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Data Article

Surface electromyography dataset from different movements of the hand using a portable and a non-portable device

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A B S T R A C T

This work presents the MuscleTracker Hand Movement dataset, containing Surface Electromyography (sEMG) data from the right arm of 49 healthy subjects without neuromuscular or cardiovascular issues. Subjects performed five hand movements—pronation with extended fingers, flexion, extension, pronation with flexed fingers, and relaxation—while standing, with one hand palm-down. Data was recorded from two sEMG channels using Biopac MP36 (1000 Hz) and MuscleTracker (512 Hz), with three and four repetitions per device, respectively, for each movement. The dataset includes 825 samples, along with subject details such as gender, age, physical condition, and, for MuscleTracker subjects, anthropometric measurements. This data supports machine-learning development for classifying hand gestures in sEMG signals, with applications in prosthetics control and human-computer interaction. In addition, validation experiments were performed to validate the database and stablish a comparison baseline.

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Specifications Table

Subject	*Biomedical Engineering; Machine learning; Human-computer interaction*
Specific subject area	*Movements of the Hand modelled from Surface Electromyography Dataset captured using two acquisition devices.*
Type of data	Timeseries
Data collection	*A total of 825.txt files with sampled signals of the forearm muscular activity from two channels acquired from 49 subjects. The acquisition systems recorded the signals in with 1.5 to 2cm between electrodes; one electrode was placed on the wrist extensor muscle (channel 1) and the other on the wrist flexor muscle (channel 2), both of the right hand.*
Data source location	*The data was collected at the Advanced Cyberphysical Systems Laboratory, Tecnológico de Monterrey, campus Guadalajara. Zapopan, Jalisco, Mexico, CP. 45138.*
Data accessibility	*Repository name: MuscleTracker (MuscleTracker-Hand-Movement)* *Data identification number:* DOI: 10.5281/zenodo.10988409 *Direct URL to data:* https://github.com/RQ-FA/MuscleTracker-Hand-Movement
Related research article	*No*

1. Value of the Data

- The data is from two acquisition devices. One is the Biopac MP36 which is highly used by academics and in clinic protocols. The other is an open-source and low-cost device that might allow replicability in further acquisition processes.
- The database was generated with an equidistant arrangement of the electrodes, contemplating that an armband may be placed in the middle of the forearm, and the information of the conditions in which the signals were acquired make the acquisition replicable, facilitating the replication of the experimental setup for multiple studies.
- Anthropometric measures were taken by a certified International Society for the Advancement of Kinanthropometry (ISAK) professional.
- The continuity of the acquisition without rest between movements makes the database closest to a real environment. A rest was made between repetitions, but not between movements.
- This database allows the development of machine learning models with potential applications in human computer interaction.

2. Background

Electromyography (EMG) signals represent muscle electrical activity during spontaneous and voluntary contractions, providing insights into nerve action potentials, the signal amplitude and frequency being the key parameters in EMG studies [1,2]. Amplitude ranges from 0 to 10 mV, typically between -5 to 5 mV, helping identify muscle activation levels and duration [3]. Frequency, from 10 to 500 Hz, assesses muscle fatigue. The sEMG signals can be captured invasively with needle electrodes or non-invasively through surface electrodes, known as surface electromyography (sEMG) [4]. These signals lack clear patterns, making diagnosis difficult, in addition, the signals are highly susceptible to noise from biological and environmental sources. Therefore, successful classification depends on accurate signal capture, effective processing, feature selection, and appropriate algorithms to detect patterns [5,6]. EMG has become a key tool in understanding neurological and neuromuscular activities [7]. It is widely used to represent

Table 1
Average duration and number of samples by class.

