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Optical Estimation of Facial Muscle Activity for Emotion Detection: Validation Against Electromyography and Real-Time Prototype Evaluation

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Przemysław Jaworski[1], Miłosz Makowski[2], Maciej Pondel[3]

Abstract:

Purpose: *This paper proposes and validates a novel three-stage framework for non-invasive emotion detection based on the transformation of facial video recordings into biosignal-like time series analogous to surface electromyography (EMG). The study aims to investigate the extent to which optically derived facial signals can serve as reliable proxies for physiological muscle activity and support real-time emotion recognition without the need for direct sensor contact.*
Design/Methodology/Approach: *The research was conducted in three consecutive stages. In Stage 1, concurrent facial video and surface EMG recordings were collected from five participants exposed to emotionally valenced stimuli. Optical signals were extracted using the FLAME morphable face model and Facial Action Coding System (FACS)-based descriptors and compared with EMG ground-truth measurements across four facial muscle channels. Cross-modal correspondence was evaluated using Pearson correlation analysis and temporal alignment procedures. In Stage 2, the validated optical signal extraction pipeline was implemented within a remote-capable data collection application, enabling contactless acquisition and processing of facial-expression data. In Stage 3, the methodology was integrated into a portable real-time prototype system designed for automatic emotion recognition and tested on twenty participants.*
Findings: *The results demonstrate that facial video data can be transformed into meaningful biosignal-like representations corresponding to underlying muscular activity. The strongest optical–EMG correspondence was observed for the Zygomaticus major muscle ($r = 0.733 \pm 0.188$), while moderate correlations were obtained for the Corrugator supercilii ($r = 0.282 \pm 0.147$) and Orbicularis oculi ($r = 0.239 \pm 0.216$) muscles. Frontalis measurements exhibited greater variability ($r = 0.239 \pm 0.309$). The analysis identified a systematic electromechanical delay of approximately 0.2 seconds between physiological and optically derived signals. The final prototype successfully classified ten discrete emotional categories*

[1]*Corresponding author, Shen.AI OÜ, Tallinn, Estonia, ORCID: 0009-0009-1849-193X, e-mail: pjaworski@shen.ai;*
[2]*Faculty of Mathematics and Computer Science, Adam Mickiewicz University in Poznań, Poland and Shen.AI OÜ, Tallinn, Estonia*
[3]*Corresponding author, Institute of Information Systems in Economics, Wroclaw University of Economics and Business, Wrocław, Poland, ORCID: 0000-0002-1978-6571, e-mail: maciej.pondel@ue.wroc.pl;*

in real time across twenty consecutive participants, confirming the feasibility of the proposed approach.

Practical Implications: *The proposed framework offers a scalable and non-invasive alternative to traditional physiological emotion-monitoring techniques. Potential applications include human–computer interaction, affective computing, healthcare monitoring, psychological assessment, adaptive educational systems, customer experience research and wearable or mobile technologies requiring real-time emotion recognition without physical sensors.*

Originality/Value: *The paper introduces an innovative methodology that bridges computer vision and physiological signal analysis by converting facial video streams into EMG-like representations of muscle activity. Its originality lies in the validation of optical–EMG correspondence, the identification of temporal synchronization characteristics and the successful implementation of a portable real-time emotion recognition system. The study contributes to the development of contactless affective computing technologies and provides a foundation for future research on physiologically informed emotion detection methods.*

Keywords: *Facial electromyography, optical biosignal, FLAME, FACS, emotion recognition, affective computing, real-time prototype.*

JEL codes: *C88, O33, D83, I19, L86.*

Paper type: *Research paper.*

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Conflict of interest: *The authors declare no conflicts of interest.*

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process: *During the preparation of this manuscript, the authors used ChatGPT Business, a generative AI tool developed by OpenAI, solely for language editing purposes, including improvement of grammar, clarity, style, and readability of the text. The tool was not used to generate research data, conduct data analysis, create results, formulate conclusions, or make substantive scientific decisions. All AI-assisted edits were reviewed, verified, and approved by the authors. The authors remain fully responsible for the accuracy, originality, integrity, and final content of the manuscript.*

1. Introduction

1.1 Background and Motivation

Emotion detection technologies offer growing potential across psychology, human-computer interaction, marketing, healthcare, and other fields. In customer service, real-time affective analysis can help agents adapt to client emotional states. In health care, monitoring emotional responses during therapy or routine assessments can support early identification of mood disorders. In the recruitment domain, non-verbal cues such as facial expressions and vocal tone may complement conventional competency assessments. Creditworthiness evaluation and affective response research represent further emerging application areas.

