THE EFFECT OF AGING ON FACIAL MOVEMENT AND HEAD POSING IN A FIVE-YEAR WINDOW

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Abstract

Automated analysis of facial expressivity is a promising tool for the early detection of hypomimia in Parkinson's disease. However, accurately distinguishing pathological decline from normal aging requires a robust normative baseline. This study aimed to quantify spontaneous facial movement and structural changes in healthy aging over a five-year longitudinal interval. We analyzed video recordings of a minute-long spontaneous speech from 21 healthy individuals (mean age 60.0 ± 9.2 years) at baseline and five-year follow-up sessions using an automated pipeline based on 478 facial landmarks. Longitudinal analysis revealed remarkable stability in facial kinematics, with no significant degradation in dynamic expressivity observed over the five-year window. In contrast, cross-sectional correlation with age identified significant structural changes, specifically reductions in cheek, lateral canthal, and nose root areas, reflecting cumulative muscle tightening and tissue sagging. Furthermore, we identified distinct sexual dimorphism; women exhibited significantly greater mouth openness and mouth movement variability compared to men, with mouth mobility positively correlating with age in the women cohort. We conclude that facial aging is a slow, cumulative process that does not significantly disrupt facial mobility in the short term. Consequently, rapid declines in facial expressivity observed over five-year intervals can be confidently attributed to neurodegeneration rather than typical aging. Our findings underscore the necessity to streamline feature sets to eliminate redundancy and to account for sex and age balance between study groups.

Keywords

facial movement, head posing, aging, automatic assessment

Introduction

Facial movement is a complex interplay of neuromuscular coordination and expressive behavior, often subtly modulated by age and neurological health. In the context of Parkinson's disease (PD), disruptions in facial expressivity—commonly referred to as hypomimia—are among the earliest and most visually apparent symptoms [1]. Automated facial expression analysis has emerged as a promising tool for quantifying these changes. However, to accurately detect and quantify such disruptions, it is essential to first understand the natural variability and progression of facial movements in healthy cohort [2].

Facial expressions arise from the coordinated movement of facial skin and underlying fascia, driven by the contraction of facial muscles. These contractions result in the formation of folds, lines, and wrinkles, as well as the displacement of key facial landmarks. The facial nerve plays a central role in innervating the muscles responsible for expressive gestures, which are essential for communication and subtle, complex movements. Notably, muscles in the lower face are predominantly innervated contralaterally, allowing for precise and independent control of each side. In contrast, upper facial muscles receive mostly bilateral innervation, which limits the ability to perform asymmetrical and fine movements in that region [3].

Age-related changes in facial movement are driven by transformations in muscles, skin, bone, and fat. As individuals age, facial muscles tend to elongate and exhibit increased resting tone, often approaching a state of near-constant contraction. This results in a reduced amplitude of movement and a general tightening of the facial musculature, which limits expressive range and contributes to the formation of static wrinkles. Simultaneously, the skin undergoes intrinsic aging marked by the degradation of elastic microfibrils and thinning of the dermis. This deterioration reduces the skin's ability to stretch and recover, further increasing wrinkle formation and sagging [4, 5].

Several clinical scales are routinely used to assess facial movement impairments. Systems such as the

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House–Brackman scale and the Facial Nerve Grading System 2.0 were developed to evaluate facial nerve paralysis, which often presents as altered facial expressions [6]. For a more comprehensive analysis of facial behavior, the Facial Action Coding System (FACS) is widely used. It breaks down facial movements into discrete action units, each representing a specific muscle movement, allowing detailed characterization of expressions [7]. However, these systems rely heavily on expert observation and subjective scoring. In contrast, well-designed computer vision approaches offer objective, high-resolution analysis of facial movements, capable of detecting subtle and rapid changes that may be missed by human observers.