Class / Acquisition system	Data points	Duration (s)	Samples
Biopac (1000 Hz)			
Open hand in supine with extended finger	5064 ± 439	5.06 ± 0.43	89
Wrist flexion	5165 ± 260	5.16 ± 0.26	89
Wrist extension	5163 ± 246	5.16 ± 0.24	89
Pronation with flexed fingers	5001 ± 266	5.00 ± 0.26	89
Relaxation	4896 ± 559	4.89 ± 0.26	89
Total	5058 ± 389	5.05 ± 0.38	445
MuscleTracker (512 Hz)			
Open hand in supine with extended finger	2354 ± 267	4.59 ± 0.52	76
Wrist flexion	2287 ± 283	4.46 ± 0.55	76
Wrist extension	2319 ± 282	4.52 ± 0.55	76
Pronation with flexed fingers	2370 ± 231	4.63 ± 0.45	76
Relaxation	2440 ± 465	4.76 ± 0.91	76
Total	2354 ± 320	4.59 ± 0.63	380
Total	3745 ± 1397	4.83 ± 0.57	825

human movements and postures, aiding in the control of rehabilitation devices, prostheses, and robots [8]. However, a major challenge remains in correlating EMG signals to specific movements, especially in amputees [5,7]. Several methodologies have been explored to create robust models for classifying EMG signals in fields like disease diagnosis, prosthetic development, and biomechanical analysis [9]. For example, EMG parameters help assess rehabilitation progress and control devices like instrumented gloves for assisted mobility [10]. However, a limitation in human-assistive robotics is the need for user-specific calibration [11]. sEMG also enables remote control of prosthetics [12], and beyond assistive devices, EMG has been used for stress level estimation during virtual reality games [13] and relate muscular activation to movement [14]. Many studies aim to classify hand movements for computer interfaces, but existing databases often involve a small number of subjects (5 to 30), use nonportable devices or many electrodes, complicating the electrode placement process and limiting free movement during experiments. These factors hinder dataset reproducibility and further research [15,16]. These limitations motivated us to create and publicly share this surface electromyography (sEMG) dataset, capturing hand movements using both portable and non-portable devices to facilitate further research. Additionally, this dataset provides an example of combining data from multiple acquisition systems to train machine learning algorithms. It is valuable for human-computer interaction applications, enabling systems to interpret human gestures not commonly used in daily activities.

3. Data Description

The dataset consists of five classes, each representing a specific hand movement: 1) open hand in supine with extended fingers, 2) wrist flexion, 3) wrist extension, 4) pronation with flexed fingers (fist), and 5) relaxation (Fig. 1). These gestures were chosen for being natural, neutral, and easy to perform. They are distinct from common task movements, making them suitable for human-computer interaction. The inclusion criteria consisted in allowing only healthy participants, with no visible neurological or musculoskeletal disorders, and aged between 18 and 37 years, regardless of race or ethnicity.

Table 1 presents the statistical information of the data collected from the two acquisition systems, Biopac with a sampling rate of 1000 Hz and MuscleTracker with a sampling rate of 512Hz. The statistics are presented by acquisition system and hand movements. The table includes information such as the data points obtained by the acquisition system, which later were converted in seconds (s). Additionally, it includes the number of samples for each class and its summary, after the validation step. Thus, each class has 89 repetitions independently of the subject that performed the movements, with a total of 445 repetitions for the Biopac and 380 for

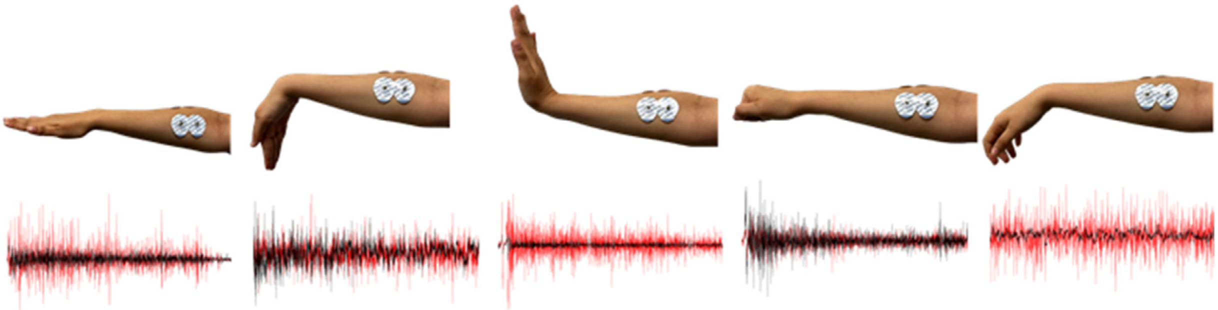

Fig. 1. Hand positions during movements and electromyography signal; the red signal is related to channel 1 (wrist extensor), and the black signal corresponds to channel 2 (wrist flexor).

