wilk test was performed on the voltage distributions within each unique combination of frequency, method, and voltage, and results were further examined using visual inspection through Q-Q plots and density-overlaid histograms. These tests guided the use of parametric analyses and confirmed distribution assumptions in the data.

To establish a predictive model, regression analyses were conducted to develop a method for deriving OSC values based on EMG measurements. An ordinary least squares (OLS) linear regression model was computed, along with 95% confidence intervals and p-values. The OSC values predicted by the EMG model were subsequently compared to observed OSC values to evaluate prediction accuracy. Errors were quantified using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to gauge the degree of agreement between OSC and predicted OSC values. All statistical analyses, data visualization, and output documentation were performed in R (version 4.4.1).

Results

To establish a predictive relationship between the electromyograph (EMG) output readings and the corresponding input voltage measured by an oscilloscope (OSC), a simple linear regression analysis was conducted. The goal was to derive an equation that would allow the estimation of the oscilloscope input voltage solely from the EMG output. The regression model significantly predicted the oscilloscope input voltage, accounting for a substantial proportion of its variance. The overall model fit statistics are presented in Table 1. The model produced an R-squared of 0.994, indicating that 99.4% of the variance in oscilloscope readings (OSC) can be explained by EMG output readings. The F-statistic confirmed the model's significance ($F(1, 3227) = 5.382 \times 10^5$, $p < .001$). To further quantify the model's predictive accuracy, the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were calculated. The analysis yielded an MAE of 28.1 arbitrary units

(a.u.) and an RMSE of 37.67 a.u., providing a direct measure of the average prediction error and demonstrating the practical precision of the calibration equation.

Table 1. *Goodness-of-Fit Statistics for the Linear Regression Model Predicting Oscilloscope Voltage (OSC)*

Statistic	Value
R-squared	0.994
F-statistic (df ₁ , df ₂)	5.382×10^5 (1, 3227)
Model p-value	< .001
Mean Absolute Error (MAE)	28.1
Residual Standard Error (RMSE)	37.67

The estimated coefficients for the regression model are presented in Table 2. Both the intercept and the EMG predictor term were highly significant ($p < .001$). The positive coefficient for EMG ($B = 13.41$) indicates a strong positive linear relationship between EMG output and oscilloscope input voltage: as EMG output increases, the measured oscilloscope voltage also increases proportionally.

Table 2. *Coefficient Estimates for the Linear Regression Model Predicting Oscilloscope Voltage (OSC) From EMG Output.*

Predictor	B (Estimate)	SE (Std. Error)	t value	p-value
(Intercept)	83.62	1.06	78.73	< .001 *
EMG	13.41	0.02	733.65	< .001 *

Figure 2 visually illustrates this strong positive linear relationship between the measured EMG output and the oscilloscope input voltage, displaying the observed data points along with the fitted regression line. The close adherence of the data to the line visually confirms the high R-squared value and the appropriateness of the linear model.

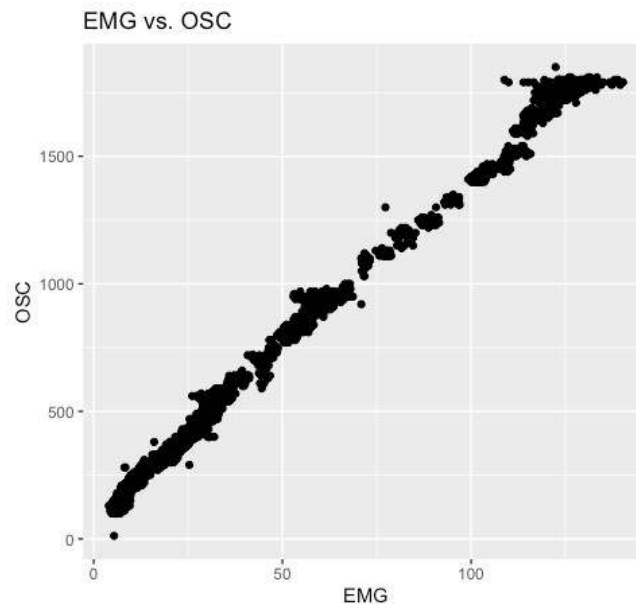


Figure 2. *Scatter plot illustrating the relationship between EMG readings and the oscilloscope (OSC) input voltage.*

