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RESEARCH

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Comparative analysis of electrical signals in facial expression muscles

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Abstract

Background: Facial expression muscles serve a fundamental role in the orofacial system, significantly influencing the overall health and well-being of an individual. They are essential for performing basic functions such as speech, chewing, and swallowing. The purpose of this study was to determine whether surface electromyography could be used to evaluate the health, function, or dysfunction of three facial muscles by measuring their electrical activity in healthy people. Additionally, to ascertain whether pattern recognition and artificial intelligence may be used for tasks that differ from one another.

Results: The study included 24 participants and examined three muscles (m. Orbicularis Oris, m. Zygomaticus Major, and m. Mentalis) during five different facial expressions. Prior to thorough statistical analysis, features were extracted from the acquired electromyographs. Finally, classification was done with the use of logistic regression, random forest classifier and linear discriminant analysis. A statistically significant difference in muscle activity amplitudes was demonstrated between muscles, enabling the tracking of individual muscle activity for diagnostic and therapeutic purposes. Additionally other time domain and frequency domain features were analyzed, showing statistical significance in differentiation between muscles as well. Examples of pattern recognition showed promising avenues for further research and development.

Conclusion: Surface electromyography is a useful method for assessing the function of facial expression muscles, significantly contributing to the diagnosis and treatment of oral motor function disorders. Results of this study show potential for further research and development in this field of research.

Keywords: Facial expression muscles, Electromyography, Oral motor function, Orofacial system, Pattern recognition

Background

Facial expression muscles play a crucial role in the orofacial system, significantly contributing to oral motor function, overall health, and well-being [1]. These muscles are not only responsible for expressing emotions and facial expressions, but also facilitate essential functions such as speech, chewing, and swallowing [2]. Understanding the development, function, and potential disorders associated with facial expression muscles is vital for assessing their importance in both health and disease. This group encompasses the Orbicularis Oculi, Zygomaticus Major and minor, Orbicularis Oris, Buccinator, among others, which synergistically operate to generate expressions that include smiling, frowning, and blinking [3].

Oral motor function encompasses all movements of oral structures, including the lips, tongue, cheeks, and jaw [4]. Facial expression muscles are central to these movements, ensuring proper articulation, chewing, and swallowing. Effective oral motor function is essential for clear speech, efficient digestion, and safe swallowing. Speech largely depends on the coordinated actions of the facial expression muscles. For instance, the Orbicularis Oris is essential for producing bilabial sounds (e.g., /p/, /b/, /m/), while the buccinator and other cheek muscles help shape the oral cavity for producing various vowels and consonants [5]. Chewing, or mastication, involves a complex interaction of facial expression muscles with the muscles of mastication (e.g., masseter, temporalis). Swallowing, or deglutition, is another key function facilitated by the Facial expression muscles. The Orbicularis Oris and other facial muscles help create the initial vacuum needed to draw food and liquids into the mouth, while the coordinated action of the tongue and cheek muscles propels the bolus toward the pharynx [6–10].

The Orbicularis Oris, Zygomaticus Major, and Mentalis muscles exhibit distinct characteristics that enable them to fulfill specific roles in facial expressions and oral motor functions. These muscles are integral to the complexity of human communication and expression.

The Orbicularis Oris muscle encircles the mouth, facilitating lip movements essential for speech and facial expressions. Its unique fiber arrangement allows for precise control over lip closure and manipulation, crucial for both vocalization and non-verbal communication [11]. Aside from Orbicularis Oris, the Zygomaticus Major muscle plays an intricate role in facial expressions, as it is primarily responsible for elevating the corners of the mouth. This muscle is key in smiling and expressing joy. It contains a higher proportion of fast-twitch fibers, enabling rapid contractions necessary for quick facial expressions [12]. Finally, the Mentalis muscle contributes to expressions of doubt and disdain, through raising and protruding the lower lip. Its anatomical composition, more precisely a deep muscle belly, contributes to more nuanced movements. It is important to note that when injected with botulinum toxin, complications can arise with this muscle, leading to limited lower facial expressions [13, 14].

While these muscles are specialized for distinct functions, their interconnectivity means that alterations in one can impact the others, highlighting the complexity of facial musculature and expression.

The health and functionality of facial expression muscles have a profound impact on overall health [3]. Damage to these muscles can lead to a range of problems, from communication difficulties and social isolation to nutritional deficiencies and respiratory complications. Effective communication is fundamental to mental and emotional well-being. Facial expression muscles enable the expression of emotions, facilitating social interactions and relationships. Nutritional health is directly linked to the efficiency of facial expression muscles in mastication and swallowing. Respiratory health can also be affected by facial expression muscles, especially in conditions that impair their function [15].

Surface electromyography (sEMG) applies electronic devices to measure muscle energy and analyze and display the data from these measurements. This field relies on the understanding of anatomy, physiology, and the instruments used in the process. It is a multidisciplinary field that utilizes electronics, physiology, psychology, physical therapy, and more. Surface electromyography has various applications, from diagnostics, treatment planning, rehabilitation, outcome monitoring, and research. It is applied in all branches of both medicine and dentistry [16, 17].

The use of electromyography (EMG) in muscle function assessment has evolved significantly since its early applications in the 1600s, with clinical use beginning in the 1960s. Over time, advancements in technology have allowed for improved electrode placement strategies and data processing techniques, enhancing the precision of muscle activity analysis, particularly in the orofacial region.

Facial expression muscles are crucial for oral motor function, playing key roles in speech articulation, mastication, and swallowing. Their coordinated activity supports both emotional expression and essential physiological functions, making their assessment vital in diagnosing dysfunctions that impact communication, nutrition, and quality of life.

It is necessary to consider the unique anatomy of facial musculature, including various aspects. The fact that there is high variability in the morphology and position of individual muscles, as well as the soft tissue surrounding them, makes it difficult to standardize electrode placement. Electrodes used for facial sEMG must allow firm and secure attachment to the skin due to the physiology of the muscles, fascia, and skin covering them, as well as possible deformities in their structure [18].

Innervated by the facial nerve, these muscles are vital for core activities including emotional displays, social communication, chewing, and the act of swallowing [19]. Although the clinical ramifications of facial expression muscles are thoroughly documented, the signal processing and engineering obstacles associated with their precise evaluation remain intricate.

Given the intricate nature of facial muscle anatomy, the analysis of these muscles via sEMG frequently necessitates the creation of customized electrode arrays and meticulous strategies for electrode placement. Furthermore, signal processing algorithms must accommodate the variability in muscle activation patterns and the pronounced degree of asymmetry frequently observed in pathological conditions, such as Bell's palsy or facial paralysis resulting from a stroke. Advancements in signal filtering, feature extraction, and real-time data analysis are imperative for augmenting the diagnostic and therapeutic applications of sEMG in the context of facial muscles [20].

The amalgamation of advanced computational techniques, inclusive of machine learning and deep learning paradigms, possesses the potential to transform the interpretative processes of sEMG signals. These models may facilitate the identification of subtle alterations in muscle activity, which are indicative of early-stage muscular dysfunction or rehabilitation progress. The establishment of robust sEMG systems tailored for facial muscle analysis could substantially enhance the diagnosis, treatment, and rehabilitation of individuals afflicted with orofacial disorders [21].

Our hypothesis is that the electrical activity of these three muscles will differ significantly across various tasks due to their unique anatomical roles and functional contributions to facial expressions and oral movements. Furthermore, we hypothesize that these differences can be quantitatively identified using surface electromyography (sEMG) and associated feature extraction methods.

Given the significant role of facial expression muscles in oral motor function, this study aims to assess the feasibility of utilizing sEMG for their functional analysis, with the goal of improving diagnostic and therapeutic approaches.

This manuscript will examine the contemporary landscape of sEMG technology as it pertains to facial expression muscles, the signal processing challenges encountered within this sphere, and the engineering innovations that are fostering more precise and reliable assessments. Also, we will assess the upcoming applications of sEMG in medical, dental, and rehabilitation spheres, and advance potential research directions intended to enhance sEMG technology for orofacial evaluations.

Results

Feature extraction and initial amplitude analysis

We analyzed the results obtained from 24 participants and compared the amplitude values for the three muscles during specific movements. Afterwards, previously defined features were extracted and statistically compared.

