Received: May 10, 2024
Accepted: October 10, 2024

Acad Med J 2024;4(3):96-107
UDC: 616.74-009-073.7:004.85
https://www.doi.org/10.53582/AMJ2443096p
Original article

EXPLOITING EMG SIGNALS FOR THE RECOGNITION OF FINGER FLEXIONS USING WAVELET TRANSFORM AND MACHINE LEARNING

Paunkoska Klimentina[1], Nadzinski Gorjan[1], Hristov Blagoj[1], Zhivadinovikj Julija[2], Dodevski Ace[2], Paunkoska Anamarija[2], Gjorgjeski Antonio[3]

[1]Faculty of Electrical Engineering and Information Technologies, Ss. Cyril and Methodius University in Skopje, Republic of North Macedonia
[2]Institute of Anatomy, Faculty of Medicine, Ss. Cyril and Methodius University in Skopje, Republic of North Macedonia
[3]University Clinic for Gynecology and Obstetrics
e-mail: kpaunkoska@gmail.com

Abstract

Electromyography (EMG) is a technique that measures and records electrical activity in response to a nerve's stimulation of the muscle. EMG signals are biomedical signals that represent electrical currents generated in muscles during their contraction. EMG signals acquired from muscles require advanced methods for detection, decomposition, processing and classification. Various mathematical techniques have received extensive attention and one of the most popular is Wavelet transform. Wavelet transform is a mathematical tool for analyzing data where the signal values vary at different scales, such as in EMG signals, so it is widely used in EMG signal processing systems. This study explored the potential of applying wavelet transform to EMG signals, which were collected using two sensors placed on the forearms of eight subjects performing individual finger flexions. We experimented with various mother wavelets and decomposition levels to determine the most effective combination. After evaluating the results obtained from training models, we selected the Daubechies wavelet (db1) with a second level of decomposition as the optimal solution. To generate meaningful features from the wavelet coefficients, we extracted time-frequency domain features, which were then used as inputs for training and testing machine learning models. We employed five classification algorithms: K-nearest neighbors, Support Vector Machine, Decision Tree, Random Forest, and Extreme Gradient Boosting (XGBoost). By evaluating and comparing the performance of these algorithms, we demonstrated enhanced accuracy and robustness achieved by the combination of wavelet transform and feature extraction in EMG signal analysis.

Keywords: electromyographic signals, wavelet transform, feature extraction, machine learning

Introduction

Hands play a crucial role in almost every activity we perform daily, from simple tasks like gripping objects, typing and eating, to more complex actions such as writing or operating machinery. They are essential tools for interaction, communication and expressing creativity. For amputees, the loss of a hand can have a significant impact on their ability to perform these basic tasks independently, leading to challenges in daily living, reduced autonomy and a need for assistive devices or support. The statistics, which is maintained by the health organization Amputee Coalition, presents the numbers for upper limb amputees worldwide, which show up to 3 million people who have upper limb amputation, of which 2.4 million people live in developing countries. There are a number of reasons that cause the amputation of a human limb, some of the most common reasons are due to diabetes, trauma, malignant diseases, cardiovascular diseases as well as congenital defects of the limb. There are 1.4 million people who have forearm amputation, while 700,000 people have upper arm amputation, 200,000 people have shoulder amputation and 100,000 people have palm amputation[1].

A prosthetic arm is an effective solution to overcome these obstacles. With the purpose of automating the control of prosthetic arms for more efficient use, electromyographic signals and machine learning models play a vital role in the refinement process. In the realm of healthcare and rehabilitation, the domain of prosthetic limbs has experienced a renaissance over the past decade. The traditional view of a prosthetic as merely a passive, cosmetic appendage has evolved. Today’s prosthetics boast functionality and adaptability that is leagues ahead of their predecessors. Historically, prosthetics were made from heavy materials like wood and metal. Today, thanks to advancements in materials science, we have lighter, more durable, and flexible materials like carbon fibers, silicone, and advanced polymers. These not only make the prosthetic limb lighter and more durable but also allow it to mimic the look and feel of natural skin, providing users with a more comfortable and natural experience. Looking toward the future, the incorporation of Artificial Intelligence (AI) into prosthetics opens up a realm of possibilities. AI-enabled prosthetic limbs can learn and adapt to the user’s habits and preferences over time, ensuring optimal functionality. By analyzing the user’s gait, grip and other movements, these smart limbs can make real-time adjustments, providing smoother and more natural motions[2]. Figure 1 shows the first mechanical prosthesis and today's modern electric prosthesis.

Fig. 1. A representation of the first models of prosthetic hands and today's modern electric prosthetic hands

Processing electromyographic (EMG) signals with wavelet transform is a process that has already been successfully applied in some cases for the classification of finger movements obtained from measurements taken from forearm muscles, presented in several studies [3-5].