Based on these findings, the derived linear regression equation to predict the oscilloscope input voltage (OSCpred) from the EMG reading is $OSC_{pred} = 83.62 + 13.41 \cdot EMG$. This equation serves as a practical calibration tool, enabling conversion of the “raw” (non-physical unit) readings from the open-source EMG device into scaled, reliable values that are directly comparable to what would be produced by a reference system under the tested conditions. This demonstrates that the EMG output can be dependably used to estimate the corresponding input voltage that an oscilloscope would measure under these conditions.

Dicussion

The rigorous validation of open-source technologies, as performed in this study, is an essential step for sports science professionals to confidently adopt these tools. The growing adoption of open-source technologies in sports science and digital health is increasingly appealing due to their low cost and flexibility. Our calibration method provides a straightforward and reliable way to ensure data quality from low-cost sEMG systems, enabling applications such as muscle fatigue monitoring, analysis of activation in specific technical gestures, biofeedback for sports rehabilitation in resource-limited settings, or even hands-on teaching of biomechanics.

Nevertheless, various studies emphasize the need for rigorous methods to validate measurements, even when devices are accessible or certified (De Maria et al., 2019; 2020; Turner et al., 2024; Répai et al., 2025). Approaches such as generating reference signals or comparing with commercial systems can enhance data reliability, particularly in clinical or sports settings with high precision demands (de Lathauwer et al., 2024; Hao et al., 2024).

Recent literature has highlighted numerous examples of validating low-cost electromyography (EMG) devices against commercial references, underscoring the growing interest in providing more affordable solutions without sacrificing measurement accuracy. Hence, several authors have tested their prototypes against certified devices (NORAXON, Delsys, BTS, among others) to assess parameters such as root mean square error (RMSE), intraclass correlation coefficient (ICC), or Spearman's correlation coefficient (Radeef & Faihan, 2022; Molina-Molina et al., 2020; Guzmán-Quezada et al., 2024; Zhang et al., 2024; Bawa & Banitsas, 2022). In most of these studies, concordance metrics exceed 0.8 (moderate-high) or even 0.9 (excellent), confirming that low-cost solutions can yield results comparable to certified systems when using proper design, filtering, and calibration protocols. Some studies have gone beyond raw EMG recordings, incorporating validations of multimodal devices (for instance, ECG, EDA, and EMG combined) or wireless and portable designs that facilitate real-time monitoring (McNaboe et al., 2022).

While many reported validations are “live” tests—commonly involving volunteers performing contractions and directly comparing them to commercial systems—our approach uses simulated electrical signals along with a laboratory “gold standard” (an oscilloscope) for controlled and specific calibration of the intrinsic sensor-ADC response across various frequencies and amplitudes. This is essential to understand the device's baseline behavior prior to its use in real-world contexts with more variability. Although our approach differs, we share similarities with the literature regarding the use of error metrics (MAE and RMSE in our case, paralleling RMSE or MAPE used by others) and statistical tests (linear regression, paired t-tests) to quantify reliability and resolve discrepancies (Radeef & Faihan, 2022; Guzmán-Quezada et al., 2024; Bawa & Banitsas, 2022; Garouche & Thamsuwan, 2023; Jayaraman et al., 2024). In contrast to other works that implement more complex or targeted adjustment equations for certain biases, we propose a simple yet robust linear regression for a general signal scaling.