Amplitude values, measured in μV, illustrate the electrical activity of the muscles during various facial movements across all participants. For the zygomaticus major muscle, the average amplitude values for swallowing, lip pursing, lip pressing, "PA", and tongue protrusion movements show varying levels of muscle activity, with notable highlights in specific characteristics, indicating greater muscle engagement. Similarly, the Orbicularis Oris muscle demonstrates different amplitude patterns, with average values highlighting significant activity during specific movements such as swallowing and lip pursing, while standard deviations reflect variability in responses among participants. Finally, the mentalis muscle exhibits varied average amplitude values across characteristics, with notable prominence in lip pressing and tongue protrusion movements, reflecting muscle engagement in these states. Standard deviations for all muscles and characteristics provide insights into the consistency of muscle activation levels among different participants, highlighting variability in muscle responses throughout the study. The differences in the amplitude can be seen in the EMG envelope, in Fig. 1.

Statistical analysis

The ANOVA test results revealed an F-statistic of 6.036 and a p-value of 0.015. The ANOVA test indicates statistically significant differences in the mean amplitude values between the muscles, as the p-value is <0.05.

The Tukey's HSD test results show a significant difference between the Mentalis muscle (m. Mentalis) and the Zygomaticus Major muscle (m. Zygomaticus Major), with a p-value of 0.015. No significant differences were found between the Mentalis muscle (m. Mentalis) and the Orbicularis Oris muscle (m. Orbicularis Oris), with a p-value of 0.095, and between the Orbicularis Oris muscle (m. Orbicularis Oris) and the Zygomaticus Major muscle (m. Zygomaticus Major), with a p-value of 0.662. Thus, it is concluded that the Mentalis muscle (m. Mentalis) and the Zygomaticus Major muscle (m. Zygomaticus

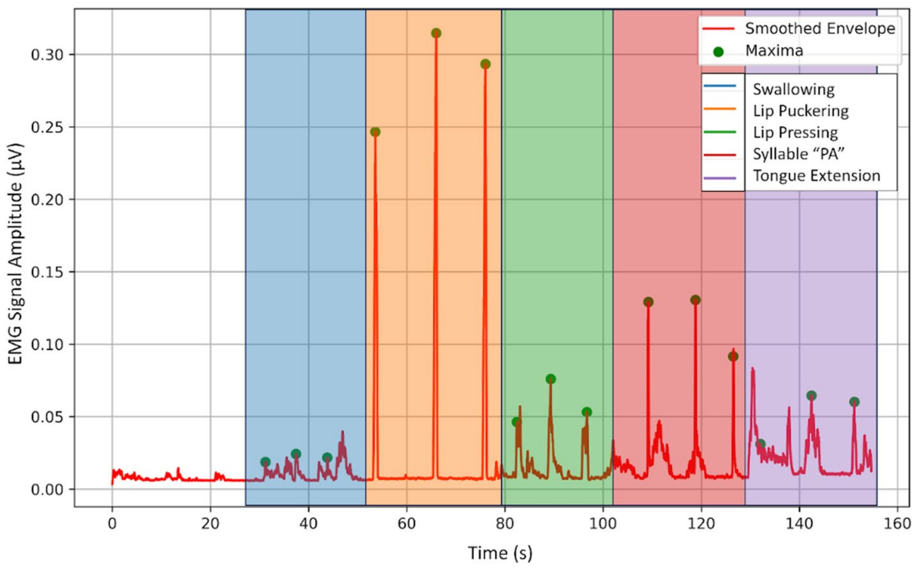

Fig. 1 Amplitude of muscles during various movements

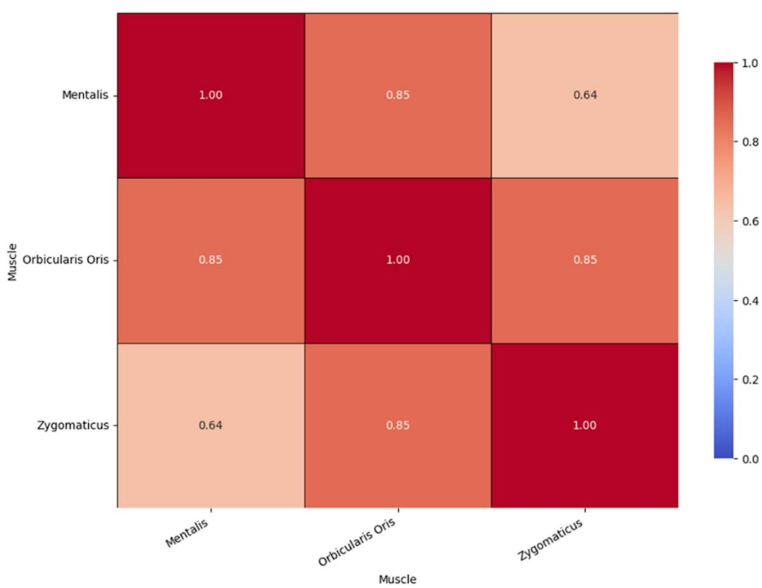

Fig. 2 Correlation matrix of muscles based on all tasks together

Major) have significantly different mean amplitude values, while the other comparisons do not show significant differences.

Following amplitude analysis, multivariable statistical analysis was done, aside from descriptive statistical methods. During this step we analyzed all features, their interactions with one another, as well as compared how each feature is different between muscles and tasks.

The heatmap, in Fig. 2, displays correlation between musculus Mentalis, Orbicularis Oris, and Zygomaticus Major based on their activation patterns during different functions. A strong positive correlation (values close to 1) suggests that the muscles tend to activate in a similar manner during the same functions, implying coordinated muscle activity. This can be seen with musculus Orbicularis Oris and Zygomaticus Major, with correlation coefficient of 0.85. Somewhat lower correlation coefficient can be seen between musculus Mentalis and Zygomaticus Major. The high correlation between Orbicularis Oris and Zygomaticus Major stems from the fact that these muscles are likely working together during the execution of given tasks. Conversely, a lower or negative correlation suggests that the muscles may be functioning more independently, with less coordinated activity during those functions. It is important to note that muscle cross-talk is possible as these muscles are close to one another, as well as they are active during same and similar tasks. With the surface EMG it is important to keep electrode placement constant, as they have a lower precision than needle-based electrodes for EMG signal acquisition.

Similarly to the correlation matrix in Fig. S1 and Fig. S2, six more complex correlation matrices are shown in the supplementary, describing the relations between extracted features and given tasks (Fig. S1) and between extracted features (Fig. S2). The latter one gives insight into which extracted features are closely tied to one another, while Fig. S1 shows the significance of different features when performing a specified task.

The radar chart provides a clear visual comparison of the standardized mean EMG features across five muscle functions, with each function represented by a different color. As can be seen in all three subfigures (Fig. 3a, c, e), the action of "Lip puckering" has the overall highest values in power spectrum-related features, indicating significant muscle engagement during this function. Furthermore, in Fig. 3a, c, for musculus Mentalis and Orbicularis Oris, the act of "swallowing" has significantly lower values for features related to the power spectrum indicating less engagement. For musculus Mentalis and Orbicularis Oris, in Fig. 3a, c, kurtosis is highly pronounced during the act of pronouncing the syllable "PA", while for musculus Zygomaticus Major, in Fig. 3e, the act of "swallowing" produces the highest value of kurtosis. As can be seen in Fig. 3 the act of "lip pressing" has higher values for musculus Mentalis (a), and an overall similar pattern for musculus Orbicularis Oris (c) and Zygomaticus Major (e). Furthermore, max power as a feature is overall lower in acts related to musculus mentalis, except for the act of "lip puckering".

The other half of Fig. 3 displays the mean values of 12 EMG features for three different muscles across different tasks. As it can be seen, the power bands are highly active in all five tasks. For example, all features have a strong response during the act of "lip puckering", for all three muscles. The features are more evenly present for musculus Zygomaticus Major (Fig. 3f), while for musculus Orbicularis Oris (Fig. 3d), there is a clear distinction in tasks which give a stronger response reflected in extracted features and those that do not. The similarity in features can be observed between musculus Orbicularis Oris (Fig. 3d) and musculus Mentalis (Fig. 3b).