Hristov *et al*. [3] use multiple machine learning algorithms to predict the flexion of individual fingers, as well as certain combined flexions, by using two EMG sensors placed on the forearm. The data is first preprocessed by extracting necessary time and frequency domain statistical features, and is then sent to each classifying algorithm individually. The best result of 96.6% was achieved with the XGBoost algorithm, followed closely by Extra Trees at 95.4% and Random Forest at 95.2%. Azhiri *et al*.[4] achieved an accuracy of around 95.5% with a neural network with six hidden layers with 32 neurons per layer. The data are collected with the help of two surface electrodes that are placed on the forearm of eight subjects and the database contains individual and combined movements of the fingers of the hand. After applying a wavelet transform to the data, where db1 is used as the mother wavelet with the second level of decomposition, they extract temporal features, where there are 12-time domain conventional ones that are used frequently and 5 new ones that increase the classification accuracy. Azhiri *et al.* got their measurements from a volunteer performing six daily upper extremity movements and two forearm muscle channels. EMG signals were recorded on two muscles of the volunteer's right forearm with two pairs of surface electrodes. After EMG signals were obtained, they applied a wavelet transform to the data and tried several wavelets in order to determine which one gave the best results and at what level accordingly. With the reconstructed EMG signals and subsets of wavelet coefficients they extracted features that would be used in the classifier. They used mean absolute value and mean square root as the most famous characteristics. The results showed that only EMG features extracted from reconstructed EMG signals from first level and second-level detail coefficients provided an improvement in class separability in the feature space.

The main goal of this study was to process EMG data using wavelet transform before training different machine learning models to recognize the movements that the person using the prosthetic arm attempted to make. The main emphasis was placed on the wavelet transform in order to see if it improved classification results.

Electromyography

Electromyography (EMG) is an electrodiagnostic test that assesses the health and function of the muscles and the nerves that control them by measuring the electrical activity of the skeletal muscles. The EMG sensor, that is the device that measures the electrical signals of the muscles during the process, detects the potential of the motor unit, which is a complex potential generated by the muscle fibers of the motor unit during the spontaneous activity of the muscle cells, and thus enables the analysis of the muscle activity. Muscle contraction and relaxation occur as a result of electrical stimulation, and these phenomena occur in several muscles, causing the body to move. When the brain tells the muscles to contract, the central nervous system, which is connected to the brain, releases neurotransmitters, and the neurons that receive those substances act to transmit electrical signals to the muscles, which prompt the body to move. An example of what an EMG signal looks like, a signal measured when a muscle contracts and relaxes is shown in Figure 2.

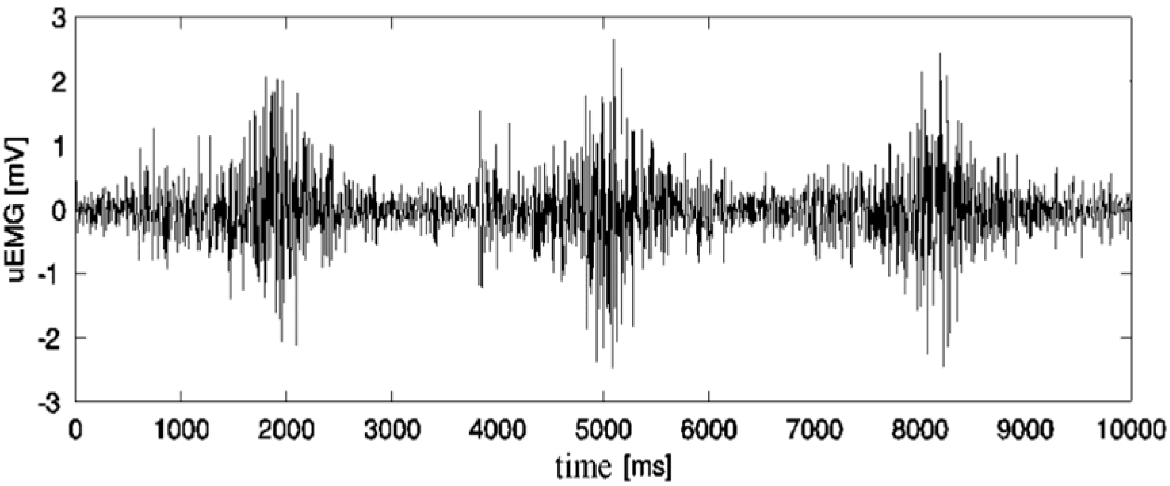

Fig. 2. EMG signal measured
when a muscle contracts and relaxes

Electromyography is a valuable tool in medicine, rehabilitation and research, especially in understanding muscle function, diagnosing neuromuscular disorders and developing prosthetics or other assistive devices. When the body is unable to move for some reason, an EMG sensor is used to diagnose whether it is due to a problem in the nervous system or damage to the muscle that cannot be moved. When a muscle cannot contract or relax due to a problem with muscle function, the electrical signal can be measured by EMG. It is also possible to check the muscles that are activated during certain movements and activities and through this, it is possible to study more efficient movements and activities.