Several studies have explored age-related facial changes using objective measurement techniques that provide unbiased results. Cotofana et al. [8] examined healthy volunteers with a mean age of 42.6 ± 19.6 years. Electromyography was used to assess facial muscle activity and showed that sex significantly influenced signal strength, with males showing higher activity levels. Although a decline in muscle activity with age was observed across most facial muscles, the changes were not statistically significant. Research conducted by Kurosumi et al. [9] on Japanese women (mean age 49.2 ± 12.9 years) revealed age-related static structural changes in facial shape, including spots, wrinkles, and sagging, but also changes in dynamic skin characteristics. Delay in cheek skin movement and decrease in cheek skin stretchiness was observed with increasing age. Ko et al. [10] applied OpenFace software to automatically detect FACS action units and analyzed age-related differences across six basic emotions in two age-segregated cohorts (one with ages between 18 and 39 and second with ages between 62 and 84). Their findings indicated that older individuals generally expressed emotions with greater intensity, particularly negative ones, and six action units showed significant age-related differences.

This study investigates aging-related changes in facial movements and head pose of spontaneous speech over a five-year window in healthy individuals. By establishing a normative baseline, we aim to enhance the accuracy of future automated systems designed to detect facial changes in PD.

Methods

Participants

All participants provided written informed consent prior to their inclusion in the study. The research was approved by the Ethics Committee of the General University Hospital in Prague, Czechia, and conducted in accordance with the ethical principles outlined in the Declaration of Helsinki.

Healthy participants were recruited from the Department of Neurology at Charles University and the General University Hospital in Prague to serve as a control group in iRBD/BIO-PD project [11]. During the study, 55 participants were evaluated at the baseline examination, and 21 participants completed the 5-year follow-up examination. The major reason for dropout was an unwillingness to continue, followed by the development of health conditions that met the exclusion criteria for the control group. These two time points are referred to as the baseline (BL) and five-year (5Y) groups. A total of 21 individuals were included in this study, with a mean age of 60.0 ± 9.2 years (range 45–72). The cohort consisted of 11 men (M; mean age 65.5 ± 5.2 years, range 56–72) and 10 women (W; mean age 54.0 ± 8.9 years, range 45–71). Summarized paper workflow is depicted in Fig. 1.

Study protocol

Participant videos were recorded in a controlled environment with consistent lighting conditions using a Panasonic HC-VX1 digital camera (Panasonic Holdings Corporation, Japan) positioned approximately one meter from the face. Participants were free to move naturally during the recording. Each video was captured at a resolution of 1920 × 1080 pixels with a frame rate of 30 RGB frames (24 bits) per second. The recordings featured a freely spoken monologue on a topic of the participant's choice, conducted as part of a comprehensive speech assessment protocol administered by a speech specialist during a single session.

Video processing

From each recording, a minute-long segment (approximately 1800 frames) minimizing unspoken pauses was extracted for further processing. From these segments, the position of facial landmarks was detected using a Google MediaPipe (Google LLC, USA) framework. It's an open-source solution, which was utilized in Python 3.12 (Python Software Foundation). This algorithm is based on warping a canonical face mesh to a detected face and results in head rotation information (jaw, pitch and roll) as well as 3D positions of facial landmarks [12]. All 478 available landmarks were tracked in every frame. To eliminate jitter, but also keep rapid signal changes in landmark positions, a Savitzky-Golay filter with a window length of 10 samples and a third-order polynomial was used for every landmark. Based on this data, 16 features were designed for further analysis, grouped into four primary categories.

Distance features were computed as 3D Euclidian distances between pairs of landmarks relative to the Euclidian distance between medial eye corners. This normalization stems from the stability of medial eye corner position of each participant over the course of the