In Fig. 4, box and whiskers plots are shown for all features separately. Each participant is depicted as a point. Some features exhibit wider ranges, suggesting differences in muscle control or physiological variations, while others show more consistent responses. As can be seen in Fig. 4a, c, e the boxplots for frequency at max power, mean and median frequency have similar distributions, in terms of the middle 50% of the data. However, all features exhibit higher variability in the lowest quartile in Fig. 4b, having no outliers

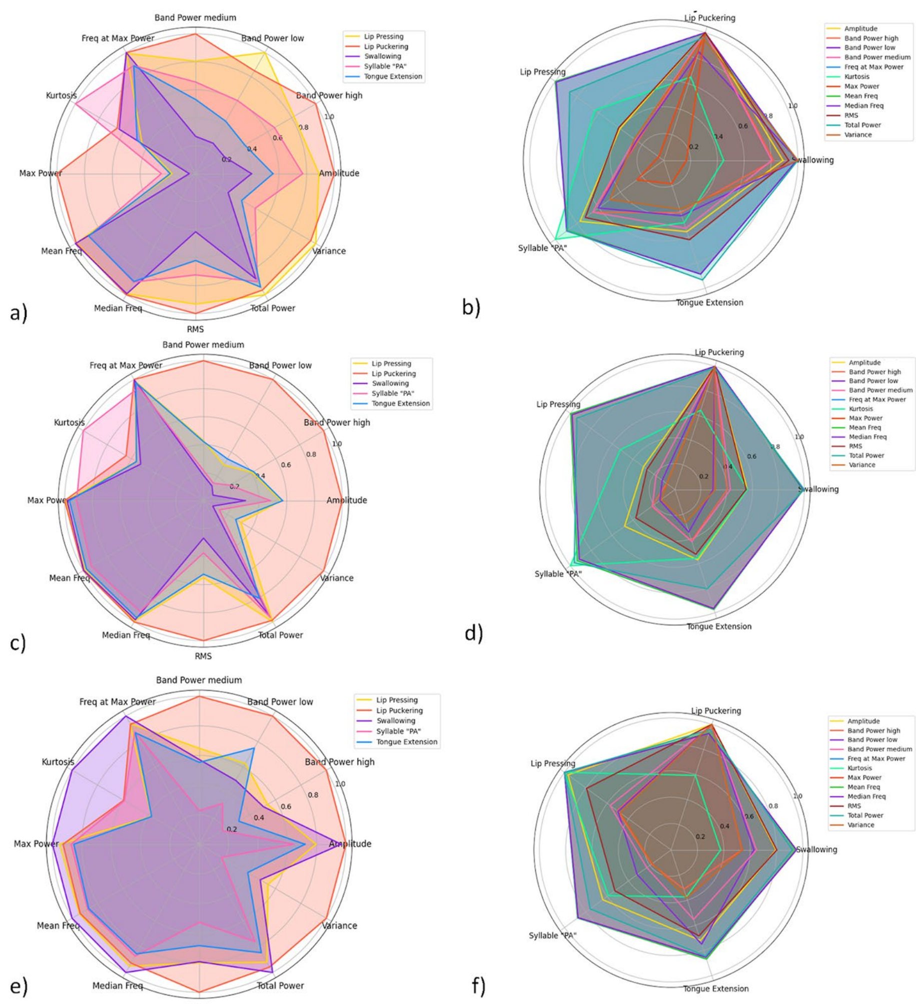

Fig. 3 Radar charts of the database grouped by: **a** standardized mean EMG features for M. Mentalis; **b** tasks for m. Mentalis; **c** standardized mean EMG features for M. Orbicularis Oris; **d** tasks for m. Orbicularis Oris; **e** standardized mean EMG features for M. Zygomaticus Major; **f** tasks for m. Zygomaticus Major

in the highest one. This is contrary to Fig. 4a, b, in which a more even distribution of outliers is seen. Furthermore, amplitude, RMS and variance are tightly packed near zero, suggesting lower variability of data. In Fig. 4b, d, f power spectrum features are shown. These box and whisker plots indicate higher variability of values in the highest quartile. Some features may exhibit a wide range of values, which results in high standard deviation as seen in Fig. 4, suggesting differences in how participants activate muscles during specific functions, while others show a more consistent response across individuals. This variability could be due to differences in individual muscle control, measurement conditions, or inherent physiological differences between participants. For example, some participants have high values of band power, while others do not. Additionally, there is a difference in which bands of power (high, medium or low) exhibit the highest values during each task per individual. However, the maximum power, which is the standardized resulting power of all three bands together, is close to the average value across all individuals.

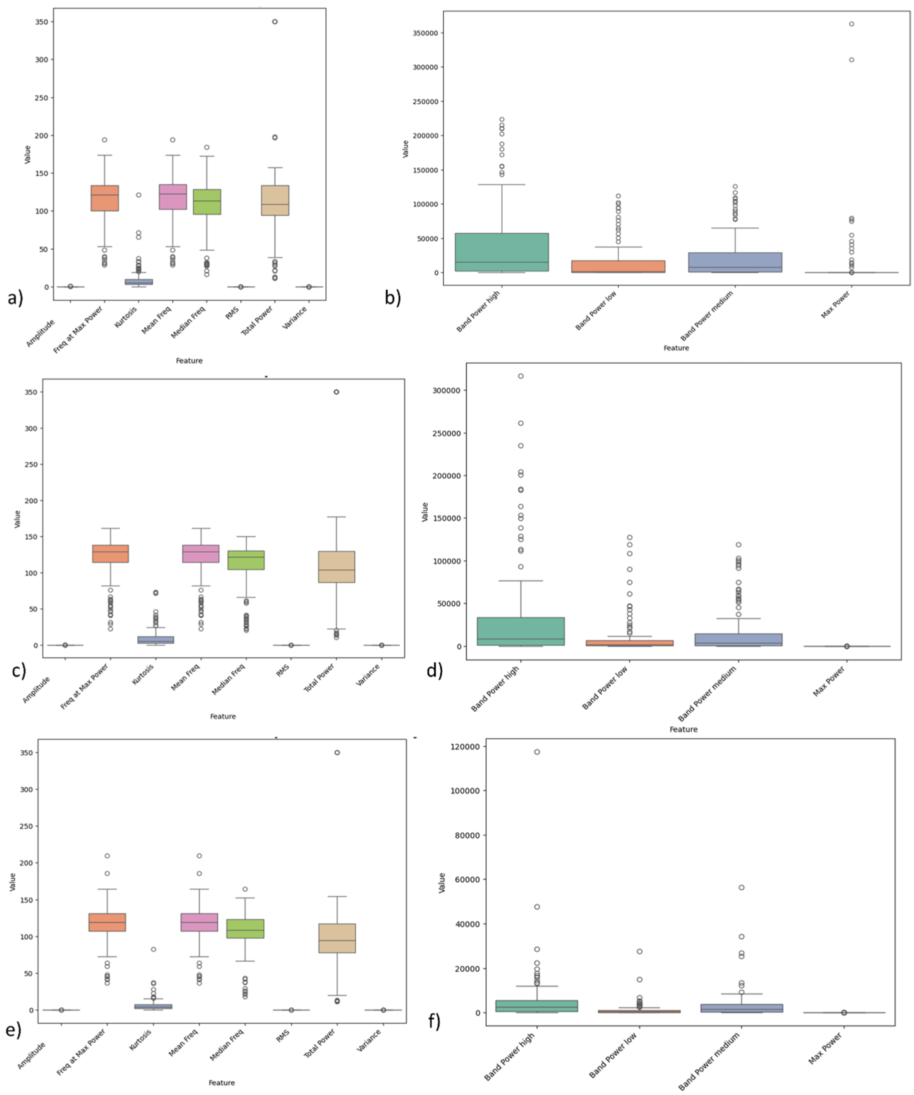

Fig. 4 Boxplots of EMG features across participants, per muscle: amplitude, frequency at max power, kurtosis, mean frequency, median frequency, RMS, total power, variance: **a** of musculus Mentalis; **c** of musculus Orbicularis Oris; **d** of musculus Zygomaticus Major; as well as band power high, band power low, band power medium and max power: **a** of musculus Mentalis; **c** of musculus Orbicularis Oris; **d** of musculus Zygomaticus Major

Figure 5 shows how participants are grouped into distinct clusters based on similarities in their EMG profiles. Participants within the same cluster are closer together, indicating similar muscle activity patterns. Moreover, the distribution of points across PCA components suggests that some clusters are more tightly grouped (indicating less variability within the cluster), while others are more spread out. This spread is not wide when analyzing musculus Mentalis (a) and musculus Orbicularis Oris (c), however, when looking at Fig. 5e, for musculus Zygomaticus Major there are some participants exhibiting values relatively different in comparison to others. Furthermore, clustering profiles divided by tasks are shown in Fig S3 (b) for musculus mentalis, (d) for musculus Orbicularis Oris and (f) for musculus Zygomaticus Major. Interestingly