Further expanding the review of biomedical component calibration, we explored both techniques aimed at calibrating signal amplifiers and those applied to analog-to-digital converters (ADCs)—fundamental elements in open-source sEMG systems. The literature indicates that in many studies, calibration is performed internally to correct errors such as mismatch, offset, and non-linearities via digital methods or algorithms (Galjan et al., 2009; Chang et al., 2017; Zahrai et al., 2015 for amplifiers; Huang et al., 2023; Mohapatra & Mohapatra, 2020 for ADCs). By contrast, our approach generates controlled artificial signals to externally compare the sEMG output (including its ADC) against a gold-standard instrument (e.g., an oscilloscope). Notably, the amplitude and frequency ranges used in our calibration (10 μ V to 5 mV and 10–400 Hz, with most energy between 50–150 Hz; Moritani & Muro, 1987; Abdelouahad et al., 2018; Pires et al., 2018) align with real values for myoelectric signals. We used an OLS linear regression model together with paired t-tests, MAE, and RMSE to measure and correct discrepancies across a broad spectrum of frequencies and amplitudes.

In summary, while traditional calibration methods focus on internal error correction for individual components (amplifier, ADC), our comprehensive approach calibrates the entire system (sEMG + ADC) by externally comparing it with a reference standard. This ensures that the final digitized signal accurately reflects the true amplitude of the electrical activity at the input—crucial for sports science and education applications that demand precise quantification. Moreover, this study fits into a growing ecosystem of open-source hardware and software for biomedical analysis (e.g., MAVIN, MUedit, VETA, NeuroMotion, BioSig, OpBox, among others cited in the bibliography), wherein rigorous validation of each component is vital to the reliability of the entire system.

Conclusions

This study introduces a straightforward and robust calibration method for an open-source sEMG system, demonstrating its high reliability through comparison with a reference standard. The proposed approach streamlines the process of ensuring data validity, a critical step for adopting open-source technologies in both research and applied practice. By simplifying access to reliable, cost-effective muscle activity measurement devices, this work contributes to the democratization of technology in sports science and education, enabling a broader range of professionals and researchers to conduct precise and efficient analyses for performance monitoring, injury prevention, and training optimization.

The primary implication of this work is the empowerment of practitioners in under-resourced settings—such as grassroots sports, public education, and independent clinics—to adopt evidence-based practices previously limited by high equipment costs. For future research, we recommend two key pathways: first, validating the calibrated open-source sEMG system against commercial-grade devices during dynamic, field-based athletic activities to confirm its real-world utility. Second, the principles of this calibration methodology should be extended to other low-cost sensor technologies, fostering a broader ecosystem of reliable and accessible tools for sports science.

Conflicts of interest – The authors declare no conflict of interests.

Acknowledgments – This article is derived from the first author's doctoral thesis.

References:

