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Electromyographic Indicators for Assessing Facial Palsy Severity: Findings from a German Cohort and Prospects for Biofeedback Applications

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Abstract

Facial palsy (FP) considerably reduces patients' quality of life, making accurate severity assessment essential for personalized treatment. EMG-based biofeedback has shown potential in enhancing recovery outcomes. This prospective study aimed to identify EMG time series features that can both classify FP severity and inform biofeedback. Surface EMG was recorded from FP patients and healthy controls during three facial movements. Repeated-measures ANOVAs (rmANOVA) examined the effects of MOTION (movement/rest), SIDE (healthy/affected), and House–Brackmann (HB) score across 20 EMG parameters. Correlations between HB and EMG asymmetry indices were calculated, and Fisher scores assessed the relevance of features in distinguishing HB levels. A total of 55 participants (51.2 ± 14.73 years; 35 female) were included. RmANOVAs revealed a highly significant effect of MOTION across nearly all movement types ($p < 0.001$). Combining rmANOVA, correlation, and Fisher score analyses, at least 5 of 20 EMG parameters emerged as robust indicators for evaluating paresis severity and guiding biofeedback. These findings demonstrate that sEMG can reliably quantify FP severity and inform biofeedback interventions, even in severe cases, supporting its integration into personalized rehabilitation strategies, though further research is needed to optimize recovery outcomes.

Keywords: Facial palsy, Grading, Electromyography, Time series features, Biofeedback, Rehabilitation

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Introduction

Facial palsy (FP) can substantially reduce quality of life by affecting aesthetics, psychological well-being, and physical functions such as oral competence, eye closure, or temporomandibular joint movement [1–5]. While idiopathic FP patients often experience rapid recovery, post-iatrogenic FP can involve prolonged rehabilitation [6, 7]. Accurate, objective assessment of FP severity is essential for monitoring recovery and guiding therapy. Traditional grading scales, such as the House–Brackmann (HB) score and Sunnybrook scale, are widely used but rely heavily on examiner judgment [8–11]. Invasive EMG (iEMG) can objectively measure muscle activity but is painful and time-consuming.

Surface EMG (sEMG) offers a non-invasive alternative, capturing the summed electrical activity of multiple motor units, though it may include interference from adjacent muscles. Despite being less precise than iEMG, prior studies have shown that sEMG can effectively assist in FP grading [12–16]. For example, Franz *et al.* [13] demonstrated significant sEMG variability on the affected

side in FP patients post-vestibular schwannoma surgery and a correlation with the Sunnybrook score. Another study developed a semi-automated sEMG-based system to provide an objective alternative to the HB score, showing promising classification performance, particularly after vestibular schwannoma surgery [12]. However, these studies were limited by small sample sizes, and the specific EMG features for grading remain unclear due to reliance on machine learning.

sEMG is also increasingly applied in biofeedback training for FP and post-facial nerve reconstruction [17–24]. Research indicates that sEMG biofeedback can reduce synkinetic activity in facial aberrant reinnervation syndrome (FARS) [17, 24] and improve facial symmetry, function, and movement even in chronic FP when combined with neuromuscular retraining [20]. Existing biofeedback programs vary widely in patient selection, timing, and training frequency. EMG assessment can include multiple time series features, such as root mean square (RMS), mean absolute value (MAV), and variance (VAR) [25–27], but most commercial biofeedback systems are designed for limb muscles and primarily use MAV, RMS, or integrated EMG (iEMG) [28].

Despite these advances, it remains unclear which EMG parameters are optimal for facial applications to monitor FP severity and support biofeedback. This study aimed to identify sEMG time series features suitable for both classification and biofeedback in FP.

Materials and Methods

Study cohort

This prospective, single-center investigation involved 55 German participants to identify sEMG parameters effective for evaluating the severity of facial palsy (FP) and guiding biofeedback interventions. Participants were recruited from both inpatient and outpatient services at the Department of Neurosurgery, University Hospital Tübingen, Germany, between July and December 2024. The study group included individuals who had either undergone tumor resection in the cerebellopontine angle or had idiopathic FP, presenting with varying degrees of unilateral FP based on the House–Brackmann (HB) scale. A group of healthy volunteers without any history of cranial surgery was also included. Exclusion criteria encompassed bilateral FP, cognitive impairments, pregnancy, and conditions preventing accurate facial EMG measurement (e.g., significant facial hair or skin lesions). The study received ethical approval from the local committee and adhered to the Declaration of Helsinki, with written informed consent obtained from all participants.