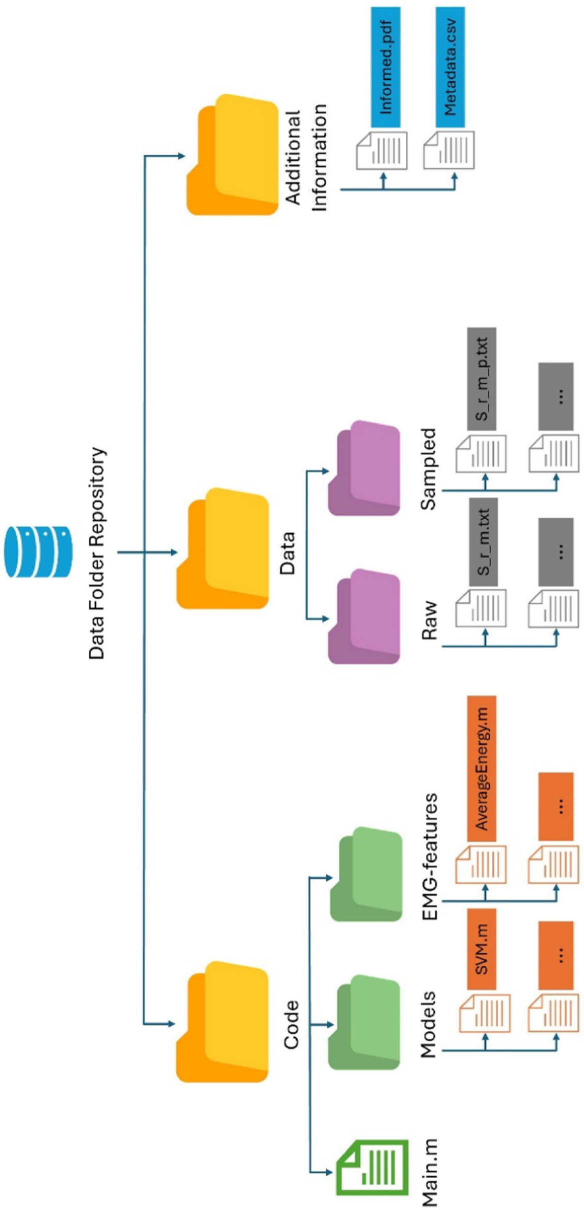

Fig. 2. Data folder layout of the repository.

Table 2
Statistics of the subjects which signals were acquired with the MuscleTracker device. NA: Not Applicable.

Value	Female	Male	Total
Age (average)	25.60 ± 4.131	24.69 ± 4.67	25.00 ± 4.42
Arm length (cm avg.)	31.00 ± 2.17	32.65 ± 2.05	32.13 ± 2.22
Forearm Length (cm avg.)	25.25 ± 0.94	27.34 ± 1.99	26.68 ± 1.98
Wrist diameter (cm avg.)	18.73 ± 0.53	16.60 ± 1.08	17.27 ±1.09
Arm diameter (cm avg.)	28.83 ± 3.42	31.73 ± 3.30	30.81 ± 3.60
Physical Activity (yes/no)	0%	92%	63%
Gender	31%	63%	NA

the MuscleTracker, this gives a total of 825 repetitions in total for the dataset with and average duration of 4.83 ± 0.57 seconds.

The repository (Fig. 2) contains three main folders: Code, Data, and Additional Information. The "Code" folder includes scripts to replicate the experiments, with the Main.m file needing the folder path and data parameters to run the experiments; detailed guidelines are provided in the file's comments. A linked submodule (EMG-Feature-Extraction-Toolbox @ca1e67c) includes the feature extraction methods used. The "Models" folder provides instructions for training and validating machine learning models to classify hand movements. The "Data" folder contains the dataset files from Biopac and MuscleTracker.