Electromyography can be performed in two ways: a non-invasive method, i.e. surface EMG, and an invasive method, i.e. intramuscular EMG. Surface electromyography is used more widely because it has a great advantage in terms of stability. However, more accurate results are obtained with intramuscular electromyography than with surface electromyography, since a needle is inserted directly into the muscle. Figure 3 shows how the procedure of performing the two EMG methods looks like.

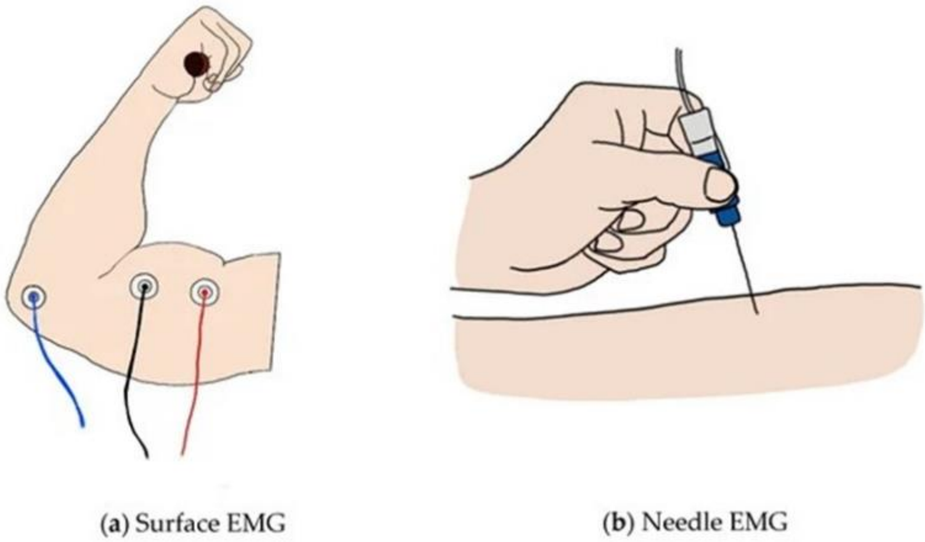

Fig. 3. The surface EMG shown on the left side and the intramuscular EMG shown on the right side of the picture

a. Surface electromyography

Surface electromyography is the best known and most widely used method for measuring muscle contraction. It is recorded with surface electrodes, which measure the electrical potential difference between them, which means that at least two electrodes are needed. But, in addition to the two electrodes, a third electrode is also used, which is known as the reference electrode, which is placed on a part that is separated from the muscle in order to compare the measured potential with respect to it. In addition to the advantages obtained with surface electromyography, there are also some significant limitations when it is used. The biggest limitations are that it can be used in muscles that are close to the surface of the skin, subject to mutual interference between adjacent muscles, but also negatively affected by the thickness of the subcutaneous tissue.

b. Intramuscular electromyography

Unlike surface EMG, intramuscular electromyography records the electrical activity of the muscle by inserting two needle electrodes directly into the muscle and measuring the potential difference between them. As with the surface method, this method uses a reference electrode that can be a non-invasive surface electrode. Needle electrodes are solid devices that can pierce the skin and muscle and be placed in the required location to measure the electrical potential. They are completely insulated except for the tip which is needed for measurement[6].

There are several levels of precision in this type of electrodes, and because of this, intramuscular electromyography is often used when high precision and accuracy of measurements are required. Figure 4 shows the Delsys electrodes used for EMG and their placement on the examinees.

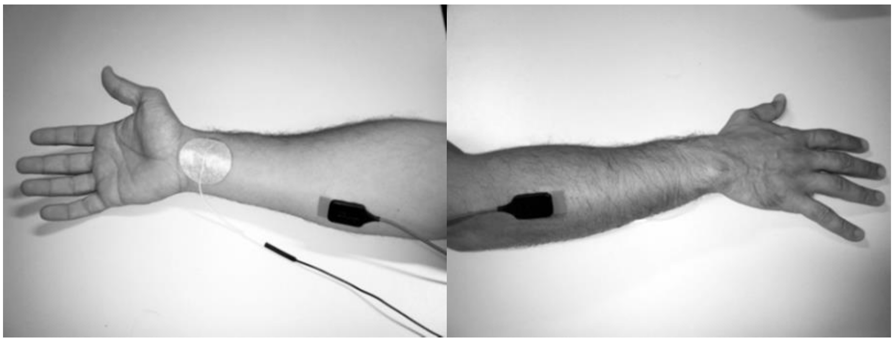

Fig.4. Delsys electrodes placed on the forearm of an examinee

Data acquisition

The dataset used and processed in this study was taken from a ready- made database from the Biosignals Repository[7]. The measurements were performed on eight subjects, six men and two women aged between 20-35 years who performed the necessary finger movements. The subjects did not have any neurological or muscular disorders.