Data acquisition and experimental setup

After assessing FP severity using the HB grading system (I = no palsy to VI = complete paralysis), electrodes (4 mm reusable Ag-AgCl snap electrodes, Biopac Systems, Inc., Goleta, CA, USA) were placed in a bipolar configuration as depicted in **Figure 1**. The bipolar setup was chosen due to its advantages over monopolar or common average reference configurations [29], and care was taken to minimize impedance to ensure optimal signal quality [30]. Each participant completed a 30-minute sEMG recording session, consisting of six facial movement tasks presented in random order: strong smile, light smile, forceful eye closure, gentle eye closure, strong forehead raise, and slight forehead raise. Each task was repeated 20 times with a 3-second movement phase followed by a 4-second rest phase. Instructions were provided on a computer screen, with an auditory cue marking the beginning of each rest period. Participants were trained in advance to ensure correct execution: maximal versus subtle smile, complete versus gentle eye closure, and full versus slight forehead elevation.

Throughout the session, a trained investigator monitored performance to verify that all movements were correctly performed. EMG signals were recorded using the Neuro Omega system (software version 1.6.5.0, Alpha Omega Engineering, Nof HaGalil, Israel) at a sampling frequency of 2000 Hz and stored on an external computer for subsequent analysis.

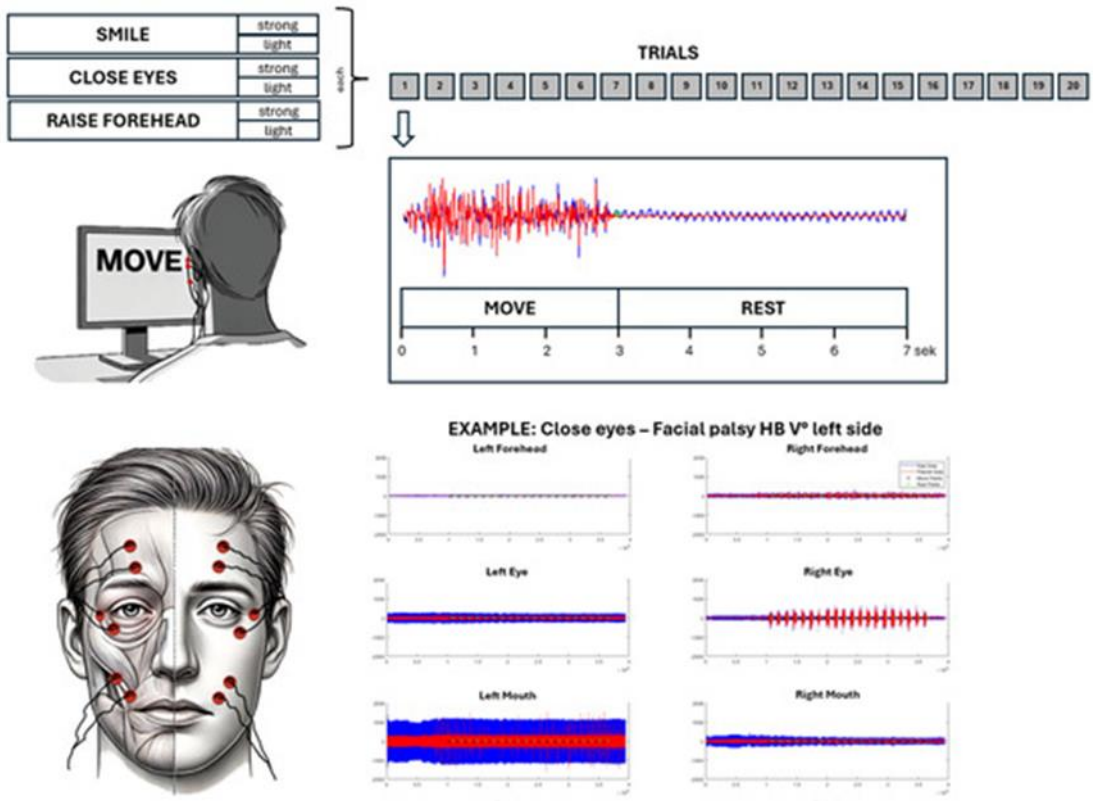


Figure 1. Experimental Setup

Six EMG channels were recorded following the layout shown (bottom left) while participants performed six facial movement tasks/runs (top left). Each run included 20 repetitions, with each trial consisting of a 3-second MOVE phase followed by a 4-second REST phase (top right).

EMG analysis and feature extraction

EMG data were processed offline using custom MATLAB scripts (R2022b, MathWorks Inc., Natick, MA, USA). Raw signals from all movement runs were imported and preprocessed using a 4th-order Butterworth bandpass filter (10–250 Hz) and a 4th-order bandstop filter to remove 48.5–51.5 Hz interference. Based on the experimental timing (3 s MOVE, 4 s REST), the recordings were automatically segmented into MOVE and REST intervals to ensure precise alignment with the stimulus protocol.