Despite this potential, a core technical challenge persists: reliably capturing facial muscle activity in real-world, uncontrolled conditions. Surface electromyography (EMG) provides high-fidelity physiological ground truth but requires skin-contact electrodes, constraining natural behaviour and precluding deployment outside the laboratory. Optical methods using standard cameras offer deployment flexibility but have historically struggled with sensitivity to low-amplitude expressions and with robustness under head movement or variable illumination.

1.2 Research Problem and Gap

No established framework bridges both paradigms by using EMG as a ground-truth reference to validate optically derived facial muscle signals, and then deploying the validated optical system in a portable real-time device. The core questions addressed here are: (a) to what extent do biosignal-like time series derived from standard facial video agree with concurrently recorded surface EMG, and (b) can such signals support real-time emotion inference on portable hardware?

Existing video emotion recognition literature (Yi *et al.,* 2025) identifies persistent challenges in temporal modelling, dataset ecological validity, and multimodal fusion. Direct cross-modal validation against simultaneous EMG remains rare, and interpretable intermediate representations — rather than opaque end-to-end classifiers — are seldom prioritised.

1.3 Contributions

This paper makes three contributions: (1) an empirically grounded optical-EMG correspondence analysis using concurrent facial video and four-channel surface EMG across five participants; (2) a remote-capable data-collection protocol validated with a broader cohort; and (3) a portable real-time prototype evaluated in interview-like conditions, demonstrating operational feasibility and identifying engineering limitations.

2. Literature Review

2.1 Facial EMG and Affective Computing

Facial surface EMG has a long history as a direct measure of emotional muscle activity (Cacioppo and Tassinary, 1990). The Zygomaticus major is reliably activated during positive affect; the Corrugator supercilii responds to negative valence.

The Orbicularis oculi, involved in Duchenne smiling, and the Frontalis, linked to surprise and brow raising, provide additional discriminative channels. These four muscles form a standard monitoring set for valence-arousal modelling. The key limitation is practical: EMG requires electrode placement, constrains natural behaviour, and cannot be applied at scale.

2.2 Optical Facial Analysis and FACS

The Facial Action Coding System (Ekman and Friesen, 1978) provides an anatomically grounded taxonomy of facial movements mapped to specific muscle group contractions.

Automated FACS coding has matured considerably; systems such as OpenFace demonstrate performance comparable to trained human coders in controlled conditions (Pfeffer, 2023).

The FLAME morphable face model (Li *et al.,* 2017) enables dense parametric reconstruction of facial geometry from monocular video, producing per-frame muscle deformation estimates grounded in the same anatomy as EMG recording sites.

Yi *et al.* (2025) survey video emotion recognition challenges, identifying temporal dynamics, dataset limitations, and multimodal fusion as persistent issues. De Jesus et al. (2023) demonstrated that Action Unit time series from interview video can support behavioural profiling, but without concurrent EMG validation. Wu *et al.* (2023) and Saganowski *et al.* (2023) emphasise the value of physiological grounding for affective computing; the present work provides this grounding explicitly via simultaneous EMG collection.

2.3 Electromechanical Delay

The delay between muscle electrical activation (measured by EMG) and resulting visible skin deformation (measured optically) is a well-characterised physiological phenomenon, typically 30–200 ms for facial musculature (Merletti and Farina, 2016). This delay has direct implications for cross-modal temporal alignment, and its identification provides a methodologically useful calibration parameter.

2.4 Ethics and Governance

Barker *et al.* (2025) identify privacy, demographic bias, and transparency as primary governance concerns for emotion recognition in high-stakes settings including employment and healthcare. These concerns motivate the present work's emphasis on interpretable FACS-grounded intermediate representations rather than opaque end-to-end classification. The companion paper (Jaworski *et al.,* 2026) addresses governance for AI-augmented recruitment interviews specifically; the present paper focuses on the technical validation underpinning that application.