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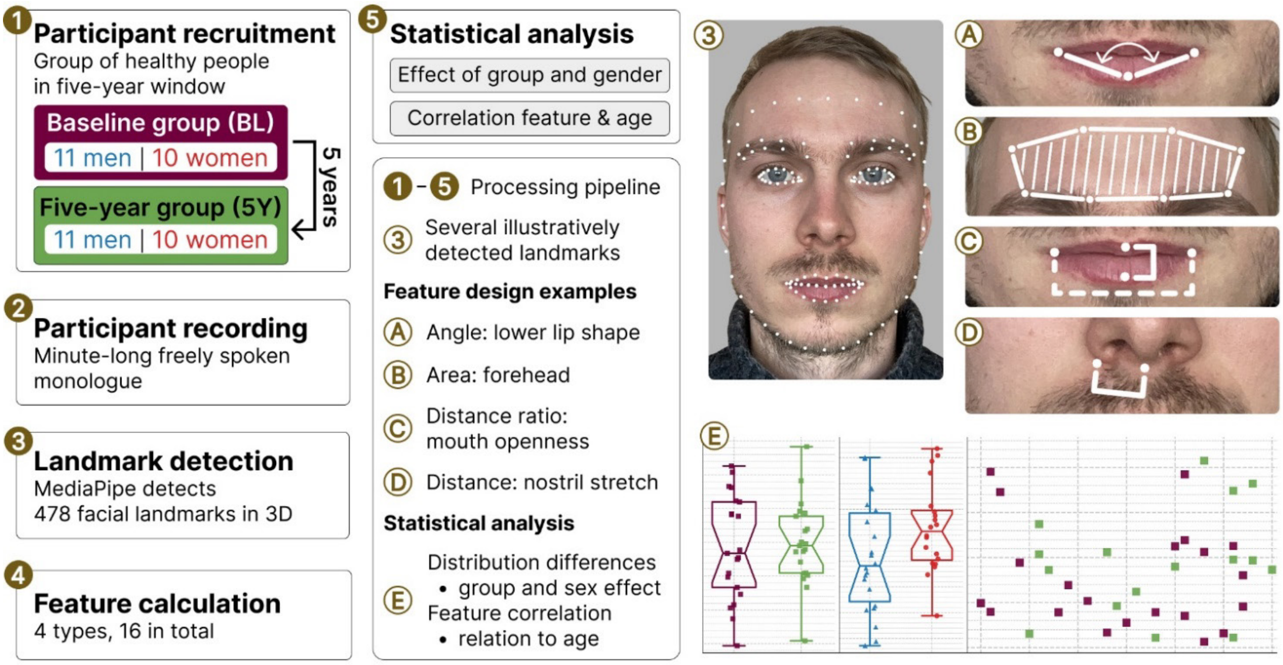

Fig. 1: Summarized workflow from participant recruitment to statistical analysis. Numbers 1 to 5 depict work progress. Figures on the right side show landmark detection (3), feature type examples (A to D) and statistical analysis result (E).

experiment and has proved to be very effective for comparing different subjects [13]. Distance features were used to describe changes of lip shape (lower lip position relative to the chin, upper lip position relative to the nose tip, and mouth corner position relative to the center of the upper lip), vertical movements of the center of the jaw (jaw position relative to the nose tip), and eyebrow movement (eyebrow center position relative to the nose tip).

Distance ratio features are given by ratio of Euclidian distances between two pairs of landmarks and are used here to assess eye and mouth openness (height to width ratio is used in both cases).

Area features give the area of 3D polygons formed by the landmarks relative to the square of the distance between medial eye corners. The areas studied here are those of the forehead, nose root, lateral canthus and cheek.

Angle features give the angle between three landmarks or two pairs of landmarks and are used here to describe eyebrow movement (eyebrow shape as the angle between eyebrow corners and eyebrow center and eyebrow tilt as the relative angle to line between medial eye corners). Finally, head angle features (yaw, pitch and roll) were used to assess head position.

For each feature array derived from all frames, the median and standard deviation were computed. The median represents the overall static facial expression and is further reported with previously described feature labels. The standard deviation reflects the degree of facial movement and is further reported with feature labels with an added suffix of "variability". This process yielded 32 aggregated values per subject, which were subsequently used for statistical analysis. For bilateral features, the final value was calculated as the mean of the left- and right-sided feature values.