The "Metadata.csv" file contains anthropometric data for subjects recorded with the MuscleTracker device. This includes: (i) participant ID (1 to 19), (ii) age, (iii) physical activity, (iv) gender (Male or Female), and (v) anthropometric measurements in centimeters. Table 2 summarizes the participants' data by gender, including age, arm length, forearm length, wrist diameter, arm diameter, and physical activity statistics. These measurements provide useful information for future studies.

The data is organized into text files with values separated by commas, where each row represents a datapoint of the sEMG signal and columns 1 and 2 correspond to the two channels. Each file contains the signal for a specific subject, hand movement, and repetition. The naming convention (s_r_m.txt or s_r_m_p.txt) simplifies identification and retrieval of the data. In this format, s represents the subject number, r indicates the movement repetition (1 to 4), and m denotes the movement (1 for pronation with extended fingers, 2 for extension, 3 for flexion, 4 for pronation with flexed fingers, 5 for relaxed hand). The optional p indicates a partition of the sample. The data is also partitioned into three subsamples to capture before and after movement transitions.

4. Experimental Design, Materials and Methods

The samples were captured using two acquisition systems. The first was the Biopac MP36 (BIOPAC SYSTEMS, U.S.A.), a physiological signal acquisition system offering flexible filtering options through hardware and software, though these options were not used in this study. The second system, MuscleTracker, is a portable device with one sEMG channel and gain adjustment through its software. The "MuscleTracker Interface" was developed as a graphical user interface to manage patients, check equipment status, perform data acquisition, and provide signal visualization over time. It saves data in CSV or TXT format. However, the device can only capture one signal at a time, so two devices were used. A preview of the hardware and software used for acquiring and processing the signals is listed below in Table 3, for reference.

The signals were processed using a computer with an AMD Ryzen 7 3700 × 8-Core CPU, complemented by 16.0 GB of RAM and a Nvidia GeForce RTX 3080 Ti GPU implementing the software in Python (version 3.9.7) and Matlab (R2022b). Sklearn, scipy, NumPy, pandas, OS, matplotlib, statistics, seaborn, Keras, TensorFlow, as well as the Statistics and Machine Learn-

Table 3
Resources used for the acquisition and pre-processing of the signals.

Resource	Type
CPU	AMD Ryzen 7 3700X, 8-Core
RAM	16.0 GB
GPU	Nvidia GeForce RTX 3080 Ti
Programming languages	Python (version: 3.9.7), Matlab (R2022b)
IDE	Spyder, Matlab
Toolboxes	Sklearn, scipy, NumPy, pandas, os matplotlib, statistics, seaborn, keras, tensor-flow, statistics and machine learning toolbox, Signal processing toolbox.
Acquisition systems	BIOPAC MP36, MUSCLETRACKER

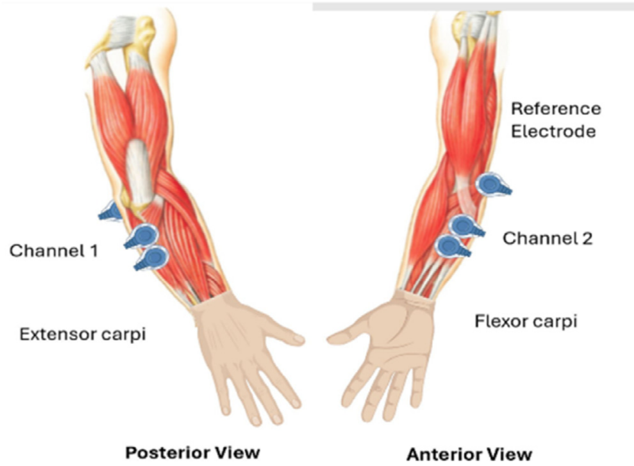

Fig. 3. Location of the electrodes for the two channels. Channel 1 was placed in the wrist extensor muscle and channel 2 in the wrist flexor muscle. Based on the SENIAM guide (Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles, seniam.org).

ing Toolbox and Signal Processing Toolbox. The acquisition systems employed in the study are the BIOPAC MP36 and MUSCLETRACKER.