- Guthold, R., Stevens, G. A., Riley, L. M., & Bull, F. C. (2018). Worldwide trends in insufficient physical activity from 2001 to 2016: A pooled analysis of 358 population-based surveys with 1.9 million participants. *The Lancet Global Health*, 6(10), e1077-e1086.
- Warburton, D. E. R., & Bredin, S. S. D. (2017). Health benefits of physical activity: A systematic review of current systematic reviews. *Current Opinion in Cardiology*, 32(5), 541-556.
- Wicker, P., & Breuer, C. (2014). Exploring the organizational capacity and organizational problems of sport clubs in Europe. *International Journal of Sport Policy and Politics*, 6(1), 38-54.
- Baca, A., & Kornfeind, P. (2006). Rapid feedback systems for elite sports training. *IEEE Pervasive Computing*, 5(4), 70-76.
- Gabbett, T. J., Hulin, B. T., Blanch, P., & Whiteley, R. (2016). High training workloads alone do not cause sports injuries: How you get there is the real issue. *British Journal of Sports Medicine*, 50(8), 444-445.
- Downey, J. A., Downey, M. R., & otros. (2018). Advancements in wearable technology and sports analytics: A review. *IEEE Reviews in Biomedical Engineering*.
- Pfeiffer, M., & Hohmann, A. (2012). Applications of neural networks in training science. *Human Movement Science*, 31(2), 344-359.
- McGrath, M. J., & Scanail, C. J. (2013). Wearable technology: A systematic review of its applications in sport. *Journal of Sports Sciences*.
- Zdravevski, A. M., Lameski, I., & otros. (2020). Application of machine learning techniques for predicting performance in sports: A review. *Applied Sciences*, 10(1), 27.
- O'Donoghue, P. A. (2015). The impact of video analysis on performance in sports: A systematic review. *International Journal of Performance Analysis in Sport*.
- Gómez-López, M., Baena Extremera, A., & Abalades, J. A. (2014). Aplicación de las tecnologías del aprendizaje y el conocimiento para el aprendizaje de las actividades físico-deportivas en el medio natural en las clases de Educación Física. *Espiral. Cuadernos del Profesorado*, 7(13).
- Prat, Q., & Camerino, O. (2012). Las tecnologías del aprendizaje y el conocimiento (TAC) en la educación física, la WebQuest como recurso didáctico. *Apunts. Educación Física y Deportes*, 109, 44-53.
- Ergeneç, M., Carter, D., & Kosmas, P. (2022). sEMG Onset Detection via Bidirectional Recurrent Neural Networks With Applications to Sports Science. *IEEE Sensors Journal*, 22, 18751-18761.
- Felici, F., & Del Vecchio, A. (2020). Surface Electromyography: What Limits Its Use in Exercise and Sport Physiology?. *Frontiers in Neurology*, 11.
- Spanu, A., Botter, A., Zedda, A., Cerone, G., Bonfiglio, A., & Pani, D. (2021). Dynamic Surface Electromyography Using Stretchable Screen-Printed Textile Electrodes. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 29, 1661-1668.
- Xu, T. (2023). Review on current research and application of sEMG. , 12611, 1261117 - 1261117-4.
- Massó, N., Rey, F., Romero, D., Gual, G., Costa, L., & Germán, A. (2010). Aplicaciones de la electromiografía de superficie en el deporte. *Apunts. Medicina de l'Esport*, 45(165), 127-136.
- De Maria, C., Di Pietro, L., Ravizza, A., Díaz Lantada, A., & Ahluwalia, A. (2020). Open-source medical devices: Healthcare solutions for low-, middle-, and high-resource settings. En *Biomedical Engineering Tools for Management for Patients with COVID-19* (pp. 7–14). Academic Press.
- De Maria, C., Di Pietro, L., Díaz Lantada, A., Ravizza, A., Mridha, M., Torop, J., Madete, J., Makobore, P. N., & Ahluwalia, A. (2019). The UBORA E-Infrastructure for Open Source Innovation in Medical Technology. En A. Ahluwalia (Ed.), *Converging Clinical and Engineering Research on Neurorehabilitation III* (Vol. 76, pp. 878–882). Springer.
- Turner, S., Chen, C., Acosta, R., Boeck Daza, E. F., Floden, L., Langford, J., Simmat, L., Terluin, B., & Fromy, P. (2024). Methods for analytical validation of novel digital clinical measures: A simulation study.
- Répai, A., Földi, S., Sótónyi, P., & Cserey, G. (2025). An Open Source Validation System for Continuous Arterial Blood Pressure Measuring Sensors.
- de Lathauwer, I. L. J., van Es, V. A. A., Van Leunen, M., Onkelinx, S., Brouwers, R. W. M., van de Sande, D. AJP., Funk, M., & Kemps, H. (2024). Validation of a medically certified, wrist-worn sensor for the