For each segment, 20 distinct time series features were extracted separately for the healthy and affected facial sides. Analyses included the absolute values of features for MOVE and REST, as well as the calculation of an asymmetry index (AI) to quantify differences between the two sides. Using the mean absolute value (MAV) as an example, an AI of 0% indicates perfect symmetry, while higher AI values indicate increasing asymmetry between the healthy and affected sides:

$$AI_{MAV} = \frac{(MAV_{healthy} - MAV_{lesioned})}{(MAV_{healthy} + MAV_{lesioned})} \times 100 \quad (1)$$

Statistical analysis

All analyses were conducted using MATLAB (R2022b, MathWorks Inc., Natick, MA, USA) and SPSS (Version 30.0, IBM Corp., Armonk, NY, USA). Univariate repeated-measures ANOVAs (rmANOVAs) were performed separately for each facial movement (strong smile, light smile, strong eye closure, light eye closure, strong forehead raise, light forehead raise) using the absolute values of the time series features. The analyses tested the effects of movement state (MOTION: MOVE vs. REST), facial side (SIDE: healthy vs. affected), and House–Brackmann (HB) grade on all 20 sEMG features. MOTION and SIDE were treated as between-subject factors, whereas HB grade was included as a within-subject factor. To account for anatomical relevance, only electrodes corresponding to the specific facial movement were analyzed (e.g., mouth electrodes for smile tasks). The Mauchly test assessed sphericity, with Greenhouse–Geisser corrections applied as needed.

Since HB grade is the sole within-subject factor, absolute time series values are difficult to compare across participants due to high inter-subject variability, influenced by factors such as electrode placement, impedance, and participant effort. To enable standardized comparisons, all features were normalized to the healthy side, resulting in the asymmetry index (AI). In addition to rmANOVA, Spearman's rank correlation was computed between the AI of each sEMG feature and HB grade (HB

I for healthy controls, HB I patients, HB II + III, HB IV + V, HB VI).

The discriminative capability of each feature was further assessed using the Fisher Score (FS) calculated from the AI values:

$$FS(f) = \frac{\sum_{i=1}^{c} n_i(\mu_i - \mu)^2}{\sum_{i=1}^{c} n_i \sigma_i^2} \quad (2)$$

where C represents the number of HB classes, ni the number of samples in class i, μi the mean of class i, μ the overall mean, and σi^2 the variance within class i. This metric evaluates the ratio of between-class to within-class variance, providing insight into each feature's relevance for distinguishing HB grades. Statistical significance was set at $p < 0.05$.

Results and Discussion

Participant and clinical profile

The study included 55 individuals (average age 51.2 ± 14.73 years; 35 females), of whom 40 were patients with facial palsy (HB grades II–VI) and 15 served as healthy controls (HB I). Most facial palsy cases were secondary to medical interventions (37/40, 92.5%). The mean duration of FP among patients was 1.84 years, and 8 participants (14.5%) showed signs of facial aberrant reinnervation syndrome. All subjects completed the EMG protocol without any adverse effects or complications. A detailed overview of cohort characteristics is provided in **Table 1**.

Table 1. Cohort characteristics

Characteristic	Patients (n = 48)	Total (n = 55)	Healthy Controls (n = 7)
Age (years)	53.85 ± 12.62	51.2 ± 14.73	32.57 ± 15.7
Gender			
Male	17 (35.4%)	20 (36.4%)	3 (42.9%)
Female	31 (64.6%)	35 (63.6%)	4 (57.1%)
HB Grade			
I	8 (16.7%)	15 (27.2%)	7 (100%)
II	8 (16.7%)	8 (14.5%)	0 (0%)
III	21 (43.8%)	21 (38.2%)	0 (0%)
IV	5 (10.4%)	5 (9.1%)	0 (0%)
V	4 (8.3%)	4 (7.3%)	0 (0%)
VI	2 (4.2%)	2 (3.6%)	0 (0%)
Affected Side / Surgery			
Right	19 (34.5%)	19 (34.5%)	0 (0%)
Left	29 (52.7%)	29 (52.7%)	0 (0%)
None / No FP	0 (0%)	7 (12.7%)	7 (100%)
Etiology of FP			
Idiopathic	2 (4.2%)	2 (3.6%)	0 (0%)
Tumor-related	1 (2.1%)	1 (1.8%)	0 (0%)
Iatrogenic	37 (77.1%)	37 (67.3%)	0 (0%)
No FP	8 (16.6%)	15 (27.3%)	7 (100%)
Time Since FP Onset / Surgery			
Overall	672.27 ± 2158.78 days (~1.84 years)	672.27 ± 2158.78 days (~1.84 years)	–
HB I	3.25 ± 1.04 days	3.25 ± 1.04 days	–
HB II–III	850.97 ± 2431.85 days	850.97 ± 2431.85 days	–
HB IV–V	839.44 ± 2444.37 days	839.44 ± 2444.37 days	–
HB VI	5.00 ± 1.41 days	5.00 ± 1.41 days	–
FARS			
Yes	8 (16.7%)	8 (14.5%)	0 (0%)

No	40 (83.3%)	47 (85.5%)	7 (100%)

Abbreviations: HB = House–Brackmann score; FP = facial palsy; FARS = facial aberrant reinnervation syndrome; surgery refers to posterior skull base procedures (e.g., vestibular schwannoma or meningioma).