Statistical analysis

A significance level of $\alpha = 0.05$ was used for hypothesis testing and since this study is exploratory, generally no family-wise error corrections were implemented. The normality of the distributions was assessed using a Shapiro-Wilk test. For the comparison of feature values between BL and 5Y groups, a paired t-test was used for normally distributed data. In case at least one data group was not normally distributed, a Wilcoxon Test was used. When assessing influence of sex, a two-sample t-test, or Mann-Whitney U test was used based on data normality. When evaluating group and sex influence together, ANOVA or Kruskal-Wallis tests were used based on data normality. Post hoc tests (Tukey's HSD or Dunn's test) were performed to identify differing combinations of sex and group. To quantify the linear relationship between age and the calculated features, we employed Pearson correlations. To account for the limitations of the small sample size, the magnitude of the observed effects was evaluated using effect size (Cohen's d or rank-biserial correlation, depending on normality) giving a measure of practical significance.

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Results

Distribution differences

Our longitudinal analysis between BL and 5Y groups identified yaw as the sole statistically significant feature [$t(20) = -2.68$, $p = 0.014$, $d = 0.58$]. This is illustrated in Fig. 2 alongside cheek area variability, which showed the greatest difference in standard deviation. In contrast, comparisons based on sex yielded 11 significant findings. The top five were: mouth openness [$U = 61.0$, $p < 0.001$, $r^2 = 0.72$], mouth openness variability [$t(40) = -3.10$, $p = 0.004$, $d = 0.96$], lower lip position variability [$t(40) = -2.81$, $p = 0.008$, $d = 0.87$], lower lip position [$t(40) = 2.41$, $p = 0.021$, $d = 0.75$] and upper lip position variability [$U = 131.0$, $p = 0.026$, $r^2 = 0.40$].

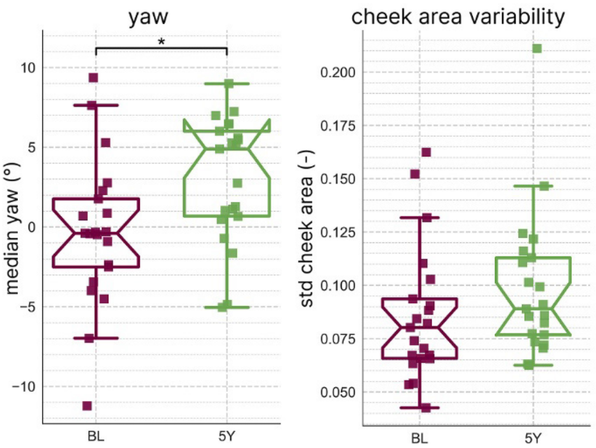

*Fig. 2: The most differing features between BL and 5Y groups for median (yaw; $p = 0.01$, $d = 0.58$) and std (cheek area variability; $p = 0.05$, $d = 0.49$). Statistically significant difference is denoted by asterisk * $p < 0.05$.*

When analyzing the combined influence of group and sex, two features proved significant: mouth openness [$F(3, 38) = 7.07$, $p < 0.001$] and mouth openness variability [$F(3, 38) = 3.06$, $p = 0.040$]. Post hoc testing for mouth openness revealed significant differences between BL-W & 5Y-W [$p = 0.005$], BL-M & BL-W [$p = 0.012$], 5Y-M & 5Y-W [$p = 0.014$] and BL-M & 5Y-W [0.034]. Mouth openness variability showed no significant post hoc contrasts. Fig. 3 details the analysis of mouth openness, as the feature with the most significantly differing distributions between sexes.

Relationship to age

Correlation analysis between facial features and age across the entire cohort identified six significant results. The five strongest associations were: cheek area [$r = -0.50$, $p = < 0.001$], lateral canthal area [$r = -0.41$, $p < 0.001$], nose root area [$r = -0.41$, $p < 0.001$], mouth corner position [$r = -0.37$, $p = 0.02$] and eyebrow position [$r = -0.34$, $p = 0.03$].

Subsequent analyses performed on specific data subgroups yielded further insights. Group-based division revealed seven significant correlations, with the 5Y cohort showing the strongest effects: cheek area (5Y) [$r = -0.67$, $p < 0.001$], mouth corner position (5Y) [$r = -0.56$, $p = 0.008$], nose root area (5Y) [$r = -0.54$, $p = 0.01$], lateral canthal area (5Y) [$r = -0.54$, $p = 0.001$] and upper lip position variability (5Y) [$r = -0.48$, $p = 0.03$].