The acquisition systems recorded signals in 2 channels, with electrodes placed 1.5 to 2 cm apart. The electrodes, with 0 to 1 MΩ impedance, ensured signal quality and stable skin contact. One electrode was placed on the wrist extensor muscle (channel 1) and the other on the wrist flexor muscle (channel 2) of the right hand (See Fig. 3). This setup enabled simultaneous signal capture from both muscles during hand movements. Subjects stood with their forearm raised in a supine position during acquisition.

The acquisition procedure had three stages: preamble, preparation, and acquisition. In the preamble, volunteers were briefed on the study's background, methodology, and objectives, followed by signing an informed consent form. Anthropometric measurements, including arm and forearm lengths and arm and wrist diameters, were taken in centimeters. In the preparation stage, volunteers' right forearms and elbows were shaved and sanitized, and electrodes were placed after performing wrist flexion and extension to highlight muscle activity (Fig. 3). Ground electrodes were fixed to the elbow. During acquisition, volunteers stood with arms extended horizontally while following instructions. The sequence began with an open hand in a supine position for five seconds, followed by wrist flexion, wrist extension, pronation with a fist, and finally relaxation. Biopac acquisitions were repeated three times, and MuscleTracker four times per volunteer (Fig. 4).

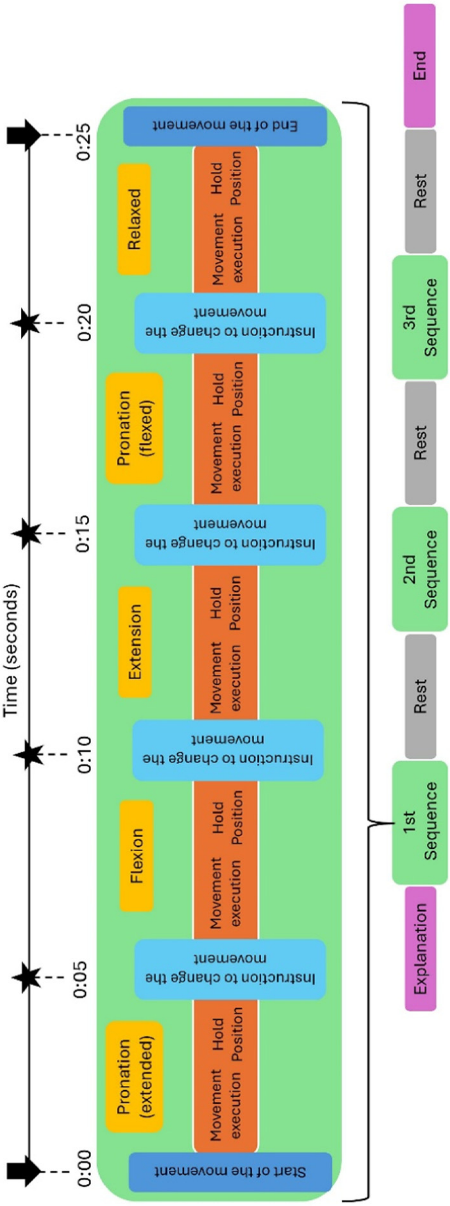

Fig. 4. Representation of an acquired sample prior to the labelling and validation steps.

A marker was placed in the signal every 5 seconds to guide the labeling, then adjusted based on visual characteristics of the signals. For example, larger amplitudes in channel 1 indicated wrist extension, while wrist flexion showed the opposite. This method helped divide and label each of the 25 signals into subsets. A file was generated for each subject, repetition, and movement, resulting in five files each. Then, a validation step discarded signals with motion artifacts or electrode detachment issues. As a result, three subjects from the initial 22 acquired with MuscleTracker and one repetition from a Biopac subject were discarded to ensure quality. A statistical analysis of the data acquired indicates that each class has 89 repetitions for the BIOPAC and 76 for the Muscle Tracker with a mean duration of 5.05 $\pm$ 0.38 s and 4.59 $\pm$ 0.63 s, respectively; Giving 825 repetitions in the database (Fig. 5).