Parameters for motion classification and biofeedback applications

When comparing MOVE and REST conditions, the rmANOVA revealed that this contrast shaped almost every movement category in a marked way, and its influence was most evident during high-intensity contractions ($p < 0.001$; **(Figure 2)**). After this global effect was confirmed, the subsequent contrasts showed that slope sign change (SSC) served as the most reliable indicator of whether a muscle was active or still. Several other time-dependent EMG descriptors performed at a very similar level, including iEMG, MAV, MMAV1, MMAV2, RMS, LOG, STD, and IAV **(Figure 3)**, all of which demonstrated strong separation between MOVE and REST.

A closer look at SSC revealed a clear pattern: on the healthy SIDE, SSC values sharply distinguished the two MOTION states. As the HB grade increased, however, the gap between MOVE and REST on the affected side narrowed progressively. Even with this reduction, SSC continued to provide a usable separation of motion states in individuals with advanced impairment, remaining informative even at HB grades VI and V **(Figure 4)**.

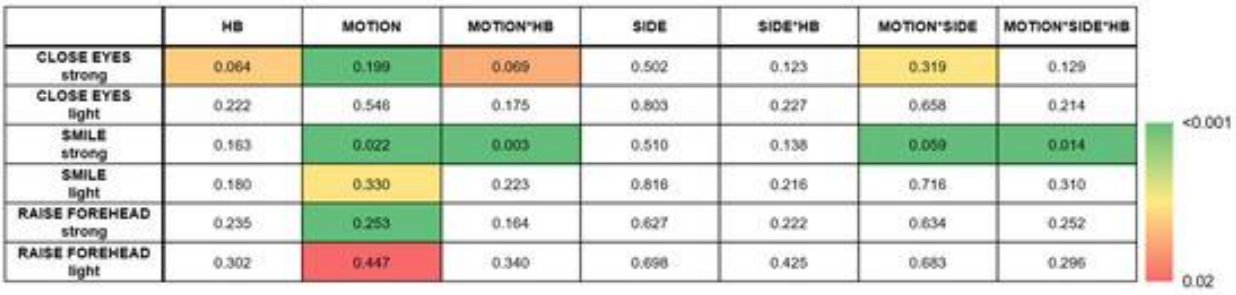


Figure 2. The multivariate component of the repeated-measures analysis highlights that MOTION produces the most pronounced statistical effect. In this visualization, the intensity of the box shading reflects the p-value associated with each comparison, whereas the numerical entries correspond to the Wilks' λ statistics. Boxes left unshaded (white) indicate results that did not reach statistical significance.

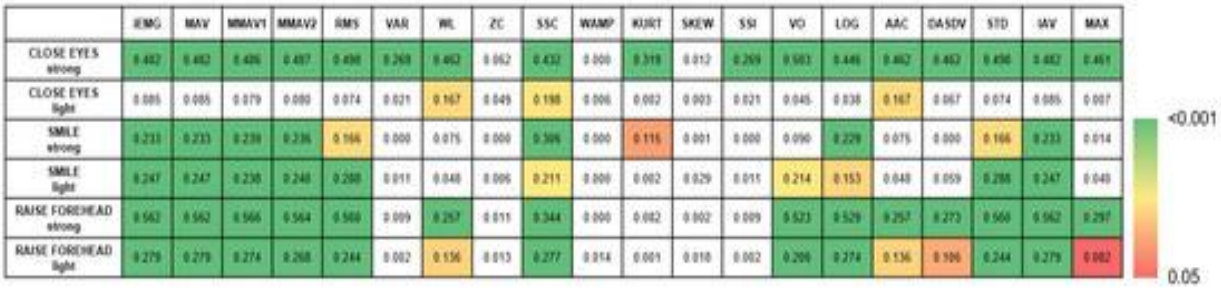


Figure 3. The univariate rmANOVA examinations for the MOTION factor are displayed here, with the color shading of each cell indicating the corresponding p-value. The numerical figures within the boxes denote the effect magnitude, expressed as partial eta-squared (η^2). Cells shown in white mark comparisons that failed to reach statistical significance.