3. Research Methodology

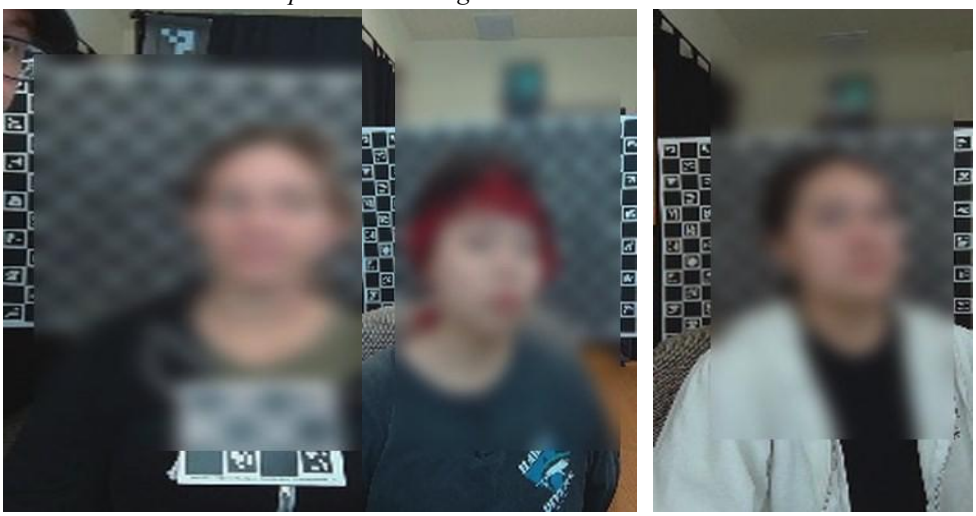
The research was conducted in three sequential stages. Institutional review and written informed consent were obtained for all participants. Face images of participants are anonymised in this publication.

3.1 Stage 1: Laboratory EMG-Optical Validation

3.1.1 Participants and Setting

Laboratory recordings were conducted at the University of California San Diego (UCSD) with N = 5 participants (sessions 11, 1400, 1401, 1701, 2000). Each session consisted of a one-hour recording in which the participant was seated at a fixed distance from the camera under controlled illumination. A chequered calibration panel was visible in the camera field to support spatial reference (Figure 1). Faces are anonymised in published images.

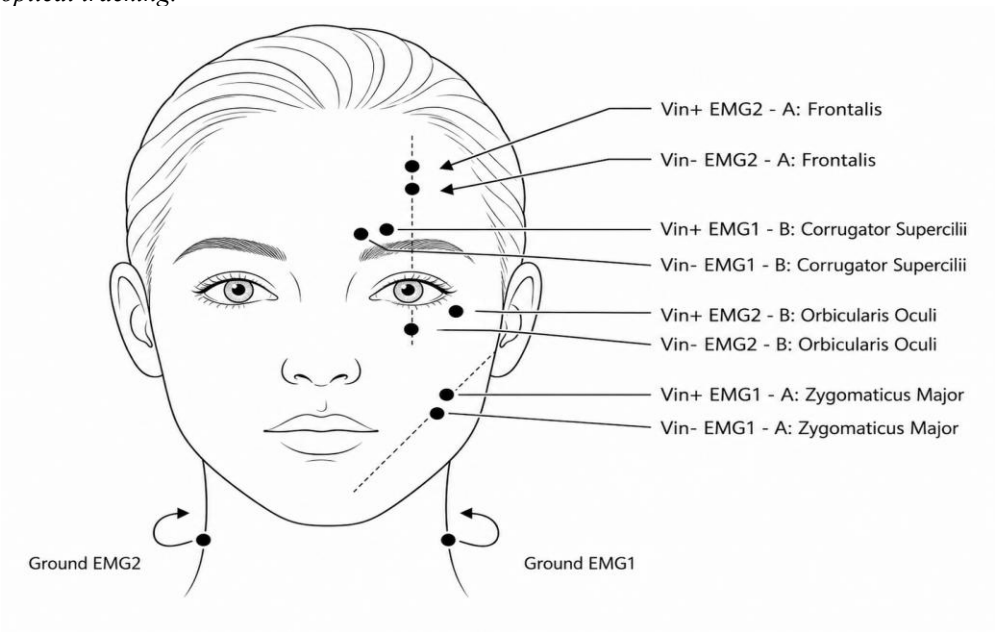
Figure 1. *Representative participants during the laboratory recording session at UCSD (faces anonymised). The chequered background serves as a spatial calibration reference. The left half of the face is unobstructed to allow simultaneous optical landmark tracking while EMG electrodes are placed on the right side.*