In the base there are ten classes of individual and combined movements of the fingers: flexion of each individual finger, i.e. thumb (T), index (I), middle finger (M), ring (R), little (L) and flexion of the combined thumb - index (T-I), thumb - middle (T-M), thumb - ring (T-R), thumb - little (T-L) and finally the hand closes - fist (HC). Accordingly, the ten classes are shown in Figure 5. Six classes were used in this study, that is, all individual movements of the fingers and fist; the other 4 classes were omitted due to computational power.

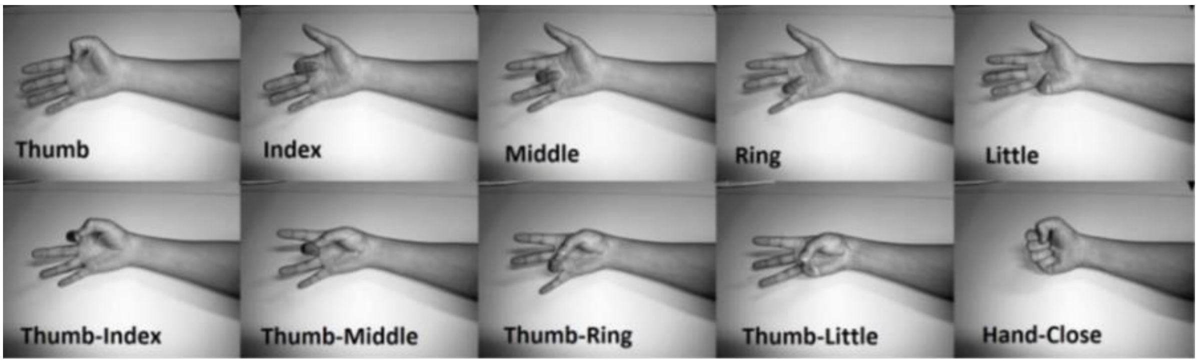

Fig. 5. Ten movements made by the examinees

Before starting the measurements, subjects were seated in a chair with their supported arm fixed in a single position to eliminate the influence of limb movement on the generated EMG signals. During the measurements, subjects were instructed to tighten the finger being tested, hold for 5 seconds, and then release. Six measurements were taken for each finger and the fist, with short relaxation periods between each trial.

The three electrodes are placed on the *flexor digitorum profundus* muscle located on the lower part of the forearm, and on the *extensor digitorum communis* muscle located on the upper part of the forearm, while the third electrode is the reference electrode, as shown in Figure 6.

After the signals were collected from the electrodes, they were amplified using a Delsys Bagnoli-8 amplifier with a total gain of 1000. Furthermore, a 12-bit analog-to-digital converter (National Instruments, BNC-2090) was used to sample the signal at 4000 Hz.

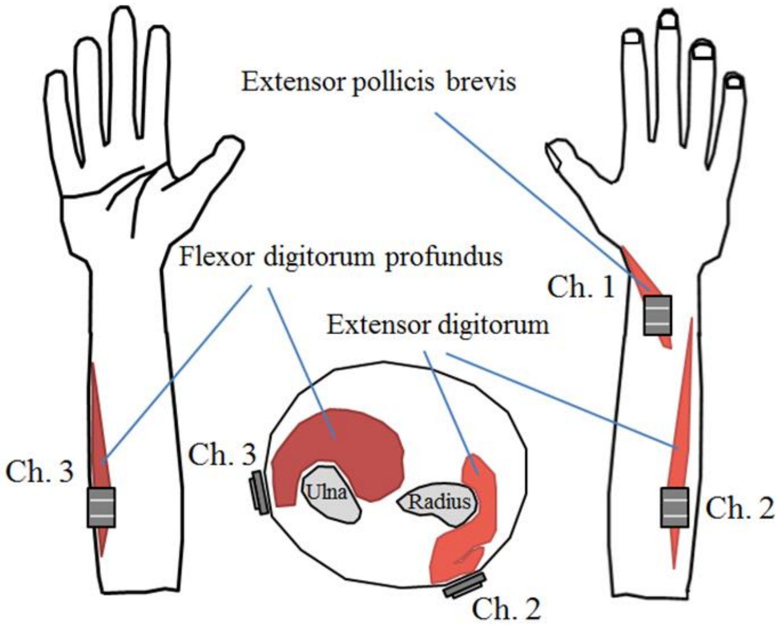

Fig. 6. Placement of the electrodes

Digital signal processing

Before training and testing a classifier, the data must be preprocessed and prepared to ensure more accurate classification. Preprocessing of EMG signals involves several key steps to guarantee the reliability and accuracy of the data for subsequent feature extraction and signal classification. The first step is signal filtering, which uses two types of filters. The first is a bandpass filter with a finite impulse response, used to filter frequencies in the range of 20-450 Hz, as this range contains most of the relevant information. The second is a notch filter, designed to remove electrical noise at 50 Hz from the power supply.