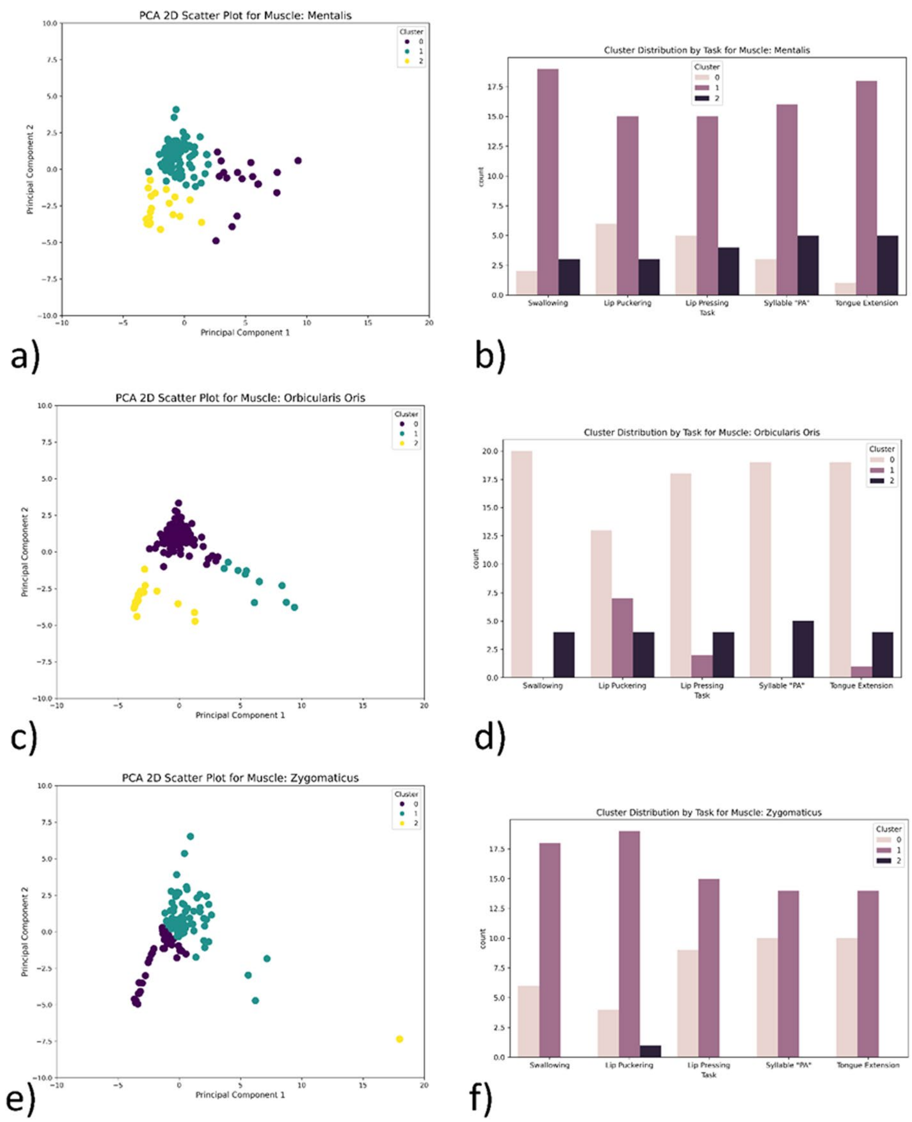

Fig. 5 Cluster separation using principal component analysis reduction on to 2 axes: **a** Musculus Mentalis; **c** Musculus Orbicularis Oris; **e** Musculus Zygomaticus Major; cluster distribution per task: **b** Musculus Mentalis; **d** Musculus Orbicularis oris; **f** Musculus Zygomaticus Major

all participants show similar muscle activation for each task, as one cluster is always dominant, regardless of task. These clusters could be influenced by factors such as muscle control, physiological differences, or even measurement conditions. The plot helps to identify these patterns, which could be useful for further studies or targeted interventions based on participant groupings. Finally, principal component analysis was done after grouping participants per muscle and per task, illuminating how consistent the results are in the figures. The ranges of principal components for each task are located in an area between −5 and 5 for both components, showing similarity between tasks, when the dimensionality is reduced. This can pose a problem for pattern recognition. These results are shown in the supplementary (Fig. S3).

Figure 6 shows extracted features sorted by their statistical significance after performing statistical test-based selection using the ANOVA F value test, as the targeted features (muscles and tasks) are categorical features, while the used features for prediction are numerical by nature. As can be seen in Fig. 6a, the amplitude of the EMG signal has the highest statistical significance, followed by RMS and power in the high band range. The lowest one for muscle prediction is the task itself, as it is a categorical value and not much discriminatory information can be found. Similarly, in Fig. 6b the use of which muscle has the lowest statistical significance in terms of the task prediction itself. Interestingly both for task and muscle prediction the group of features that has the highest statistical significance are band power high and medium, rms, variance and amplitude. In contrast to that, mean and median frequency, as well as frequency at max power have a higher statistical significance in predicting tasks than muscles which have been used (Fig. 6b). On the other hand, features such as max power and kurtosis are more significant in terms of predicting which muscle is used than the task at hand.

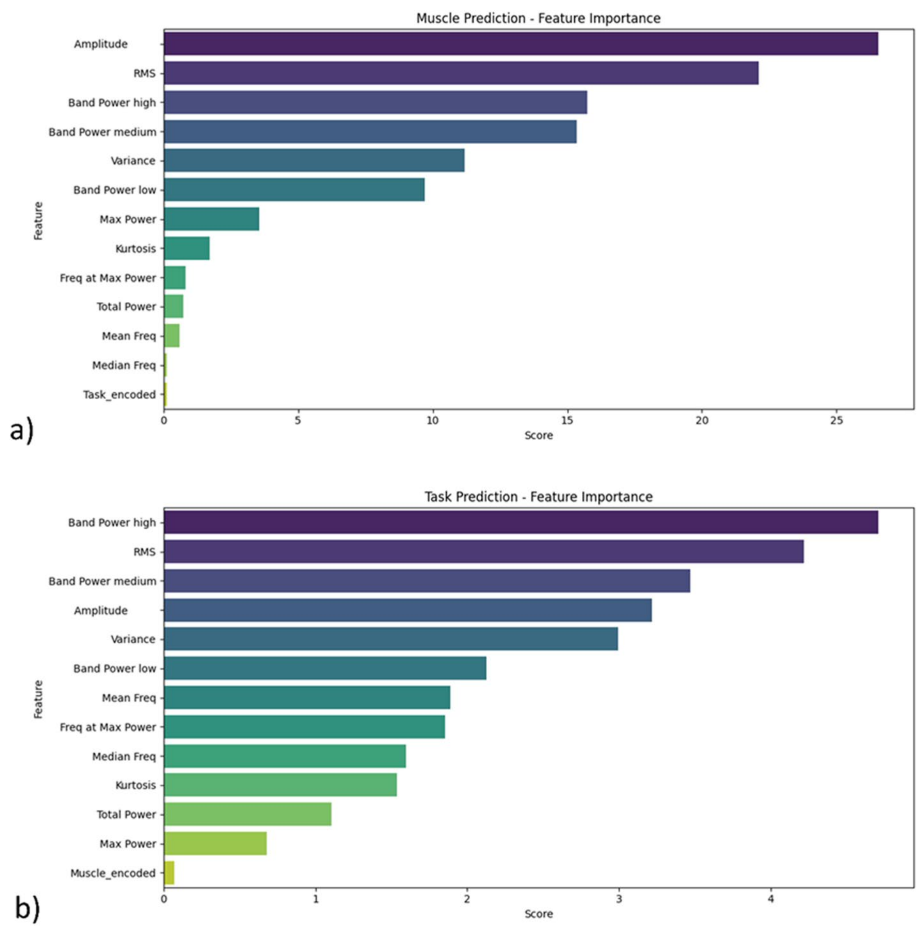

Fig. 6 Sorting of features by their statistical significance in terms of: **a** acting muscle prediction; **b** task prediction

Example of pattern recognition

In Table 2, the results of recognition of task: "Swallowing" are shown, per muscle. The presented classifier performance metrics are: accuracy, sensitivity (recall), specificity and precision. They have been multiplied by 100, and are shown per classifier (logistic regression, linear discriminant analysis and random forest).