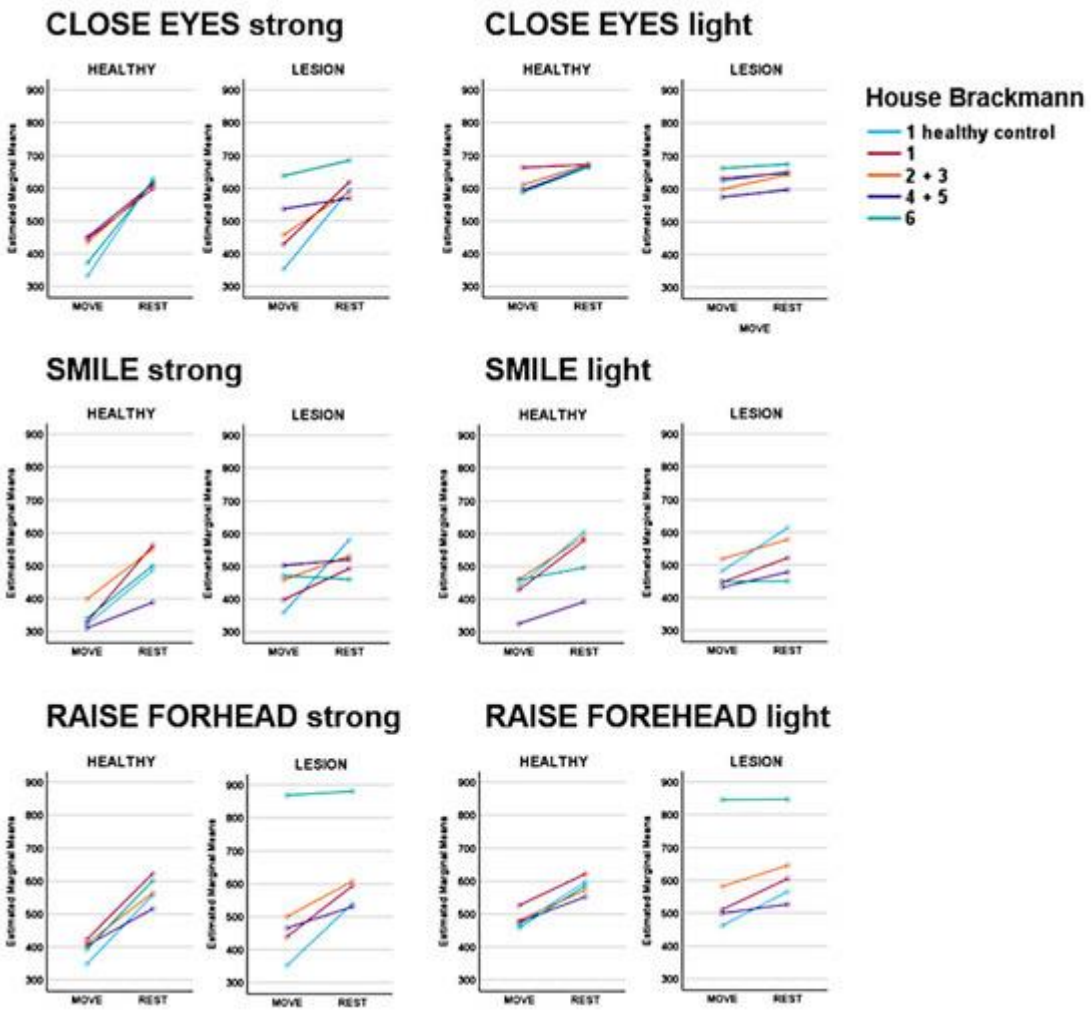


Figure 4. Analysis of slope sign change (SSC) across House–Brackmann (HB) grades revealed that SSC reliably distinguishes between MOVE and REST on the unaffected side, but this contrast diminishes on the affected side as HB severity increases, though it remains observable up to grades IV and V. No significant lateral differences (SIDE) were noted for any movements, likely because the dataset included healthy participants and resting conditions are expected to be symmetric. A notable HB effect was identified only during the "CLOSE EYES strong" task (Wilks' $\Lambda = 0.064$, $F(60, 114) = 1.77$, $p = 0.005$), with post hoc analysis showing significance for all EMG metrics except zero crossing (ZC), slope sign change (SSC), Willison amplitude (WA), kurtosis (KURT), and skewness (SKEW).

In general, sEMG measures effectively discriminate motion regardless of whether the side is impaired or healthy (MOTION). Differences between facial sides (MOTIONxSIDE) emerged only for the "CLOSE EYES strong" and "SMILE strong" movements. HB grade influenced the sEMG signal of the affected side during active movements (MOTIONxSIDExHB) but not during REST, reaching significance only for "SMILE strong." Interestingly, unilateral facial paralysis also appeared to modulate sEMG signals on the healthy side, as seen in the HB and MOTIONxHB analyses for both "CLOSE EYES strong" and "SMILE strong."

Feature extraction for facial nerve grading

When examining correlations between AI-derived EMG features and HB scores, only a small subset of time-series metrics showed significant associations for "CLOSE EYES light" and "SMILE light" **(Figure 5)**. In contrast, MMAV2-AI demonstrated consistent correlation with HB in five of six movement types **(Figure 6)**, while iEMG, MAV, MMAV1, RMS, VAR, SSI, VO, DASDV, STD, and IAV correlated with HB in four movements. Forehead-related motions produced the strongest correlations, despite relatively low Fisher scores **(Figure 7)**. Across analyses, ZC, KURT, SSC, and SKEW poorly differentiated HB grades, whereas iEMG, MAV, DASDV, and IAV proved more reliable indicators for assessing HB severity.