4.1. Machine learning experiments

Machine learning techniques were evaluated on the dataset to classify hand movements and establish a baseline comparison. The task involved three stages: pre-processing, feature extraction, and inference (Fig. 3). Pre-processing included filtering and normalization. A fourth-order Butterworth filter (20-50 Hz) and a 60 Hz Notch filter (quality factor of 30) were used to reduce noise. Then, zero-center normalization was applied to standardize amplitude variability across subjects, setting the mean signal to 0. This was done independently for each channel, aiming to improve model learning accuracy. These pre-processing steps ensured the signals were prepared for analysis and classification, although further analysis is needed to validate this approach. Three feature extraction techniques were used, and their features were concatenated into a feature vector: classical, Fourier-based, and Wavelet-based extraction. Traditional methods focus on statistical and time-domain features from the sEMG signals, including zero crossing, waveform length, mean absolute value, and interquartile range [17]. Fourier-based extraction transforms the signals into the frequency domain, calculating features like mean, median, and peak frequency from the spectrum (1-500 Hz, with a 1000 Hz sampling rate), providing insights into the dominant frequencies. Wavelet-based extraction analyses time-frequency features using wavelet transform, specifically the db2 Wavelet from the Daubechies family at six decomposition levels. Energy features from approximation and detail coefficients, as well as terminal nodes, compose the features [18].

Common classification models, including Fine KNN, Neural Network (Wide), SVM (Support Vector Machine Linear), SVM-Q (Quadratic, Order 2), and SVM-C (Cubic, Order 3), were used in the third stage. KNN employed Euclidean distance with 1 neighbor and equal distance weight. The Neural Network had 100 hidden layers, ReLU activation, no regularization, and a 100-iteration limit. SVM models used a box constraint of 1, auto kernel scale, and different orders (1 for linear, 2 for quadratic, 3 for cubic). The experiment evaluated the impact of channels and normalization on model performance, using accuracy as the metric due to the balanced dataset. The pre-processing conditions included no pre-processing (NP), filtering, and zero-center (ZC) normalization. Models were tested with channel 1, channel 2, and combined features from both channels. A 10-fold cross-validation ($k = 10$) was performed to assess model performance and prevent overfitting. The variables of the experiments are shown in Table 4.

No significant difference was found between raw and filtered signals ($T = 0.76$, $p = 0.874$), indicating that feature extraction is equally effective from raw or filtered signals. However, normalization negatively impacted accuracy ($T = -5.35$, $p = 0.00$), and normalized, filtered signals further reduced accuracy ($T = -7.65$, $p = 0.00$). Combining both channels increased accuracy by 14% over channel 2 ($T = 57.26$, $p = 0.00$) and 11% over channel 1 ($T = 45.88$, $p = 0.00$). Using both channels outperformed individual channels, ranking first, followed by channel 1, and lastly, channel 2. Among the models, SVM Linear had the lowest accuracy, while SVM-Cubic, Neural Network, and SVM-Quadratic achieved the highest, with a mean accuracy of 0.81 across parameters and 0.845 $\pm$ 0.07 without normalization using both channels. The results are consistent across channels and pre-processing methods, as seen in Table 5.