- assessment of heart rate and energy expenditure during daily activities in patients with chronic heart failure, coronary artery disease and recreational athletes.
- Hao, L.-H., Yin, C., Duan, X., Wang, Z., & Zhang, M. (2024). Novel Cost-Effective and Portable Three-Dimensional Force Measurement System for Biomechanical Analysis: A Reliability and Validity Study. *Sensors*, 24(24), 7972.
- Radeef, F. B., & Faihan, B. A. (2022). Design and validation of a low-cost wireless electromyography system. (*The Iraqi Journal of Market Research and Consumer Protection*), 14(1), 36–44.
- Molina-Molina, A., Ruiz-Malagón, E. J., Carrillo-Pérez, F., Roche-Seruendo, L. E., Damas, M., Banos, O., & García-Pinillos, F. (2020). Validation of mDurance, A Wearable Surface Electromyography System for Muscle Activity Assessment. *Frontiers in Physiology*, 11, 606287.
- Guzmán-Quezada, E., Lomeli-Garcia, S., Velazco-Garcia, J., Jonguitud-Ceballos, M., Vega-Martinez, A., Ojeda-Galvan, J., Alvarado-Rodríguez, F. J., & Reyes-Jiménez, F. (2024). Development of an Electromyography Signal Acquisition Prototype and Statistical Validation Against a Commercial Device. *Sensors*, 24(21), 6787.
- Zhang, L., Chen, J., Li, Y., & Xi, N. (2024). Design and Signal Quality Assessment of a Novel Low-Cost Wireless EMG Sensor. En 2024 IEEE International Conference on Cyber Technology in Automation, Control, and Intelligent Systems (CYBER) (pp. 66–71). IEEE.
- Bawa, A., & Banitsas, K. (2022). Design Validation of a Low-Cost EMG Sensor Compared to a Commercial-Based System for Measuring Muscle Activity and Fatigue. *Sensors*, 22(15), 5799.
- McNaboe, R. Q., Beardslee, L., Kong, Y., Smith, B. N., Chen, I.-P., Posada-Quintero, H. F., & Chon, K. H. (2022). Design and Validation of a Multimodal Wearable Device for Simultaneous Collection of Electrocardiogram, Electromyogram, and Electrodermal Activity. *Sensors*, 22(22), 8851.
- Garouche, M., & Thamsuwan, O. (2023). Development of a Low-Cost Portable EMG for Measuring the Muscular Activity of Workers in the Field. *Sensors*, 23(18), 7873.
- Jayaraman, C., Mummidisetty, C. K., Jayaraman, A., Pfleeger, K., Jacobson, M., Ceruolo, M., Sen-Gupta, E., Caccese, J. W., & Chen, D. (2024). Validity and reliability study of a novel surface electromyography sensor using a well-consolidated electromyography system in individuals with cervical spinal cord injury. *Spinal Cord*.
- Galjan, W., Hafkemeyer, K. M., Tomasik, J. M., Wagner, F., Krautschneider, W. H., & Schroeder, D. (2009). Highly sensitive biomedical amplifier with CMRR calibration and DC-offset compensation. *Proceedings of IEEE EUROCON*, 152–155.
- Chang, C.-H., Zahrai, S. A., Wang, K., Xu, L., Farah, I., & Onabajo, M. (2017). An Analog Front-End Chip With Self-Calibrated Input Impedance for Monitoring of Biosignals via Dry Electrode-Skin Interfaces. *IEEE Transactions on Circuits and Systems I-Regular Papers*, 64(10), 2666–2678.
- Zahrai, S. A., Xu, L., Chang, C.-H., Wang, K., & Onabajo, M. (2015). On-chip digital calibration for automatic input impedance boosting during biopotential measurements. *Proceedings of the International Midwest Symposium on Circuits and Systems*, 1–4.
- Huang, Y., Meng, Q., Li, F., Song, X., & Wu, J.-T. (2023). A capacitor mismatch calibration scheme for SAR ADC based on genetic algorithm. *Electronics Letters*, 59(6).
- Mohapatra, S., & Mohapatra, N. R. (2020). The Design of Ultra Low Power SAR ADC for Implantable Cardioverter Defibrillator (ICD). *International Conference on VLSI Design*, 72–77.
- Moritani, T., & Muro, M. (1987). Motor unit activity and surface electromyogram power spectrum during increasing force of contraction. *European Journal of Applied Physiology*, 56(3), 260–265.
- Abdelouahad, A., Belkhou, A., Jbari, A., & Bellarbi, L. (2018). Time and frequency parameters of sEMG signal — Force relationship. 1–5.
- Pires, M. B., Mendes Junior, J. J. A., & Stevan, S. L. (2018). Development of an 8 channel sEMG wireless device based on ADS1299 with Virtual Instrumentation. *arXiv: Signal Processing*.
- Kimchi, E. Y., Coughlin, B. F., Shanahan, B. E., Piantoni, G., Pezaris, J., & Cash, S. S. (2020). OpBox: Open source tools for simultaneous EEG and EMG acquisition from multiple subjects. *eNeuro*, 7(5), ENEURO.0212-20.2020.
- Dimitrov, H., Bull, A. M. J., & Farina, D. (2023). High-density EMG, IMU, kinetic, and kinematic open-source data for comprehensive locomotion activities. *Scientific Data*, 10(1), 789.
- Ma, S., Mendez Guerra, I., Caillet, A. H., Zhao, J., Clarke, A. K., Maksymenko, K., ... & Farina, D. (2024). NeuroMotion: Open-source platform with neuromechanical and deep network modules to generate surface EMG signals during voluntary movement. *PLoS Computational Biology*, 20(7), e1012257.
- Powell, M. P., Anso, J., Gilron, R., Provenza, N. R., Allawala, A. B., Sliva, D. D., ... & Borton, D. A. (2021). NeuroDAC: An open-source arbitrary biosignal waveform generator. *Journal of Neural Engineering*, 18(1).
- Mullins, C. R., & Hanlon, C. A. (2016). MAVIN: An open-source tool for interactive analysis and visualization of EMG data. *Brain Stimulation*, 9(2), 305–306.
- Erickson, J. C., Hayes, J. A., Bustamante, M., Joshi, R., Rwagaju, A., Paskaranandavadivel, N., ... & Angeli, T.