$$\Psi^{a,b}(x) = \frac{1}{\sqrt{a}}\Psi\left(\frac{x-b}{a}\right) \quad (1)$$

Once the data is filtered, the next preprocessing step is segmentation. Segmentation enhances feature extraction, reduces signal complexity and improves model training. Importantly, it minimizes the delay in movement, a critical factor for prosthetic arm users. To avoid noticeable delays, the segment duration is set to 250 ms, as the smallest delay users typically do not perceive is approximately 250 ms. With a sampling frequency of 4 kHz, each segment contains 1000 data points.

Wavelet Transform

The wavelet transform is a mathematical tool used in signal processing and analysis to decompose signals into their constituent components at different scales. It achieves this by breaking down the signal into a set of basic functions derived from contractions, expansions, and translations of a “mother” function Ψ(x), known as the wavelet. Wavelets are small, localized, oscillating functions that vary in scale and frequency. This method enables the simultaneous measurement of time and frequency variations in non-stationary signals. During the wavelet transform process, the signal is convolved with a scaled and translated version of the selected wavelet (also known as the “mother” wavelet), which reveals the frequency components or coefficients at different time points. Scaling or dilation stretches or compresses the wavelet, while translation shifts it to different time positions. The wavelet transform decomposes noisy signals into sub-bands of higher and lower frequencies, with high-frequency components representing detailed coefficients and low-frequency components representing approximate coefficients[8].

A family of wavelets can be constructed from the mother wavelet Ψ(x), the wavelet has finite energy as well as zero mean value. The "mother" wavelet is chosen based on the characteristics of the signal or image and the nature of the application for which the transform is being used. The "daughter" wavelets Ψa,b (x) are formed by displacement (b) and contraction (a) of the "mother". Equation (1) defines the "daughter" wavelets.

In this study, we used discrete wavelet transform due to the possible options of choosing level of decomposition on the original signal in order not to overload the computer power. During the process of choosing an appropriate "mother" wavelet, it is necessary to understand their properties. Regarding the properties possessed by the families of wavelets, we test the wavelets from the Daubechies family as the most compact. We test all of the wavelets starting from db1-db7 with corresponding levels from first to fourth and the best results and the chosen wavelet is db1 with second level of decomposition. The wavelet that we use is shown in Figure 7.

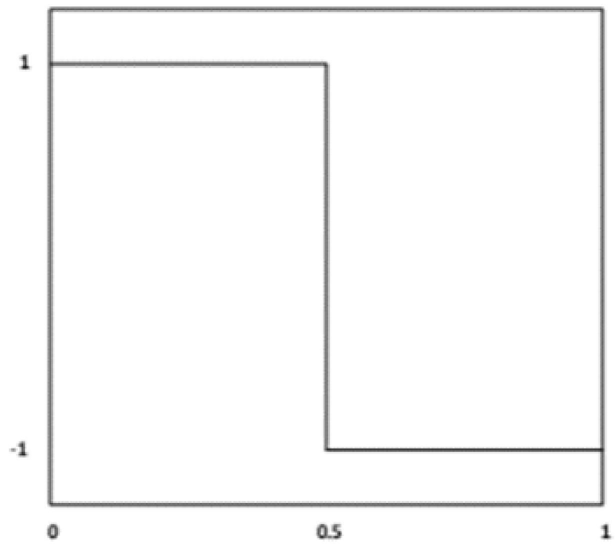

Fig. 5. Wavelet db1 or Haar

Feature extraction

Feature extraction is a process used in machine learning to reduce the number of resources needed for processing without losing important or relevant information. One of the most important parts is choosing proper features and validity of methods for selected feature ability to extract these features in real time form. In other words, feature extraction involves creating new features that still capture the essential information from the original data but in a more efficient way. By employing techniques such as statistical measures, analysis in the time or frequency domain or advanced methods such as feature extraction based on deep learning, this process generates compact yet informative representations of the data[9].

Features are components that represent complex signals as signals with smaller dimensions. These are used as inputs to machine learning models, on which their predictions are trained and tested. The EMG characteristics can be analyzed in time domain, frequency domain and time-frequency domain. The time domain is a representation of the characteristics of the signal in relation to time. Time domain features recognize the characteristics of a signal that characterize its temporal structure. An illustration of the characteristics of a signal in terms of frequency is the frequency domain representation. The frequency spectrum of some signal shows what frequency that signal relies on. The time-frequency domain features administer the information about the temporal and spectral characteristics of the signal.