Division by sex uncovered nine significant correlations; the top five were: eye openness variability (W) [$r = 0.66$, $p = 0.001$], forehead area (W) [$r = -0.65$, $p = 0.002$], eyebrow shape variability (M) [$r = 0.55$, $p = 0.008$], cheek area (W) [$r = -0.58$, $p = 0.008$] and cheek area (M) [$r = -0.51$, $p = 0.02$].

Finally, the combined analysis of group and sex demonstrated eight significant correlations. The five most significant findings were: cheek area (5Y & W) [$r = -0.88$, $p < 0.001$], eye openness variability (5Y & W) [$r = 0.84$, $p = 0.002$], forehead area (5Y & W) [$r = -0.84$, $p = 0.002$], yaw (5Y & M) [$r = 0.76$, $p = 0.006$] and mouth corner position (5Y & W) [$r = -0.70$, $p = 0.025$]. A detailed analysis of cheek area, the feature most consistently related to age, is depicted in Fig. 4.

Features relationship

An inter-feature correlation analysis was conducted to assess potential redundancy, revealing strong linear relationships between numerous feature pairs. The five most significant correlations (all $p < 0.001$) were observed between nose root area & lateral canthal area [$r = 0.89$], nose root area & eyebrow position [$r = 0.875$], cheek area variability & forehead area variability [$r = 0.86$], pitch & eyebrow tilt [$r = 0.86$] and cheek area & eyebrow position [$r = 0.77$]. Detailed test results together with figures documenting significant findings are available in the Supplementary Material.

Discussion

Group differences

The primary objective of this study was to establish a normative baseline of facial movement aging over a five-year interval to facilitate the future detection of hypomimia in neurodegenerative disorders. Our longitudinal analysis of healthy individuals demonstrated remarkable stability in facial kinematics. While yaw (head rotation) appeared to be the sole feature with a statistically significant difference between the BL and 5Y groups, a manual review of the video recordings identified this as a recording artifact. Subjects were seated slightly differently relative to the interviewing speech specialist between sessions,

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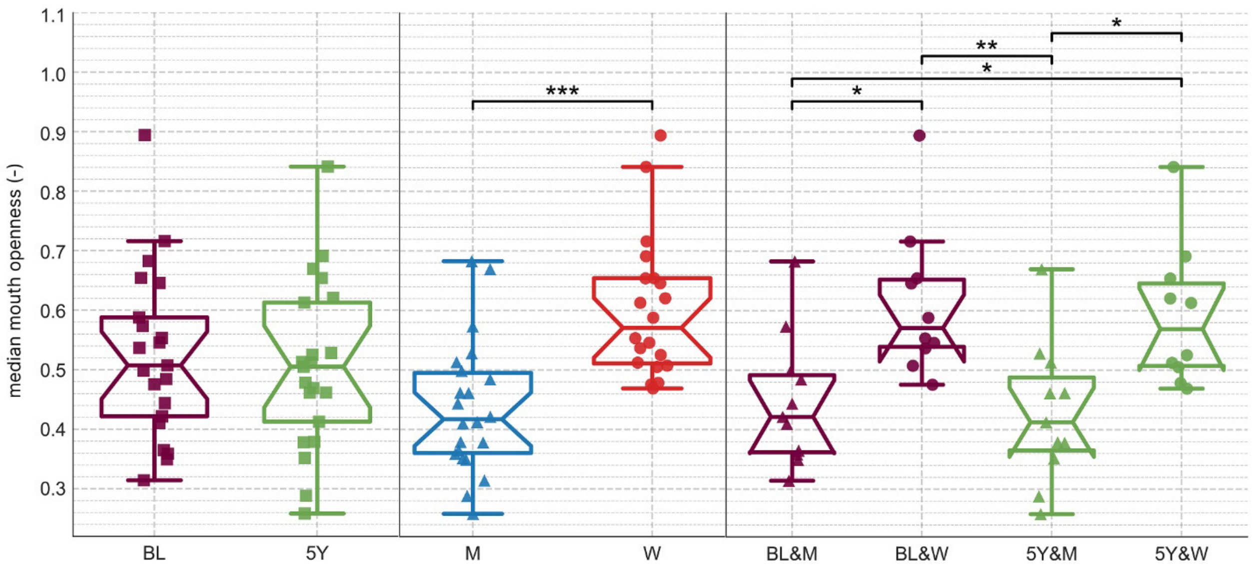