- R. (2018). Intsy: A low-cost, open-source, wireless multi-channel bioamplifier system. *Physiological Measurement*, 39(3), 035008.
- Silva, I., & Moody, G. B. (2014). An open-source toolbox for analysing and processing PhysioNet databases in MATLAB and Octave. *Journal of Open Research Software*, 2(1), e27.
- Oberg, V., Thesleff, A., & Ortiz-Catalan, M. (2021). Design of an open-source transfemoral, bypass socket. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2021, 4578–4582.
- Avrillon, S., Hug, F., Baker, S. N., Gibbs, C., & Farina, D. (2024). Tutorial on MUedit: An open-source software for identifying and analysing the discharge timing of motor units from electromyographic signals. *Journal of Electromyography and Kinesiology*, 77, 102886.
- Jackson, N., & Greenhouse, I. (2019). VETA: An open-source Matlab-based toolbox for the collection and analysis of electromyography combined with transcranial magnetic stimulation. *Frontiers in Neuroscience*, 13, 975.
- Chen, M., & Zhou, P. (2024). StairFit MUNE: A free and open-source MatLab program for CMAP scan processing. *Clinical Neurophysiology*, 160, 111–112.
- Vidaurre, C., Sander, T. H., & Schlögl, A. (2011). BioSig: The free and open-source software library for biomedical signal processing. *Computational Intelligence and Neuroscience*, 2011, 935364.
- McKenzie, L. R., Pretty, C. G., Fortune, B. C., & Chatfield, L. T. (2021). Low-cost stimulation resistant electromyography. *HardwareX*, 9, e00178.