3.1.2 EMG Recording and Bilateral Symmetry Assumption

Surface EMG was recorded from four facial muscles on the right side of the face: Zygomaticus major (ZYGO), Corrugator supercilii (CORR), Orbicularis oculi (ORBI), and Frontalis (FRONT). Electrode placement is shown in Figure 2. The left side of the face was intentionally left unobstructed to enable unimpeded optical landmark tracking by the camera. The session-11 pilot recording used a Platysma (PLATY) channel in place of FRONT.

Figure 2. *Surface EMG electrode placement scheme. Electrode pairs target four muscles: Frontalis (brow), Corrugator supercilii (inner brow), Orbicularis oculi (eyelids), and Zygomaticus major (cheek). Right-side electrodes only; the left side is unobstructed for optical tracking.*



A key methodological assumption of this study is bilateral facial symmetry: EMG electrodes capture right-side muscle activity, while the optical pipeline tracks both sides.

We treat facial expressions as approximately symmetric across the face's midline — an assumption standard in facial EMG research and an explicit design choice in this protocol. Stimulus materials (ADFES dynamic expressions) were selected to evoke symmetric expressions, and the analytical protocol excluded trials in which visible asymmetry was observed.

Raw EMG signals were sampled at 1000 Hz and processed through bandpass filtering (10–450 Hz), signal whitening, and linear envelope extraction (full-wave rectification followed by 5 Hz low-pass filter).

3.1.3 Stimulus Protocol

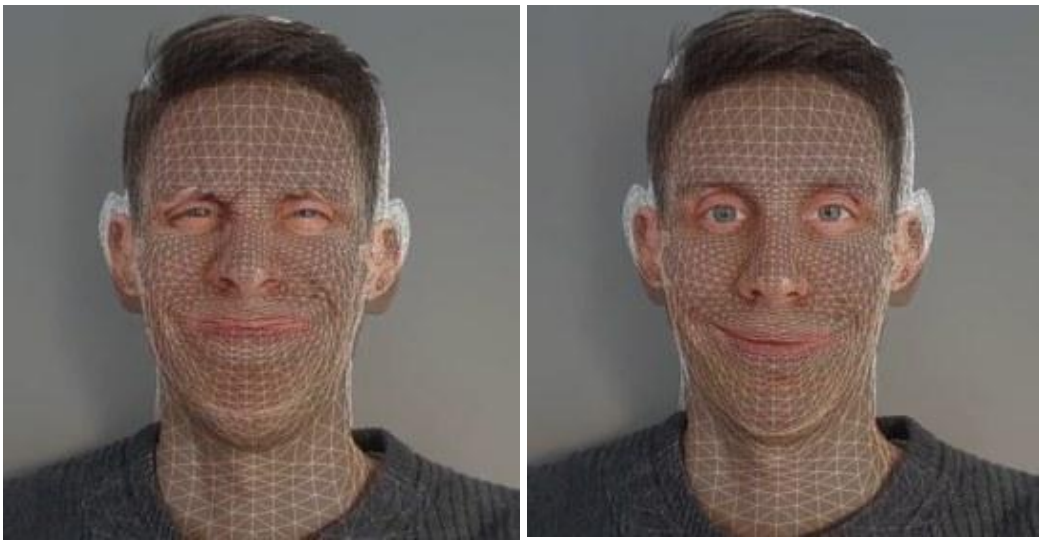
Each session comprised two stimulus blocks. The dynamic block used video clips from the Amsterdam Dynamic Facial Expression Set (ADFES; van der Schalk et al., 2011). The static block used images from IAPS, NAPS, and WSEFEP. Both blocks covered five emotion categories: anger, disgust, fear, happiness, and sadness (5 exemplars per emotion per block). A shared synchronisation signal — a green rectangle marker in the upper portion of the video frame, matched to the EMG trigger channel — enabled temporal alignment between the two modalities.