*Fig. 3: Feature mouth openness distribution analysis. BL and 5Y groups (left figure) didn't reveal any significant differences ($p = 0.07$, $r^2 = 0.34$), whereas sex division (middle figure) yielded significant distribution differences ($p < 0.001$, $r^2 = 0.72$). Division to all subgroups (right figure) confirmed significant differences in men and women distributions ($p < 0.05$ for post hoc tests between men and women in both groups). Statistically significant differences are denoted by asterisks: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.*

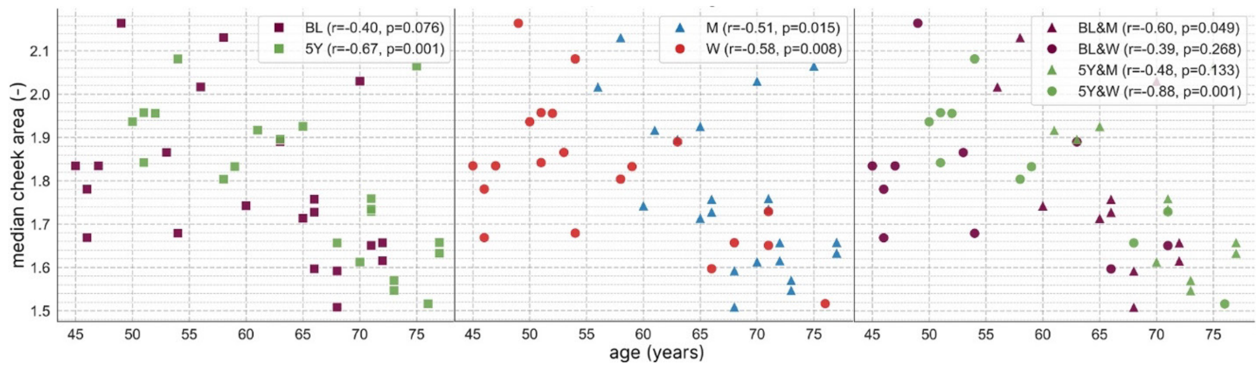

Fig. 4: Feature cheek area correlation analysis to age showed significant negative correlation ($r = -0.67$, $p = 0.001$) for 5Y group (left figure). Both men ($r = -0.51$, $p = 0.015$) & women ($r = -0.58$, $p = 0.008$) yielded significant inverse linear proportion as well. Subgroups analysis revealed significant relations for BL-M ($r = -0.60$, $p = 0.049$) and 5Y-W ($r = -0.88$, $p = 0.001$).

accounting for the change in head orientation (median difference in yaw ca. 5 degrees).

The observed kinematic stability suggests that in healthy aging, the degradation of facial expressivity is a gradual process. This aligns with current anatomical models that characterize facial aging as slow and cumulative, with changes typically manifesting over long-term observation periods [4, 5]. Consequently, any rapid decline in facial mobility observed in patients with PD over a similar five-year window can be confidently attributed to neurodegeneration rather than typical aging.

Regarding the influence of age, we found a significant relationship between seven features and subject age. All significant correlations were negative, corresponding to a general tightening or reduction in the range of facial musculature motion associated with aging. The most pronounced age-related decreases were observed in structural metrics, specifically cheek area, lateral canthal area, and nose root area. Notably, correlations were predominantly significant in the 5Y group (six features) compared to the BL group (one feature). While this might initially suggest that structural changes accelerate or become more measurable with advancing age, an inspection of the correlation plots revealed that the BL group exhibited greater data scatter, particularly among younger subjects. This variance likely stems from the recording setup differences mentioned previously, or a habituation effect. Subjects were already familiar with the protocol during the second session and behaved more naturally, reducing noise in the 5Y data.