Discussion

The aim of this study was to measure the electrical activity of three facial muscles in healthy individuals and assess the feasibility of using surface electromyography to evaluate the condition, function, or dysfunction of these muscles. Moreover, to determine if there is a possibility of application of pattern recognition and artificial intelligence in discrepancy between different tasks. Our research among individuals without health problems demonstrates a strong correlation with previously established criteria for muscle activity. Specifically, the use of surface electromyography enabled precise monitoring of muscle activation during various oral movements.

The findings from this study demonstrate the feasibility of sEMG in distinguishing between different facial muscle activities, supporting its potential application in clinical and research settings.

Mueller et al. conducted a similar study; however, they encompassed a broader array of different facial muscles. They have used high-resolution sEMG to gather raw EMG signals, which were then used to produce heatmaps and other statistical methods with the goal of observing changes in the signal during mimic movements [20]. They considered the impact of variability in EMG signals due to electrode placement on data consistency [20, 22]. Despite these challenges, their study showed a good correlation between muscle position and fiber orientation, in line with anatomical references. Similarly, our study indicated that proper electrode placement on anatomically defined muscle regions facilitates the identification of signals related to specific actions. While this study primarily focused on functional aspects of muscle activity during swallowing and tongue protrusion, the observed differences in activation patterns suggest the potential to explore emotional expressions in future research. The Mentalis and Zygomaticus Major muscles, known for their roles in facial expression, exhibited unique activity patterns that may have relevance beyond oral motor functions [23].

The correlation between EMG amplitude and facial expression effectiveness was explored by Saponaro et al., through the analysis of EMG amplitude of facial muscles [24]. In facial expression muscles, high variance can indicate abnormal or inconsistent muscle activity. Studies like Castroflorio et al., have evaluated variance in masticatory muscles, highlighting its importance in understanding muscle coordination and control [25]. RMS has been extensively used in studies on facial muscles, such as the work by Nicolini et al., which examined RMS values in the context of facial muscle training [26]. Kurtosis helps identify outliers in muscle activity, such as spasms or involuntary contractions. In facial expression muscles, this feature can be critical for detecting abnormal muscle behavior, which might not be apparent through amplitude or RMS alone. Even though abnormal muscle activity has not been analyzed in our paper, it is imperative to highlight it. Turlapaty et al. discussed the use of kurtosis in analyzing EMG signals to detect abnormal muscle activity [27]. Furthermore, muscle fatigue is best quantified through frequency-based features. Shifts in median and mean frequencies in facial expression muscles, similarly to other ones, can indicate fatigue or change in muscle fiber recruitment patterns. De Luca et al. analyzed the effect fatigue has on median and mean frequency [28]. As power distribution across different frequency bands can provide information on different types of muscle activity, as reported by Merletti et al., we have used these bands as features in our analysis [29].

In terms of pattern recognition, sEMG has been used extensively for detection of motion, complex tasks, as well as in gait correction [30]. The classification results for the three muscles—M. Mentalis, M. Orbicularis Oris, and M. Zygomaticus Major—demonstrate varying levels of performance across the tested models. For M. Mentalis, all models achieved an accuracy of 70%, with LDA and logistic regression showing perfect recall (100%) but low specificity (40%), indicating that while positive cases were correctly identified, there was a high rate of false positives. Random Forest offered a more balanced performance with a recall of 80%, specificity of 60%, and improved precision (66.67%). For M. Orbicularis Oris, Logistic Regression outperformed other models with an accuracy of 70%, a recall of 80%, and a specificity of 60%, indicating strong overall performance. In contrast, LDA showed poor results, with an accuracy of 40% and specificity of only 20%. Random Forest achieved high recall (100%) but struggled with specificity (20%), reflecting an imbalance in its predictions. Finally, for M. Zygomaticus Major, both LDA and Logistic Regression achieved high and balanced results, with accuracy, recall, specificity, and precision of 80%, indicating consistent performance in classifying this muscle's activity. However, Random Forest underperformed relative to these models, with an accuracy of 60% and specificity of only 40%. These results suggest that while logistic regression and LDA generally perform well, Random Forest may require additional parameter tuning to improve its balance between recall and specificity for certain muscle groups. These models overall do not achieve the accuracy presented in literature [30–32], this can be a consequence of various underlying effects, such as muscle cross-talk, variations in electrode placement and issues that can stem from aliasing (even though the Nyquist criterion was met). It is important to note that due to the close proximity of facial muscles, as well as the tongue muscle, cross-talk between signals is possible. This can be the underlying reason to lower model performance compared to the ones found in literature [32]. Small variations in electrode placement can consequently affect the model's performance, as well. These limitations can affect the signal quality and can show up as similarities in compared tasks within all analyzed muscles. To combat this, the extracted features were ranked beforehand using ANOVA's F-value, to see which features differ from one another the most. As facial expression muscles are densely intertwined with one another, encompassing a relatively small space, in comparison to muscles found on the human torso or limbs, significantly less research has been done in this field. Kelati et al. used classification, more precisely a support vector machine classifier (SVC), to recognize either happiness or sadness, depending on the patterns found in sEMG obtained from m. Zygomaticus Major and m. Corrugator [31]. Similarly to Kelati et al., we used SVC for our task recognition, however, we got lower accuracy than them. This can stem from various reasons. For example, our study had 24 participants, with each performing 5 tasks, repeated three times. From these EMG signals, features were extracted. In comparison to their study which had 1–2 participants, our method has a more generalized approach, not focusing on individual examinees, but the whole group. Furthermore, Paul et al. did a comparative analysis of different classifiers, similarly to the ones presented in our paper [32]. This study did not focus on facial expression muscles, but on hand movements. They used 6 basic movements, with classification done through k-nearest neighbor (KNN) and SVC, showing that the highest accuracy was acquired with SVC. We had done a preliminary analysis using different classifiers, however, logistic regression, random forest and linear discriminant analysis outperformed SVC and KNN. It is important to note, that due to the close proximity of facial muscles, as well as the tongue muscle, cross-talk between signals is possible. This can be the underlying reason to lower model performance compared to the ones found in literature [32]. Small variations in electrode placement can consequently affect the model's performance, as well. These limitations can affect the signal quality and can show up as similarities in compared tasks within all analyzed muscles. To combat this, the extracted features were ranked beforehand using ANOVA's F-value, to see which features differ from one another the most.

Clinical applicability of findings

The findings of this study have several potential clinical applications, particularly in the diagnosis and rehabilitation of facial expression muscle dysfunctions. The ability to distinguish between the electrical activities of specific facial muscles during various tasks using sEMG provides valuable insights into muscle performance and coordination.

In clinical practice, this methodology could be employed to assess muscle activity in individuals with conditions such as Bell's palsy, facial paralysis, or post-stroke facial dysfunction, helping clinicians identify affected muscles and monitor recovery progress. For example, the significant differences in muscle activation patterns observed in this study could inform personalized rehabilitation programs targeting specific muscle groups.

Furthermore, the application of pattern recognition techniques demonstrated in this study highlights the potential for developing automated tools to analyze sEMG data. These tools could aid clinicians in diagnosing subtle muscle dysfunctions or evaluating the efficacy of therapeutic interventions in real-time.

In the context of dentistry, the results could enhance the understanding of muscle coordination during oral movements, which is critical for managing temporomandibular disorders or planning prosthetic and orthodontic treatments. Future research should focus on validating these findings in larger and more diverse populations, as well as exploring the integration of sEMG systems into clinical workflows to enhance diagnostic and therapeutic precision.

Limitations

While this study provides valuable insights into the electrical activity of facial expression muscles, several limitations must be acknowledged:

1.Sample size: This study was conducted with a relatively small sample of 24 participants, limiting the generalizability of the findings to broader populations. Future studies with larger and more diverse cohorts are necessary to validate the results and explore inter-individual variability.

2.Electrode placement challenges: The high variability in facial muscle anatomy and the proximity of muscles introduce challenges in standardizing electrode placement. This could lead to cross-talk or signal interference, potentially affecting the precision of measurements.

3.Task selection: The tasks selected for this study, while clinically relevant, may not comprehensively represent all functional movements of facial expression muscles. Expanding the range of tasks in future studies may provide a more holistic understanding of muscle activity.