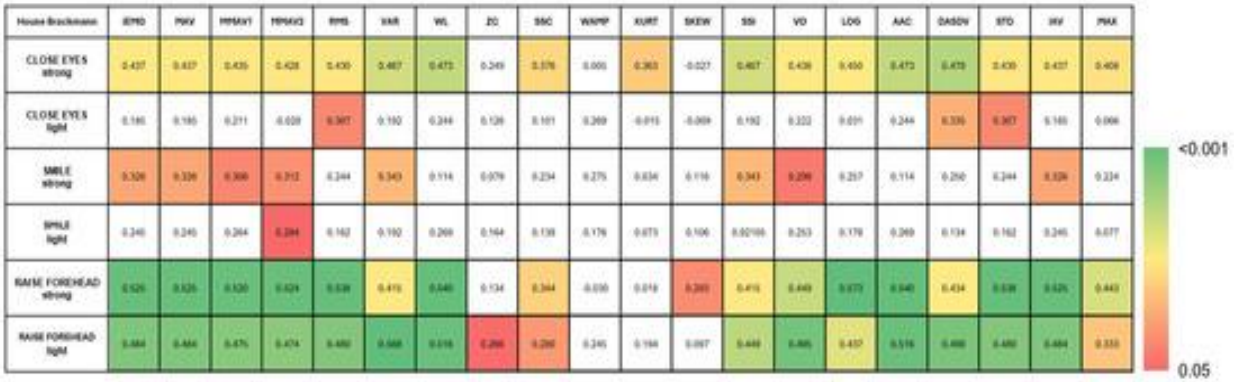


Figure 5. The correlation heatmap illustrates how the asymmetry index (AI) of 20 time-series features across various facial movements relates to the House–Brackmann score. The color of each box indicates the statistical significance (p-value), while the numerical value inside shows the correlation strength (correlation coefficient), with white boxes denoting non-significant correlations.