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Sex differences

A secondary objective of this study was to quantify the influence of sex on facial feature values. We identified 11 features that significantly differentiated men from women, with the most profound differences observed in mouth openness and mouth openness variability, both exhibiting large effect sizes. Women demonstrated significantly greater vertical amplitude and dynamic range during spontaneous speech compared to men. Notably, both features correlated positively with age in the women cohort, indicating that older women tend to exhibit greater mouth opening and mobility. This finding contextualizes the work of Ko et al. [10], who reported more pronounced facial expressions in older adults, by suggesting that this trend may be sexually dimorphic. Lower lip position was significantly smaller in women, reflecting inherent anatomical differences. Consistent with the increased mouth openness, women also exhibited greater variability in lower lip, upper lip, mouth corner, and jaw positions. A significantly greater eye openness was observed for women as well.

Unexpectedly, head pitch was significantly lower in women. Given that men are statistically taller on average [14], one might anticipate women looking upward toward the interviewer. The observed downward gaze implies a behavioral origin, potentially reflecting distinct emotional processing or discomfort during the monologue. Regarding aging effects, forehead area decreased significantly with age in women but not in men, whereas cheek area showed a significant decline in both sexes. This reduction in cheek area is in line with observation of decreased skin stretchiness and increase in tissue sagging by Kurosumi et al. [9].

Combined group and sex influence

The combined assessment of group and sex influences isolated only two features with statistically significant effects: mouth openness and mouth openness variability. This finding reinforces the conclusion that while mouth kinematics remain stable over the five-year longitudinal interval, they are subject to sexual dimorphism, distinguishing men from women regardless of the recording session (Fig. 3). The decline in cheek area with age was not found universal. Significant negative correlations were observed specifically in the 5Y women and BL male cohorts, suggesting that the detectability or magnitude of this structural change varies across subsets. In contrast, the reduction in forehead area appears to be a robust marker of aging in women, confirmed by consistent significant correlations in both the baseline (BL-W) and follow-up (5Y-W) groups.

Feature relations

Our analysis of the linear relationships between calculated features exposed high redundancy, suggesting that the feature set can be streamlined for future applications. Notably, pitch and eyebrow tilt were strongly correlated, which indicates that the designed eyebrow tilt feature is a byproduct of head nodding rather than a measure of independent eyebrow movement. Similarly, eyebrow position variability appeared to be largely a reflection of head roll variability.

In the upper face, the high correlation among nose root area, lateral canthal area, and eyebrow position points to a strong interdependence of movements. This reflects the constraints of this bilaterally innervated region, where the capacity for isolated, fine motor control is limited [3]. Interestingly, cheek area was highly correlated with this cluster as well, implying a significant kinetic coupling between the midface and the forehead.

Our study is subject to limitations, including a small sample size (total of 21 subjects) and a five-year observation window, which may be too brief to fully capture the nature of healthy aging in an individual. Additionally, the reliance on monocular 2D video limits a more precise 3D analysis and makes face detection unreliable for extreme head positions, where only a part of the face is visible to the camera.

Conclusion

This study provides a quantification of spontaneous facial movement in healthy aging. We conclude that facial expressivity in healthy individuals is highly stable over a five-year period in late middle age. While our data confirmed established structural markers of aging, specifically the reduction of facial areas associated with muscle tightening, these changes accumulate slowly and do not significantly disrupt dynamic facial mobility within this window. These findings have direct implications for the automated assessment of neurodegenerative diseases. The stability of the healthy baseline validates the use of five-year intervals for monitoring disease progression, as significant reductions in expressivity during this timeframe are unlikely to be artifacts of normal aging. Finally, our results suggest that future automated systems should streamline feature sets to eliminate redundancy and must account for sex and age balance between study groups to ensure diagnostic accuracy.

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Author contributions

FS: Writing – original draft, Writing – review & editing, Formal analysis, Visualization, Software, Data curation. MN: Writing – review & editing, Investigation, Supervision, Methodology, Funding acquisition, Project administration, Conceptualization.