4.Feature selection and pattern recognition: Although feature extraction and classification methods were employed, the limited sample size and high-dimensional feature space may have influenced the accuracy and reliability of the classification models. Future studies should incorporate advanced algorithms and larger datasets for improved robustness.

5.Pilot nature of the study: As a pilot and methodological study, the primary aim was to assess feasibility rather than establish definitive conclusions. The exploratory nature of the work necessitates cautious interpretation of the results, particularly in the context of clinical applications.

These limitations underscore the need for further research to refine the methodology, validate findings, and expand the scope of applications in clinical practice.

Conclusion

Despite the challenges associated with this method, such as individual muscle morphology, variation in muscle activity across the population and proper electrode placement, this study demonstrated, in context of surface EMG, sufficient precision in measuring muscle activity during various movements.

This study confirms the feasibility of sEMG for facial muscle evaluation, paving the way for its integration into clinical assessments and rehabilitation protocols.

Surface electromyography has proven to be an indispensable method for the detailed study of facial muscles, which are crucial for expression, swallowing, and speech. Furthermore, through examples of pattern recognition, it shows the future possibilities of detection, prediction and down the line possible assistance in correction of facial movements. In future studies, we plan to use coherence analysis and independent component analysis to combat these issues. Furthermore, we will broaden our feature ensemble to the time–frequency domain, utilizing the wavelet transform. The potential of surface electromyography in clinical practice is vast. This method can be used in tracking orthodontic treatment, diagnostics till the end of the intervention process. Another useful use of this technique can be witnessed in diagnostics, process tracking, rehabilitation status follow-up and abilitation as a whole, in patients that have suffered from stroke or other facial muscle disorders such facial nerve paresis or paralysis. Muscle activity tracking before, throughout and after the end of the rehabilitation process can help technicians not only analyze the results of their work but help guide the process of rehabilitation in the right direction.

Methods

In Fig. 7, a graphical depiction of the complete methodology has been presented. Starting from signal acquisition, defining landmarks on which the electrodes will be placed, such as anatomical features for M. Zygomaticus Major, m. Orbicularis Oris and m. Mentalis, as well as following the literature for electrode placement [33–35]. Furthermore, processing and segmentation was done on each acquired signal after which standardization was done. The EMG signal shown in "Results" section in Fig. 7, is an example of one of the signals acquired during measurement of m. Orbicularis Oris. In "Discussion" section statistical analysis was performed to evaluate and quantify the significant differences between the acquired electrophysiological signals. Descriptive and quantitative statistical analyses were used. Finally, to see if there is a possibility of discrimination of muscles in healthy individuals using pattern recognition methods, feature extraction and classification was used.

Figure 7 represents a graphical flowchart of the methodology.

Subjects and measurement setup

The study involved 24 participants, of which 7 were male and 17 were female, aged between 20 and 40 years. Ethical approval has been obtained from the Dental Clinic of Vojvodina, Novi Sad, under the 01-17/12-23 and was in accordance with the World Medical Association's Declaration of Helsinki. Participants were recruited through convenience sampling, involving students and staff from the University of Novi Sad. Starting from signal acquisition, defining landmarks on which the electrodes will be placed, such as anatomical features for M. Zygomaticus Major, m. Orbicularis Oris and m. Mentalis, as well as following the literature for electrode placement [33, 34]. The inclusion criteria for participation were:

1. Adults aged 20–40 years.
2. No history of neurological, muscular, or systemic diseases affecting facial muscles.
3. No ongoing orthodontic treatment or recent facial surgeries.
4. Ability to perform all specified facial tasks without discomfort.

Exclusion criteria included:

1. Any diagnosed orofacial or neuromuscular disorder.
2. Use of medications that could impact muscle function (e.g., muscle relaxants).
3. Presence of skin conditions or sensitivities that could interfere with electrode placement or sEMG measurements.

All participants provided written informed consent before participating in the study. Ethical approval was obtained from the institutional review board at the University of Novi Sad, ensuring compliance with the Declaration of Helsinki.

Beforehand, each participant was given a random eight-digit number, generated with a Python script. The facial muscles examined in this study were Orbicularis Oris, Zygomaticus Major and Mentalis muscles. With that in mind, each recording was named with two letters (ZM-Zygomaticus Major, OO-Orbicularis Oris, ME-Mentalis) denoting the measured muscle, followed by the eight-digit number, assigned to each examinee. This was done for ease of computing later on. These muscles were selected due to their involvement in various facial expressions and movements. The orbicularis oris muscle is responsible for actions such as raising the upper lip, lowering the lower lip, closing the mouth, whistling, and articulating vowels. The zygomaticus major muscle elevates the upper lip corner upward and outward, and assists in the pronunciation of sounds like “S”, “Z”, and “C”. The mentalis muscle tightens the skin of the chin and aids in the pronunciation of sounds like “O”, “U”, and “I” [33].

EMG signals were recorded under five different conditions/movements. Each participant was given clear instructions regarding body position, head position, and the execution of the specified movements:

1.Baseline condition (resting state): Participants were instructed to remain relaxed with minimal facial movement. This baseline condition served as a reference for comparison with other experimental conditions.

2.Swallowing: Participants were asked to swallow saliva naturally, without any forced or exaggerated movements.

3.Lip puckering: Participants were instructed to pucker their lips as if sending a kiss.

4.Lip pressing: Participants were instructed to press their lips together firmly.

5.Pronouncing the syllable "PA": Participants were instructed to sharply articulate the syllable /pɑ/ (as per the International Phonetic Alphabet, IPA), commonly used in speech analysis to assess the activity of the Orbicularis Oris muscle during bilabial plosives.

Tongue extension

Electromyography was conducted using BIOPAC MP36 (California, USA, BIOPAC Systems Inc.). Three electrodes were placed—two on the skin over the selected muscle (V− and V+) and a third (ground electrode) behind the ear. The ground electrode, also called the driven right leg electrode, is used for minimizing the common mode signal found on the differential input (V− and V+). The electrode placement was carefully and precisely determined based on specific anatomical landmarks for each muscle [35]. Silver/silver chloride, single use electrodes (manufacturer Skintact, Country UK) were used in this study to ensure optimal conductivity and signal quality. The size of these electrodes is standardized and are 30 mm in diameter. Participants sat comfortably in a quiet, well-lit room throughout the experiment. Before electrode placement, the skin surface of the targeted muscle regions was cleaned with alcohol wipes to minimize impedance. Anatomical landmarks were taken into consideration when coming up with the methodologies for the three muscles used in this study. As Orbicularis Oris muscle is the circular muscle surrounding the mouth, the electrodes were placed near the center of the muscle along the upper lip at the same distance from the modiolus, at least 1 cm apart to capture the full range of muscle activity without inter-electrode interference. For Zygomaticus Major muscle, the zygomatic bone, from which it extends to the corner of the mouth was first identified and at the midpoint between those two facial structures with 2 cm of inter-electrode distance, two electrodes were placed. On Mentalis, a small muscle located at the chin, two electrodes were placed directly below the lower lip, meeting at the midline with 1–2 cm inter-electrode distance. The placement of the electrodes can be seen in Fig. S4 in the supplementary file. To ensure the right placement, participants were instructed to perform movements related to the said muscles, such as smiling and frowning.

Foremost, the measurement procedure and tasks during the measurement process were described in detail to each examinee. Following that, to optimize the participants' readiness for the experiment, a brief rest period was provided to allow them to relax their muscles and mentally prepare for the upcoming tasks. The resting period lasted 20 s, while each movement was performed at 20-s intervals, during which the examinees repeated the designated task three times. In between tasks, the examinee relaxed for 10 s. The recording lasted 3 min per muscle. The signals were recorded for further analysis. Task repetition ensured that the data collected were reliable and representative of the participants' oral motor function.

Data acquisition

A notch filter on 50 Hz to filter out powerline noise, as it is present in the frequency range in which the recordings were done. The frequency range in question was between 30 and 250 Hz. Cutting out lower frequencies was done to eliminate the possibility of motion artifacts and DC offset, as well as any other low-frequency noise which could affect signal acquisition. The gain was set to 200 and the cutoff frequency was 250 Hz, as the highest amount of muscle activity information, for this study, is contained up to this frequency. Sampling frequency was set to 1000 Hz. All additional calculations were done after data acquisition was finished.