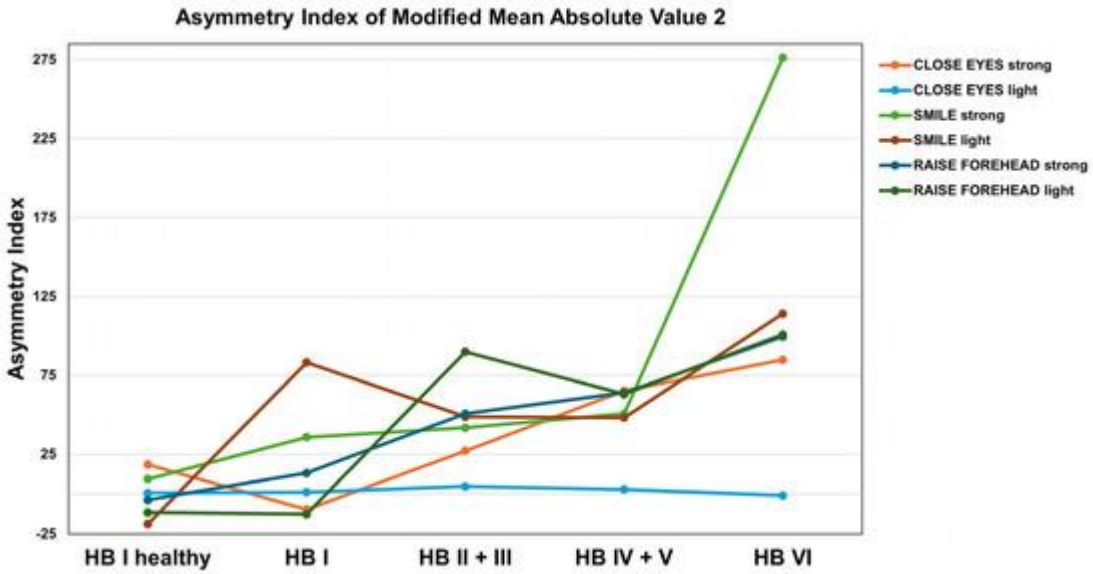
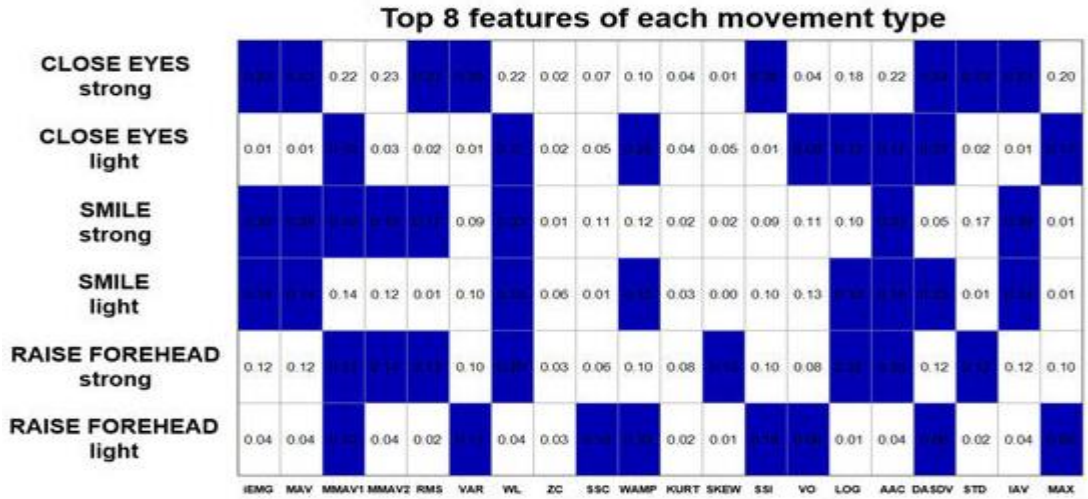
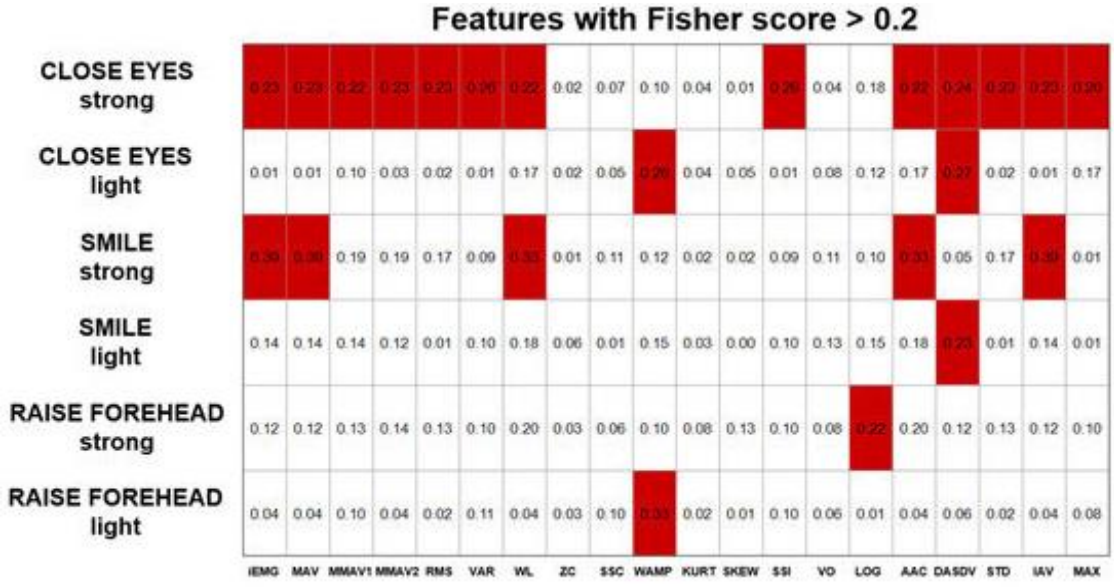


Figure 6. The asymmetry index of the modified mean absolute value 2 (MMAV2) shows the highest correlations for movements of the forehead.



a)



b)

Figure 7. Fisher scores illustrate the ability of the asymmetry index (AI) of various EMG features to discriminate between different HB grades. The upper panel displays the eight features with the highest discriminative power for each movement type, while the lower panel highlights features with Fisher scores exceeding 0.2.

Previous studies on EMG biofeedback in facial palsy (FP) have been limited by using devices originally designed for limb muscles, despite the facial mimic muscles having distinct structural characteristics compared to extremity muscles [31]. In our study, we demonstrated substantial differences among EMG time-series features both in their correlation with HB grade and in their ability to differentiate between movement and rest phases of facial muscles. These findings indicate that future research should consider specialized approaches for facial EMG analysis.

Rutkowska *et al*. [28] reported that for emotional expression studies, the most commonly employed EMG features were MAV, RMS, and integrated EMG (iEMG). In line with this, our results suggest that slope sign change (SSC) can effectively distinguish between movement states (MOVE vs. REST); however, the SSC asymmetry index showed weak correlation with HB scores across movement types and intensities. Additionally, Fisher score analysis indicated that SSC-AI is not suitable for HB grade classification. By combining repeated-measures analyses, correlation studies, and Fisher scores, features such as iEMG, MAV, MMAV1, RMS, and IAV emerged as the most reliable for the objectives of this study, corroborating the findings of Rutkowska *et al*. [28]. These measures all quantify EMG energy through mathematical operations such as integration, averaging, or squaring [26, 27]. Specifically, iEMG reflects the cumulative EMG activity, MAV calculates the mean absolute value, MMAV1 modifies MAV to better account for measurement conditions, RMS captures signal energy and is particularly responsive to high amplitudes, and IAV measures the total absolute amplitude over time, representing overall muscle activity regardless of signal polarity.