In this study, we used time-frequency features. We choose frequency domain features such as Power Spectral Density, Entropy, Dominant Frequency, Total Power, Max-Min Drop Ratio, Mean Frequency, and Variance of Frequency. Typically, time domain feature extraction is performed from the underlying EMG signal, which is an advantage for EMG signals, since the original EMG signals are displayed with respect to time. The following time domain features were used in this study:

- ***Mean***, which calculates the mean value of the EMG signal amplitude over the sample length of the signal:

$$Mean\ (\mu) = \frac{1}{M}\sum_{m=1}^{m} x_m. \tag{2}$$

- ***Standard deviation***, which measures of how dispersed the data is relative to the mean:

$$std(\sigma) = \sqrt{\frac{1}{M}\sum_{m=1}^{m}(x_m - \mu)^2}\ . \tag{3}$$

- ***Skewness***, which represents relative measure of third-order cumulative signal irregularity and asymmetry:

$$skewness = \frac{\frac{1}{M}\sum_{m=1}^{m}(x_m - \mu)^3}{\sigma^3}. \tag{4}$$

- ***Kurtosis***, which measures distribution, peak probability, calculation or fourth-order cumulative calculation:

$$kurtosis = \frac{\frac{1}{M}\sum_{m=1}^{m}(x_m - \mu)^4}{\sigma^4}. \tag{5}$$

- ***Integrated Absolute of Second Derivative***, which captures the relative changes of the second derivative of a signal that acts as a filter to reduce noise:

$$IASD = \sum_{n=1}^{N-2} |x'[n+1] - x'[n]|. \tag{6}$$

- ***Integrated Absolute of Third Derivative***, similar to the previous feature, which captures the relative changes of the third derivative of the signal:

$$IATD = \sum_{n=1}^{N-3} |x''[n+1] - x''[n]|. \tag{7}$$

- ***Integrated Exponential of Absolute Values***, which amplifies large samples and suppresses small samples for all positive and negative samples:

$$IEAV = \sum_{n=1}^{N} \exp(|x[n]|)\,. \tag{8}$$

- ***Integrated Absolute Log Values***, which suppresses large samples and boosts small samples, where T is a threshold that must be tuned empirically:

$$IALV = \sum_{n=1}^{N} |\log\,(\mathrm{x}[\mathrm{n}] + \mathrm{T})|. \tag{9}$$

- ***Integrated Exponential***, a characteristic that is similar to an integrated exponential of absolute values, where the only difference is between positive and negative samples, that is, it generally amplifies positive and suppresses negative samples:

$$IE = \sum_{n=1}^{N} \exp\,(x[n]). \tag{10}$$

After forming the dataset comprised of the extracted features from the wavelet coefficients, we apply standardization procedure to further improve the performance of the models.

Classification and results

Machine learning is a key component within the broader field of artificial intelligence that employs statistical methods to empower computers with the ability to learn and make decisions autonomously, without the need for explicit programming. It is founded on the concept that computers can acquire knowledge from data, identify patterns, and draw conclusions with minimal human intervention. Classification is a technique that involves categorizing data into distinct classes. It is a recursive process that recognizes and groups data objects into pre-defined categories or labels. This technique is used to predict the outcome of a given problem based on input features. It can be applied to structured or unstructured data, and the classes are commonly known as target, label, or categories. The aim of classification is to assign an unknown pattern to a known class. For example, classifying emails as "spam" or "not spam" is a common application of classification[10].

Before classification, the dataset was divided into training and testing sets. The training set consisted of 90% of the total dataset (6,480 data points) and the testing set comprised the remaining 10% (720 data points). The training set was used for training the algorithms through stratified 10-fold cross-validation. The testing set was reserved for the final evaluation on previously unseen data. Five different algorithms were used for classification:

- K- Nearest Neighbors,
- Support Vector Machine,
- Decision Tree,
- Random Forest,
- Extreme gradient boosting (XGBoost).

The F1 metric is an alternative metric for evaluating machine learning models that assesses a model's predictive skill by elaborating on its performance by classes rather than overall performance as done by accuracy. The F1 score of each of the five algorithms is presented in Figure 8, where we can observe that the best performer is XGBoost, while the worst is K- Nearest Neighbors.