Pre-processing, segmentation and feature extraction

Figure 8 represents a diagram showing each phase and step of this stage in the methodology. First of all, the signal was denoised using a low-pass filter (cutoff frequency at 250 Hz) and high-pass filter (cutoff frequency at 30 Hz), as an additional precaution with the goal of eliminating low and high frequency noise. After signal acquisition and filtering, to ensure adequate comparability and lower the effects of muscle asymmetries and facial hair existence, we have standardized all EMG signals to the range of 0 to 1 using Eq. 1. The x(i) stands for the *i*th value in the EMG data array, which has been standardized, while X(i) represents the non-standardized value in the same position in the array. Functions 'min' and 'max' find the minimum and maximum values, respectively, in the analyzed EMG data array, while X represents the whole data array:

$$Xnorm(i) = \left(X(i) - average(X)\right) \div std(X). \tag{1}$$

After feature extraction the data of interest were destandardized, to show the adequate amplitudes and values in their respective units. Segmentation was done next.

Segmentation was done in three steps, as seen in Fig. 8. Envelope was extracted from each EMG signal, using the Hilbert transform [35], after which the modified signal was smoothed utilizing a moving average filter with a window size of 600. Following that, maxima values were detected for each task. As each task contained three action repetitions, followed by a pause of 10 s, the maximum values were searched using Eq. 2.

Where $n\_samples = 10{,}000$, $k = \{0, 1, 2, 3, 4, 5\}$ and $(2+k)$ represents the end of the task, $20\,s + k{*}n\_samples$:

$$[x1, x2, x3] = max(x[n\_samples * k] : x[(2+k) * n\_samples]). \quad (2)$$

As a result, the maximum values of the amplitude of each task as well as the indices of those maxima were found. Depending on each index value, a window of approximately 20,000 samples was formed to encapsulate the whole task. Finally, a matrix was made as the segmented signal output.

Following that, as seen in Fig. 8, feature extraction was done. The EMG envelope, preprocessed EMG series, as well as the time series obtained from acquisition was employed in this step. From each segment time domain, frequency domain and power spectrum features were extracted. Each extracted feature is described in detail in Table 1. Time domain features are average of all three maximum amplitudes extracted from the envelope, variance of the EMG signal, root mean square (RMS) and kurtosis. Frequency domain features are mean and median frequency. Finally, power spectrum features are average power in specific frequency bands (low: 0–50 Hz; medium: 50–150 Hz; high: 150–250 Hz). Moreover, maximum and total power was calculated. The frequency at maximum power was extracted as well. For frequency domain and power spectrum features, fast Fourier transform and power spectrum density was used and calculated.

Statistical analysis

With the goal of a thorough statistical analysis, a few different approaches have been applied. In terms of descriptive statistical analysis, box and whiskers plots were employed to analyze the distribution of values of participants for each feature for each muscle. Furthermore, correlation matrices were employed to display the interplay between muscles in each task, as well as the correlation between features themselves, as some have been calculated with the use of others. Moreover, for data visualization, with the goal of displaying the relative uniformity of features between participants, heatmaps have been used. Radar charts were used to describe and display the multivariate nature of extracted features, tasks and muscles. Alongside radar charts, principal component analysis (PCA) was used to present clusters of patients in terms of each muscle and each task. More precisely, it was used to show groupings of similar muscle activity over patient groups and tasks. Finally, ANOVA test was used to determine the statistical significance of all extracted features and to sort them by significance through the use of statistical test-based selection.

Pattern recognition

As a final step in the analysis of the extracted features and how well they can be used as a discriminant between given tasks and muscles, we have done task recognition. The flowchart can be seen in Fig. 9. More precisely, classification was done between two groups. One group consisted of the “Swallowing” task, while the other group consisted of the “Tongue Protrusion” task. This was done due to having only 24 participants, and classification of multiple classes would demand a higher number of samples. Moreover, “Swallowing” was chosen, as it has significant physiological and

Table 1 Extracted features from the acquisitioned EMG database

Feature	Equation	Description	Clinical significance	Ref.
Amplitude	$A(\mu V) = mean(anv(EMG))$	Extracted from the envelope or absolute value of the signal. The average value of all maxima values in the EMG signal	It represents the strength of muscle contraction at a given moment, as higher amplitude indicates stronger muscle activity	[26]
Variance	$\mu = \frac{1}{N}\sum_{i=1}^{N}(x_i - \underline{x})^2$	A measure of the extent of which the EMG signal deviates from its mean value. It quantifies the variability of the signal	A higher variance indicates greater fluctuations in muscle activity	[27]
Root mean square (RMS)	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}{x_i}^2}$	Reflects the energy content of the signal. RMS is often more robust to noise than raw amplitude measures	It is used to assess the overall muscle activation level	[28]
Kurtosis	$k = \frac{N\sum_{i=1}^{N}(x_i - \underline{x})^4}{\left(\sum_{i=1}^{N}(x_i - \underline{x})^2\right)^2}$	A statistical measure to describe the distribution "tailedness" of the EMG signal. High kurtosis indicates the presence of more outliers or sharp peaks in the signal	It helps detect abnormal muscle activities or artifacts	[29]
Median frequency	$\int_0^{f_{median}} P(f)df = \frac{1}{2}\int_0^{f_{max}} P(f)df$	It is the frequency at which the power spectrum of the EMG signal is divided into two equal halves	Used to assess muscle fatigue, as shifts in median frequency are often associated with muscle fatigue. Median frequency tends to decrease as fatigue increases	[27]
Mean frequency	$f_{mean} = \frac{\sum_{i=1}^{N} f_i P(f_i)}{\sum_{i=1}^{N} P(f_i)}$	A weighted average of all frequencies in the EMG power spectrum. It represents the central tendency of the signal's frequency distribution	Changes in mean frequency can indicate muscle fatigue or recruitment patterns	[27, 28]
Power in low band	$BPL = \int_0^{50} P(f)df$	Measures the total power of the EMG signal within the lower frequency range, typically below 50 Hz	This range is often associated with baseline muscle tone and slow muscle activity. It provides insight into sustained or tonic muscle contractions	[30, 31]
Power in medium band	$BPM = \int_{50}^{150} P(f)df$	Measures the total power of the EMG signal within the medium frequency range, over 50 Hz and below 150 Hz	This range captures moderate muscle contractions and is indicative of voluntary muscle activity. It helps differentiate between slow and fast muscle fibers	[32]
Power in high band	$BPH = \int_{150}^{f_{max}} P(f)df$	Measures the total power of the EMG signal within the high frequency range, over 150 Hz	Higher frequency components are often associated with fast muscle contractions or muscle fiber recruitment. This measure is used to analyze rapid and intense muscle activities	[33]
Max power	$P_{max} = max(P(f))$	The highest value of power found in the EMG signal's power spectrum, indicating the most dominant muscle activity at a specific frequency	Shifts in this frequency can provide insights into muscle function and fatigue	[34]
Frequency at max power	$Maxf = argmax(P(f))$	Identifies the frequency at which the highest power occurs in the EMG signal's power spectrum	It highlights the dominant frequency of muscle activity. Shifts in this frequency can provide insights into muscle function and fatigue	[34]
Total power	$P = \int_0^{f_{max}} P(f)df$	The sum of all power values across the entire frequency spectrum of the EMG signal. It represents the overall energy content of the muscle activity	This metric is useful for assessing the total work done by the muscle during a specific period of time	[34]

Table 2 Classifier performance metrics of classification between the "Swallowing" and "Tongue Protrusion" tasks

	Accuracy	Recall	Specificity	Precision
M. Mentalis				
LDA	70.00	100.00	40.00	62.50
Log. Reg	70.00	100.00	40.00	62.50
Rand. Forest	70.00	80.00	60.00	66.67
M. Orbicularis Oris				
LDA	40.00	60.00	20.00	42.86
Log. Reg	70.00	80.00	60.00	66.67
Rand. Forest	60.00	100.00	20.00	55.56
M. Zygomaticus Major				
LDA	80.00	80.00	80.00	80.00
Log. Reg	80.00	80.00	80.00	80.00
Rand. Forest	60.00	80.00	40.00	57.14