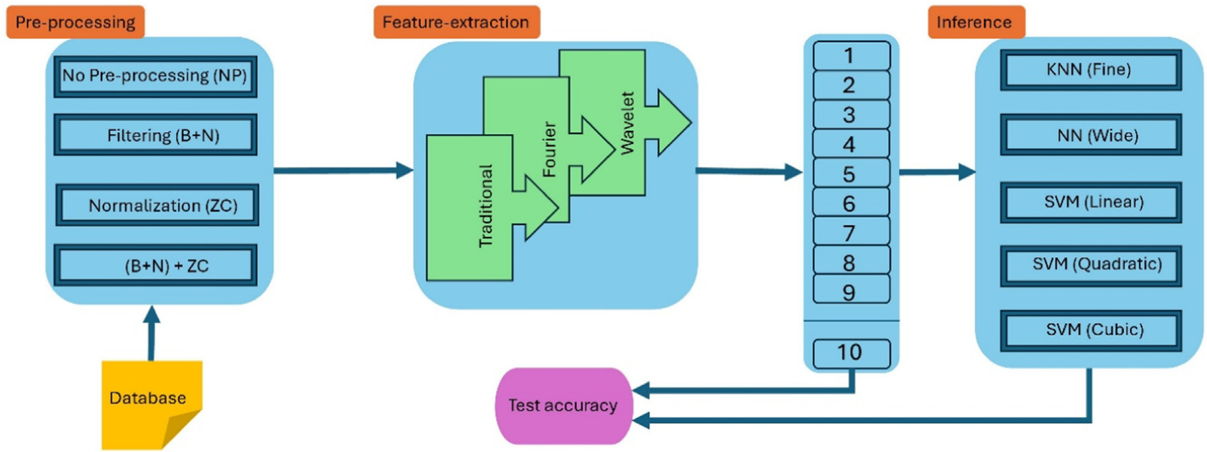

Fig. 5. Diagram of the technical validation methodology, comprising three steps: pre-processing, feature extraction, and inference. B: Butterworth, N: Notch, KNN: k nearest neighbors, NN: Neural Network; SVM: Support Vector Machine.

Table 4
Controlled variables that can influence the results.

Variable	Level
Normalization	Without normalization, zero-cross.
Filtering	Butterworth + Notch.
Features	Traditional, Fourier-based, Wavelet-based.
Models	Fine KNN, Neural Network (Wide), SVM (Linear), SVM-Q (Polynomial, Order 2), and SVM-C (Polynomial, Order 3).
Channels	Channels Channel 1, Channel 2, combined channels.
Replication	10-fold cross-validation.

Table 5
Accuracy obtained of the models for classifying the five movements comparing the use of the channels and pre-processing. WN: Without normalization, ZC: Zero Center normalization; B: Butterworth filter; N: Notch filter.

Model	WN-WF	Filtered	ZC	B+N+ZC	Total (Model)
Channel 1					
SVM-Q	0.752 ± 0.112	0.750 ± 0.113	0.705 ± 0.132	0.722 ± 0.125	0.732 ± 0.122
SVM-C	0.761 ± 0.109	0.772 ± 0.096	0.738 ± 0.124	0.748 ± 0.118	0.755 ± 0.113
SVM	0.722 ± 0.116	0.729 ± 0.111	0.695 ± 0.122	0.706 ± 0.121	0.713 ± 0.118
NN	0.755 ± 0.111	0.762 ± 0.099	0.722 ± 0.129	0.729 ± 0.127	0.742 ± 0.118
KNN	0.734 ± 0.129	0.733 ± 0.113	0.674 ± 0.148	0.681 ± 0.137	0.706 ± 0.135
Total	0.745 ± 0.116	0.749 ± 0.108	0.707 ± 0.133	0.717 ± 0.128	0.729 ± 0.123
Channel 2					
SVM-Q	0.705 ± 0.113	0.701 ± 0.116	0.683 ± 0.129	0.707 ± 0.122	0.699 ± 0.121
SVM-C	0.740 ± 0.118	0.736 ± 0.114	0.722 ± 0.118	0.730 ± 0.115	0.732 ± 0.117
SVM	0.669 ± 0.146	0.685 ± 0.134	0.681 ± 0.124	0.680 ± 0.127	0.678 ± 0.133
NN	0.735 ± 0.119	0.732 ± 0.117	0.700 ± 0.136	0.716 ± 0.120	0.721 ± 0.124
KNN	0.721 ± 0.128	0.704 ± 0.135	0.657 ± 0.155	0.671 ± 0.142	0.688 ± 0.143
Total	0.714 ± 0.128	0.712 ± 0.125	0.689 ± 0.135	0.700 ± 0.128	0.704 ± 0.129
Combined					
SVM-Q	0.845 ± 0.076	0.847 ± 0.078	0.846 ± 0.076	0.847 ± 0.077	0.846 ± 0.077
SVM-C	0.845 ± 0.079	0.845 ± 0.079	0.843 ± 0.083	0.845 ± 0.078	0.844 ± 0.080
SVM	0.775 ± 0.097	0.774 ± 0.097	0.777 ± 0.096	0.774 ± 0.097	0.775 ± 0.097
NN	0.833 ± 0.096	0.835 ± 0.091	0.841 ± 0.079	0.835 ± 0.087	0.836 ± 0.088
KNN	0.834 ± 0.089	0.834 ± 0.090	0.835 ± 0.094	0.833 ± 0.087	0.834 ± 0.090
Total	0.826 ± 0.092	0.827 ± 0.091	0.828 ± 0.090	0.827 ± 0.090	0.827 ± 0.091
General	0.762 ± 0.123	0.763 ± 0.119	0.741 ± 0.136	0.748 ± 0.129	0.753 ± 0.127