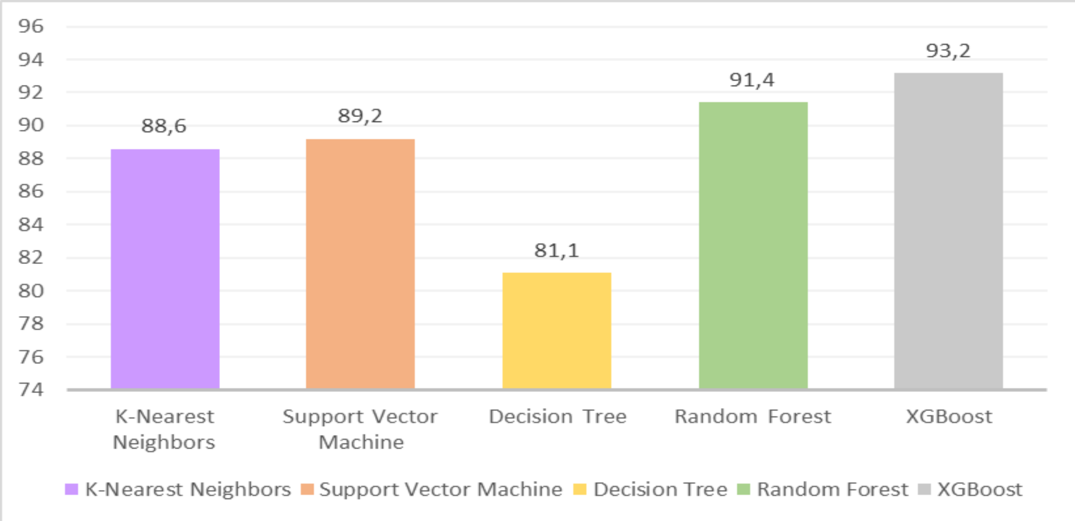

Fig. 6. Classification results with F1 metric with time-frequency domain features

Discussion

As illustrated in Figure 8, the XGBoost classifier outperforms the other four classifiers, achieving a result of 93.2%. Closely following is the Random Forest classifier with 91.4%. Next in performance are the Support Vector Machine, K-Nearest Neighbors (KNN), and lastly, the Decision Tree classifier.

To better visualize the results and errors encountered during training, we employed confusion matrices. These matrices provide a numerical breakdown of how many instances of each class were correctly and incorrectly predicted, as well as pinpointing the exact locations of classification errors. A confusion matrix is a square matrix where its dimensions correspond to the number of classes in the classification problem. For this particular task, the matrix is 6x6, reflecting the six distinct movements that need to be recognized. Figure 9

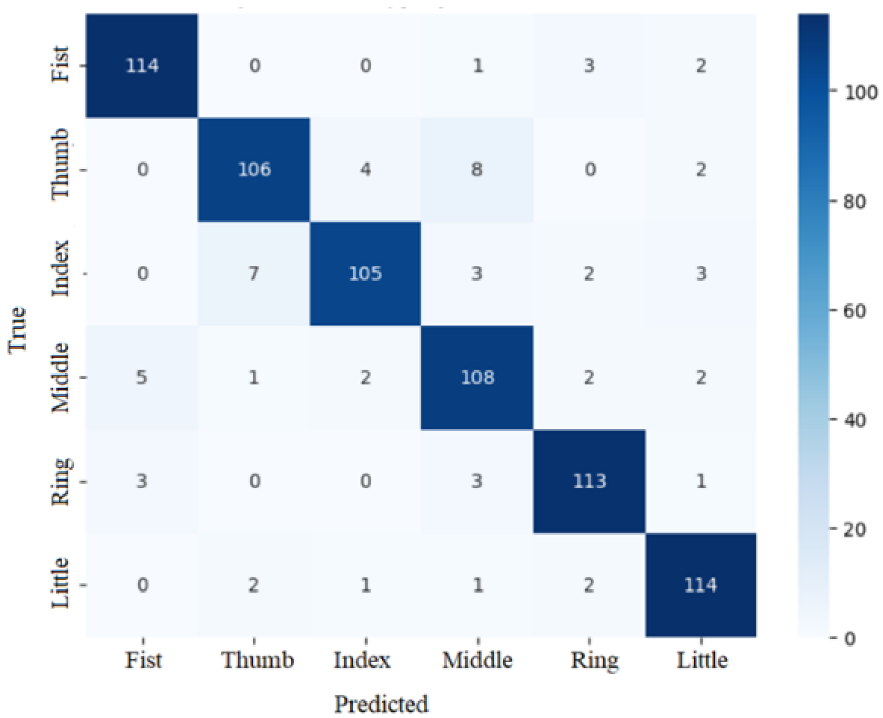

Fig. 7. Confusion Matrix of the results from XGBoost

displays the confusion matrix for the XGBoost classifier, providing a detailed view of the model's performance. In the matrix, the rows represent the actual classes to which the signals belong, while the columns indicate the predicted classes. The values within each cell denote the number of signals that were predicted as each class. From the observation, it can be concluded that most of the movements were correctly classified with some slight deviations, most of which occurred in the thumb and index finger, while smaller errors were made in the middle finger and the most accurately classified were the fist and the little finger.