Data and code availability statement

Participants' data and code that were used for this study are available upon request from the corresponding author. The facial landmark detection was performed using a publicly available Python implementation of Google's Mediapipe FaceMesh.

References

[1] Cannavacciuolo A, Paparella G, Salzillo M, Colella D, Canevelli M, Costa D, et al. Facial emotion expressivity in patients with Parkinson's and Alzheimer's disease. Journal of Neural Transmission. 2023 Oct;131(1):31–41. DOI: 10.1007/s00702-023-02699-2

[2] Sonawane B, Sharma P. Review of automated emotion-based quantification of facial expression in Parkinson's patients. The Visual Computer. 2020 Jun;37(5):1151–67. DOI: 10.1007/s00371-020-01859-9

[3] Rinn WE. The neuropsychology of facial expression: A review of the neurological and psychological mechanisms for producing facial expressions. Psychological Bulletin. 1984;95(1):52–77. DOI: 10.1037/0033-2909.95.1.52

[4] Cotofana S, Fratila A, Schenck T, Redka-Swoboda W, Zilinsky I, Pavicic T. The Anatomy of the Aging Face: A Review. Facial Plastic Surgery. 2016 Jun;32(03):253–60. DOI: 10.1055/s-0036-1582234

[5] Swift A, Liew S, Weinkle S, Garcia JK, Silberberg MB. The Facial Aging Process From the "Inside Out". Aesthetic Surgery Journal. 2020 Dec;41(10):1107–19. DOI: 10.1093/asj/sjaa339

[6] Stadio AD. Another Scale for the Assessment of Facial Paralysis? ADS Scale: Our Proposition, How to Use It. Journal of Clinical and Diagnostic Research. 2015 Dec;9(12):8–11. DOI: 10.7860/jcdr/2015/15366.6953

[7] Ekman P, Friesen WV. Facial Action Coding System. Consulting Psychologists Press. 1978. DOI: 10.1037/t27734-000

[8] Cotofana S, Assemi-Kabir S, Mardini S, Giunta RE, Gotkin RH, Moellhoff N, et al. Understanding Facial Muscle Aging: A Surface Electromyography Study. Aesthetic Surgery Journal. 2021 May;41(9):NP1208–17. DOI: 10.1093/asj/sjab202

[9] Kurosumi M, Mizukoshi K. Principal component analysis of three-dimensional face shape: Identifying shape features that change with age. Skin Research and Technology. 2017 Nov;24(2):213–22. DOI: 10.1111/srt.12416

[10] Ko H, Kim K, Bae M, Seo M-G, Nam G, Park S, et al. Changes in Computer-Analyzed Facial Expressions with Age. Sensors. 2021 Jul;21(14):4858. DOI: 10.3390/s21144858

[11] Kälble L, Tykalova T, Zogala D, Dusek P, Rusz J, Novotny M. Automatic analysis of eyelid movement in de-novo Parkinson's disease. npj Parkinson's Disease. 2025 Jun;11(1):153. DOI: 10.1038/s41531-025-01021-z

[12] Grishchenko I, Ablavatski A, Kartynnik Y, Raveendran K, Grundmann M. Attention Mesh: High-fidelity Face Mesh Prediction in Real-time. arXiv preprint. 2020;arXiv:2006.10962. DOI: 10.48550/ARXIV.2006.10962

[13] Roesler O, Kothare H, Burke W, Neumann M, Liscombe J, Cornish A, et al. Exploring Facial Metric Normalization For Within- and Between-Subject Comparisons in a Multimodal Health Monitoring Agent. In: Proceedings of the 2022 International Conference on Multimodal Interaction; 2022 Nov 7–11; Bengaluru, India. p. 160–5. DOI: 10.1145/3536220.3558071

[14] Schäppi J, Stringhini S, Guessous I, Staub K, Matthes KL. Body height in adult women and men in a cross-sectional population-based survey in Geneva: temporal trends, association with general health status and height loss after age 50. BMJ Open. 2022 Jul;12(7):e059568. DOI: 10.1136/bmjopen-2021-059568

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