Table 6
Ablation study for the features used to classify the hand movements.

Excluded	KNN	NN	SVM	SVM-Q	SVM-C	Total
None	0.868 ± 0.015	0.863 ± 0.008	0.804 ± 0.008	0.874 ± 0.016	0.872 ± 0.007	0.856 ± 0.029
Fourier	0.740 ± 0.021	0.733 ± 0.018	0.613 ± 0.028	0.760 ± 0.028	0.744 ± 0.026	0.718 ± 0.059
Wavelet	0.734 ± 0.014	0.656 ± 0.034	0.575 ± 0.021	0.693 ± 0.049	0.710 ± 0.021	0.675 ± 0.060
Classic	0.594 ± 0.035	0.600 ± 0.022	0.493 ± 0.022	0.628 ± 0.025	0.618 ± 0.024	0.577 ± 0.055
Total	0.734 ± 0.100	0.713 ± 0.101	0.624 ± 0.115	0.738 ± 0.096	0.736 ± 0.094	0.709 ± 0.111

An experiment was conducted to evaluate the classification models' performance when subsets of features were excluded from the feature extraction step. The sEMG signals were not pre-processed, as previous results showed this had minimal impact. Both acquisition system channels were used. Table 6 presents the results when certain feature extraction methods were excluded during training and validation. The highest accuracy was achieved when no features were excluded, with SVM-Q performing best, followed by SVM-C. Excluding Fourier features had the least effect ($T = -25.56$, $p = 0$, difference $= -0.138$), followed by wavelet features ($T = -17.14$, $p = 0$, difference $= -0.181$). The removal of classic features had the greatest negative impact

(T = -25.56, p = 0, difference = -0.269). These results establish a baseline for future comparisons with this database (Table 6).

Limitations

Due to the data acquisition setup for MuscleTracker, signals from the two channels were recorded on separate computers, requiring manual synchronization. This may introduce slight errors in aligning the signals. Additionally, anthropometric measurements were not initially planned in the study design, so they are only available for the subjects recorded with MuscleTracker. The absence of these measurements for other subjects may limit the ability to generalize the findings to a wider population or to accurately model the biomechanical dynamics involved.

Ethics Statement

This research was carried out in accordance with the Declaration of Helsinki, and it includes the **Ethical committee approval of the protocol** ID: 0013 reviewed by the Institutional Review Board of *Centro de Retina Médica y Quirúrgica* (Research ethics committee CONBIOETICA-14-CEI-0003-2019, Ethics committee 18 CI 14 120057). The relevant informed consent was obtained from all the subjects. A copy of the consent form (translated in English from the original in Spanish) has been submitted either in the data repository.

Credit Author Statement

Rita Q. Fuentes-Aguilar: Conceptualization, Validation, Investigation, Resources, Writing original draft, Visualization, Supervision, Project administration, Funding acquisition; **Dusthon Llorente-Vidrio:** Data curation, Software, Writing review and editing; **Leobardo Campos-Macias:** Writing Review and Editing, Funding acquisition; **Eduardo Morales-Vargas:** Software, Validation, Formal analysis, Data curation, Writing original draft.

Data Availability

MuscleTracker-Hand-Movement (Original data) (github.com/emoralesv/MuscleTracker-Hand-Movement).

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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