3.1.4 Optical Signal Extraction via FLAME

Facial muscle activity signals were extracted from video using the following pipeline. First, 68 anatomical facial landmarks are localised per frame using a convolutional neural network. Second, the FLAME morphable face model (Li *et al.,* 2017) — a statistical 3-D face model controlled by shape and expression parameters — is fitted to the detected landmarks via an iterative solver that minimises landmark and silhouette reprojection error.

The fit produces a dense parametric mesh per frame (see fig. 3a), from which deformation trajectories of the anatomical regions corresponding to the four EMG channels are computed (see fig. 3b). Third, these trajectories are encoded as FACS Action Unit time series, providing a per-frame biosignal-like representation of muscle activity. For two of the five sessions (1701 and 2000), a slightly simplified expression-fit configuration was used, omitting one photometric regularisation term. All downstream stages were identical for all sessions.

Figure 3a. *FLAME morphable face model (400-parameter mesh) fitted to facial video frames across different expressions. Top row: happiness (left) and neutral (right). Bottom row: anger (left) and surprise (right). The mesh deformation trajectories of anatomical regions corresponding to FACS Action Units form the basis of the optical biosignal time series.*



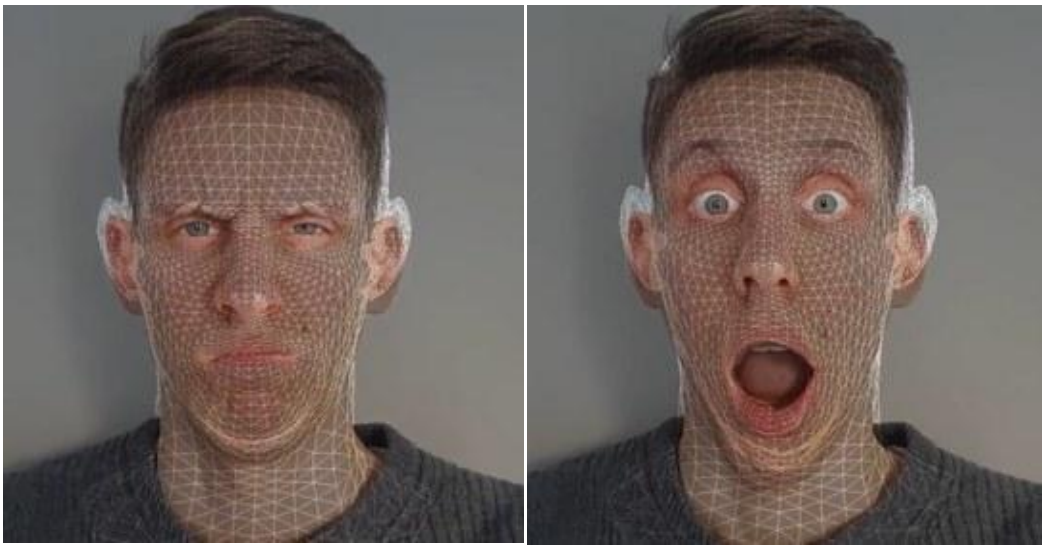
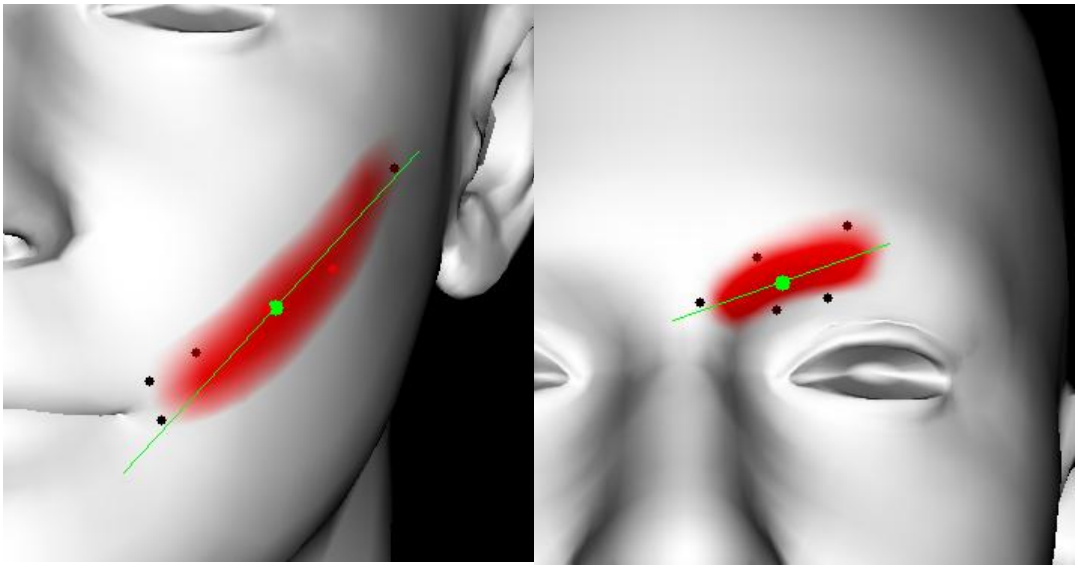