An important enhancement to our approach involved the use of wavelet transform, which significantly influenced the results by providing better performance. Wavelet transform is a powerful signal processing technique that decomposes a signal into components at various scales, allowing for the extraction of both time and frequency information simultaneously. This is particularly beneficial for analyzing EMG signals, which are non-stationery and exhibit variations over time. By applying wavelet transform, we were able to capture more relevant features from the EMG signals, leading to improved classification accuracy.

The observed results were influenced by various factors, and it's crucial to recognize that some inherent errors may arise due to several uncontrollable variables. For instance, anatomical differences such as hand size, muscle structure and forearm thickness among subjects can affect the consistency of EMG signal patterns. Additionally, variations in EMG signal measurement methods including electrode placement, skin conductivity, and signal acquisition technique can introduce variability. The quality and sensitivity of the instrumentation used to capture EMG signals, as well as the algorithms employed for signal processing, are also critical factors. Furthermore, the anatomical nature of fingers. The distribution and density of muscle fibers, as well as the location and alignment of tendons, can vary greatly between individuals, resulting in differences in how electrical activity is generated and transmitted. These anatomical differences can cause variability in the EMG signals captured from different subjects, making it challenging to develop a one-size-fits-all model. By understanding and accounting for these anatomical variations, we can improve the accuracy and reliability of EMG-based assessments and applications. Addressing and understanding these anatomical variations is key to enhancing the accuracy and reliability of EMG-based assessments and applications.

Conclusion

In this study, we explored the use of wavelet transform for enhancing the classification of EMG signals related to finger flexion, aiming to uncover how its application can improve results. We focused on analyzing six distinct movements, that is, five individual finger movements and a fist using surface electromyography signals that were meticulously filtered, segmented and standardized.

To prepare the dataset, we applied the Daubechies wavelet db1 with a level 2 decomposition to extract wavelet coefficients. From these coefficients, we derived time-frequency domain features, that later on were used as input features to train and test the machine learning models. Our comparison of different algorithms led us to conclude that XGBoost performed the best, achieving an accuracy score of 93.2% with the chosen db1 wavelet and time-frequency domain features. While this result is excellent and promising, there is potential for further improvement through additional hyperparameter optimization and more detailed feature engineering to extract even more relevant information from the data.

Future work should include investigating neural network architectures to fully leverage the wavelet coefficients and enhance signal classification performance. Employing neural networks could offer a more efficient, accurate, and adaptable solution for real-world applications in terms of processing time, accuracy, and usability.

Conflict of interest statement. The authors declare no conflict of interest.

References

1. LeBlanc M, 2008. Taken from: https://web.stanford.edu/class/engr110/2011/LeBlanc-03a.pdf.
2. Premier Surgical Prosthetic Center, The Evolution of Prosthetic Limbs: Current Technological Advancements, 2023.
   Avelable from: https://www.premierprosthetic.com/09/the-evolution-of-prosthetic-limbs-current-technological-advancements/
3. Hristov B, Nadzinski G, Ojleska Latkoska V, Zlatinov S. Classification of Individual and Combined Finger Flexions Using Machine Learning Approaches. *IEEE ICCA* 2022; 986-991. doi:10.1109/ICCA54724.2022.9831952.
4. Reza Bagherian Azhiri, Mohammad Esmaeili, Mehrdad Nourani. EMG- Based Feature Extraction and Classification for Prosthetic Hand Control, 2021; doi:10.48550/arXiv.2107.00733.
5. Phinyomark A, Limsakul C, Phukpattaranont P. Application of Wavelet Analysis in EMG Feature Extraction for Pattern Classification. *Measurement Science Review* 2011; 11(2): 45-52. doi: 10.2478/v10048-011-0009-y.
6. Raez MB, Hussain MS, Mohd-Yasin F. Techniques of EMG signal analysis: detection, processing, classification and applications. *Biol Proced Online* 2006; 8: 11-35. doi: 10.1251/bpo115.
7. Khushaba RN, Kodagoda S, Takruri M, Dissanayake G. Toward Improved Control of Prosthetic Fingers Using Surface Electromyogram (EMG) Signals. *Expert Systems with Applications* 2012; 39(12): 10731-10738, 2012; doi:10.1016/j.eswa.2012.02.192.
8. Rakesh R, Bikash CS, Ashish KB. Ocular artifact elimination from electroencephalography signals: A systematic review. *Journal of Applied Biomedicine* 2021; 41(3): 960-996. doi: 10.1016/j.bbe.2021.06.007.
9. Azmoudeh B, Cvetkovic D. Wavelets in Biomedical Signal Processing and Analysis. In book: Reference Module in Biomedical Sciences, 2019; doi: 10.1016/B978-0-12-801238-3.99972-0.
10. Amer FAHAl, Tasnim HKA. An overview of machine learning classification techniques. *BIO Web of Conferences* 2024; 97(4): 00133. doi: 10.1051/bioconf/20249700133.