Future work should further investigate these parameters in sEMG and biofeedback studies on facial palsy, particularly to determine whether combining multiple features—or integrating artificial intelligence for automated signal analysis—can improve outcomes compared to using single parameters. This is especially relevant for (i) classifying facial palsy severity and (ii) predicting facial nerve recovery. Although numerous studies have focused on automated FP classification using facial images or video [32–35], few have leveraged electrophysiological data such as EMG. In this context, Holze *et al*. developed a semi-automated system combining sEMG and machine learning to provide an objective alternative to the subjective HB score [12], achieving promising performance (AUC: 0.72–0.91).

While both our study and Holze *et al*. [12] primarily involved patients with mild to moderate FP (HB I–III), several methodological and clinical differences exist. Our study included a larger cohort and emphasized not only FP severity classification but also the identification of interpretable and robust EMG features suitable for guiding future biofeedback training. Consequently, EMG signals were analyzed during both active movement and rest to assess the ability of features to differentiate these states—a distinction critical for biofeedback, where dynamic changes and asymmetries between rest and activation are key. Moreover, whereas machine learning approaches like Holze *et al*.'s prioritize classification accuracy, they may be less appropriate for biofeedback, which requires transparent, user-understandable parameters to effectively guide patient engagement and training.

Most research on predictive models for facial palsy (FP) has concentrated on estimating the likelihood of FP occurrence following certain procedures, such as vestibular schwannoma resection, and/or on clinical factors like tumor size, patient age, or paresis severity [36–39]. Only one study by Khisimoto *et al*. explored the use of different artificial intelligence (AI) models to predict synkinesia after FP using electroneurography (ENoG) [40]. Their results showed strong predictive performance (AUC: 0.90) using a machine-learning-based logistic regression, representing an advancement compared to Azuma *et al*. [41], who were unable to predict synkinesia with conventional ENoG analysis. To our knowledge, no studies have yet combined surface EMG (sEMG) with AI to forecast FP outcomes.

When considering sEMG for facial biofeedback, it is crucial to account for the stage of nerve injury and recovery. Similar to peripheral limb nerve injuries, FP can involve varying degrees of nerve damage, including neuropraxia, axonotmesis, and neurotmesis [42–44], which influence both clinical severity and recovery speed. EMG-based biofeedback should therefore adapt to the paralytic versus synkinetic phases of facial recovery. Importantly, facial rehabilitation, such as neuromuscular retraining, does not aim for maximal muscle contraction, as excessive force can exacerbate synkinesia or dyskinesia, even during paralysis [45]. Instead, therapy focuses on controlled activation and coordination of facial muscles. Our study addressed this by evaluating three movement types at different contraction strengths (light and strong), revealing that some features (e.g., kurtosis or waveform length) are effective for strong movements but less sensitive in detecting differences between movement and rest at lower intensities. Accordingly, in early or severe paresis, robust features like RMS and MAV may be preferable, whereas in later phases—where improving coordination and minimizing synkinesia is the goal—other parameters may be more informative. A recovery phase–specific selection of EMG features could enhance the effectiveness of facial biofeedback by aligning signal analysis with functional needs. Future studies might objectively control contraction intensity, for example, by referencing the sEMG from the healthy side, grading efforts as a percentage of maximal force, or combining sEMG with kinematic or visual measurements [46, 47].

Limitations

A key limitation of this study is the use of only 12 electrodes (six per facial side, bipolar configuration), whereas the mimic musculature includes over 15 muscles. This may introduce crosstalk and limit the precision of muscle-specific measurements. High-density EMG could provide more detailed insights [48–51], though additional electrodes might reduce facial mobility, which is counterproductive for biofeedback applications. Another limitation is the unbalanced cohort, with only seven healthy controls compared to 48 patients; however, the study focused on identifying suitable EMG features for biofeedback rather than comparing groups. Uneven distribution across HB grades reflects clinical reality but restricts generalizability of subgroup analyses. Future research with larger, more balanced cohorts is needed to validate these findings. Additionally, factors such as training frequency, session duration, and type of feedback (visual, auditory, or multimodal) were not addressed, though they likely influence biofeedback efficacy and patient compliance and should be systematically explored in subsequent studies. Integrating these aspects could help optimize biofeedback interventions for different FP stages and individual patient needs.

Conclusion

The results of this study demonstrate that sEMG can reliably assess the severity of facial palsy and inform biofeedback interventions. Selecting appropriate EMG features, such as iEMG, RMS, or MAV, enables optimal differentiation between movement and rest, even for small or weak movements in severe paresis. This work provides a foundation for future development of biofeedback algorithms and training strategies tailored for facial palsy rehabilitation.

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Conflict of interest: None

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Ethics statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Ethics Committee of the university Tuebingen (protocol code: 326/2024BO1).
All participants gave written informed consent.

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