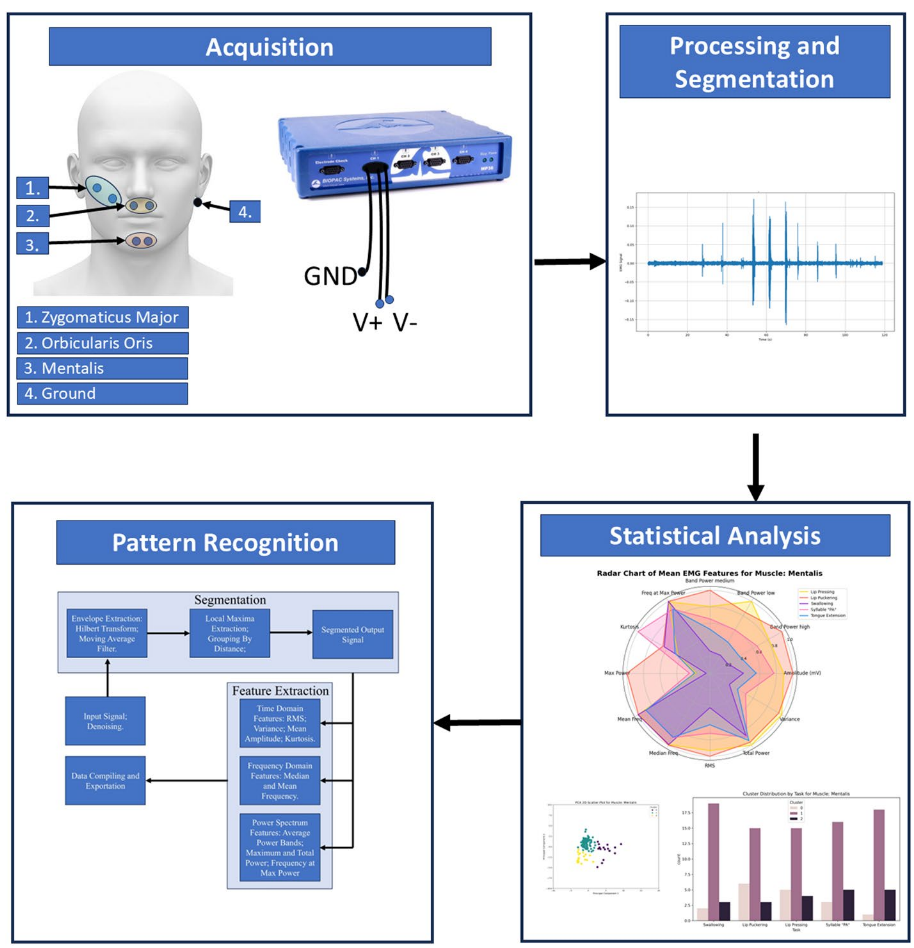

Fig. 7 Graphical representation of the Methodology section

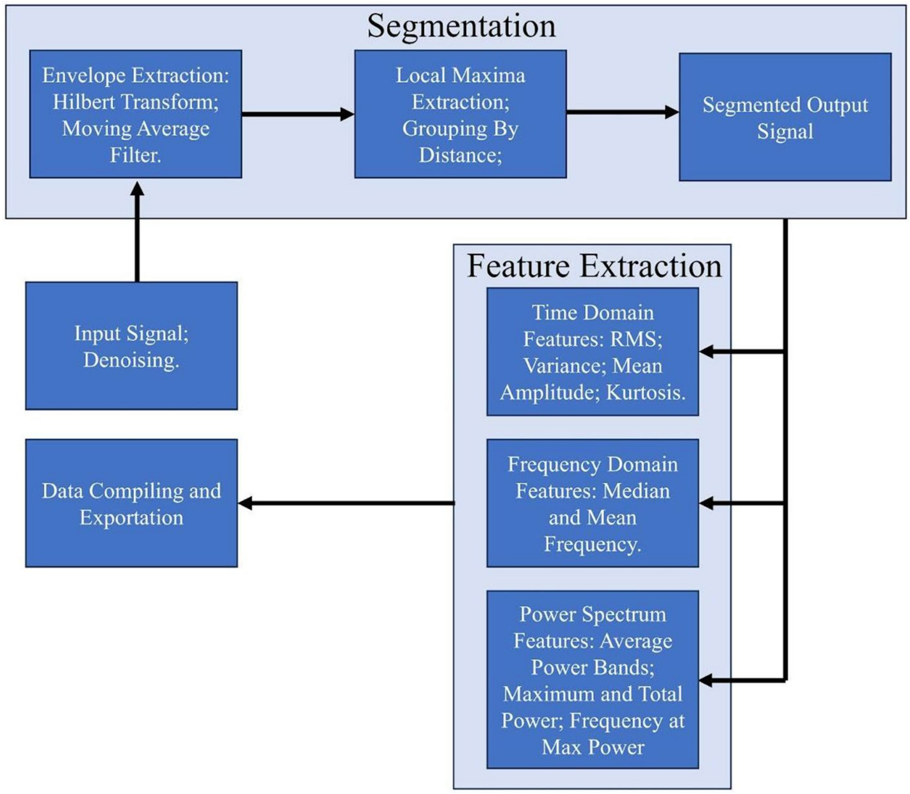

Fig. 8 Graphical depiction of the algorithm used for feature extraction and segmentation of the acquisitioned EMG database

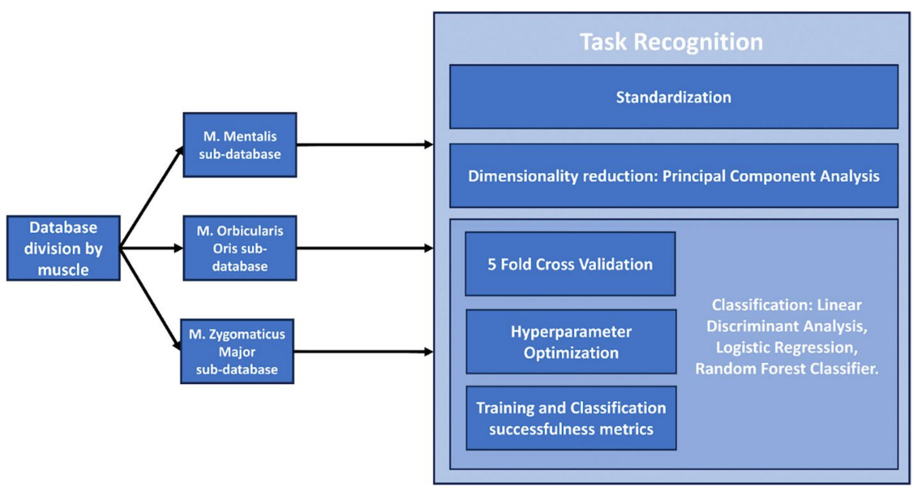

Fig. 9 Flowchart of the task recognition process

medical importance. In contrast to that "Tongue Protrusion" uses mostly different facial muscle groups, except for m. Orbicularis Oris.

Following that, standardization was done, with the goal of eliminating any high value differences between features (e.g., power spectrum features and statistical features show significant value differences). Furthermore, through principal component analysis, the feature space was reduced to three dimensions, with the goal of lowering the "emptiness" of the feature space, increasing the likelihood of a successful classification. Following that, three different classifiers were tested: linear discriminant analysis (LDA), logistic regression and Random Forest classifier. On all of them, fivefold cross-validation was done, to ensure reliability and repeatability of classification metrics, as well as to not get overly optimistic classifier results. During cross-validation grid search was done to optimize hyperparameters, significant to each classifier. Finally, classification successfulness metrics were calculated from the confusion matrix.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12938-025-01350-3.

Additional file 1.

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Author contributions
LA, BP and GS did the conceptualization. LM did data curation. LA, BP and GS did the formal analysis. GS was responsible for funding acquisition. BP, LA, LM and GS did the investigation. LA, BP and GS specified the methodology. SK was responsible for project administration. LA, BP and VS were responsible for resources. LM and VS developed the algorithm and used the software. BP and GS were responsible for supervision. KJ, LA, BP and GS did the validation. KJ and SK did the visualization. LA, LM and BP were responsible for writing the original draft. LA, LM, BP, GS, VS, SK and KJ were involved in writing the final manuscript. All authors reviewed the manuscript.

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Data availability
No datasets were generated or analyzed during the current study.

Declarations

Ethics approval and consent to participate
The study protocol was approved by the Research Ethical Committee of the Dentistry Clinic of Vojvodina in Novi Sad, Serbia, and was in accordance with the World Medical Association's Declaration of Helsinki.

Competing interests
The authors declare no competing interests.

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