Figure 3b. *Muscle definitions visualized on the FLAME model, drawn with a brush tool based on human anatomy. From left: zygomaticus major, and corrugator supercilii. The black-to-red dots are the mesh vertices affected by a given muscle, with their color representing weights (black: 0, red: 1). The green line is the axis of average muscle motion, with the green dot at the muscle's center.*



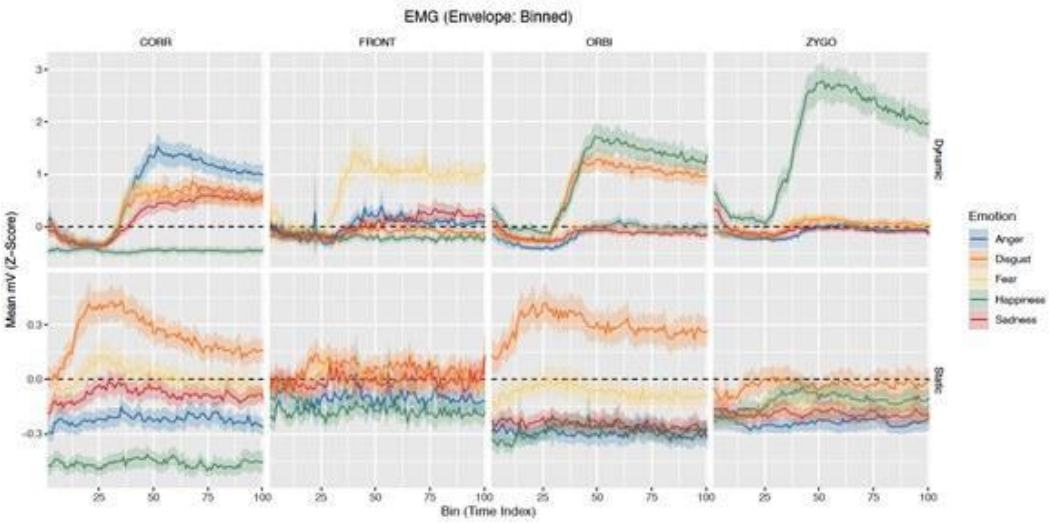
3.1.5 Temporal Alignment and Cross-Modal Correlation

Optical and EMG signals were aligned using the shared green marker signal. Additionally, a per-stimulus overlap-based alignment with a ±0.25 s lag search was

applied to identify the optimal cross-correlation peak for each stimulus pair; this procedure consistently identified a systematic lead of approximately 0.2 s in the EMG signal relative to the optical signal, consistent with the known electromechanical delay between muscle electrical activation and resulting skin motion.

The correlation values reported in this paper use this alignment. Grand-mean Pearson r values are reported across all five sessions.

Figure 4. *Mean EMG envelope signals (Z-score, 100 time bins) for four muscle channels (CORR, FRONT, ORBI, ZYGO) across five emotion categories, for dynamic (top) and static (bottom) stimulus blocks. Shaded bands indicate 95% confidence intervals. Zygomaticus major shows the largest emotion-differentiated amplitude, particularly for happiness in the dynamic condition.*

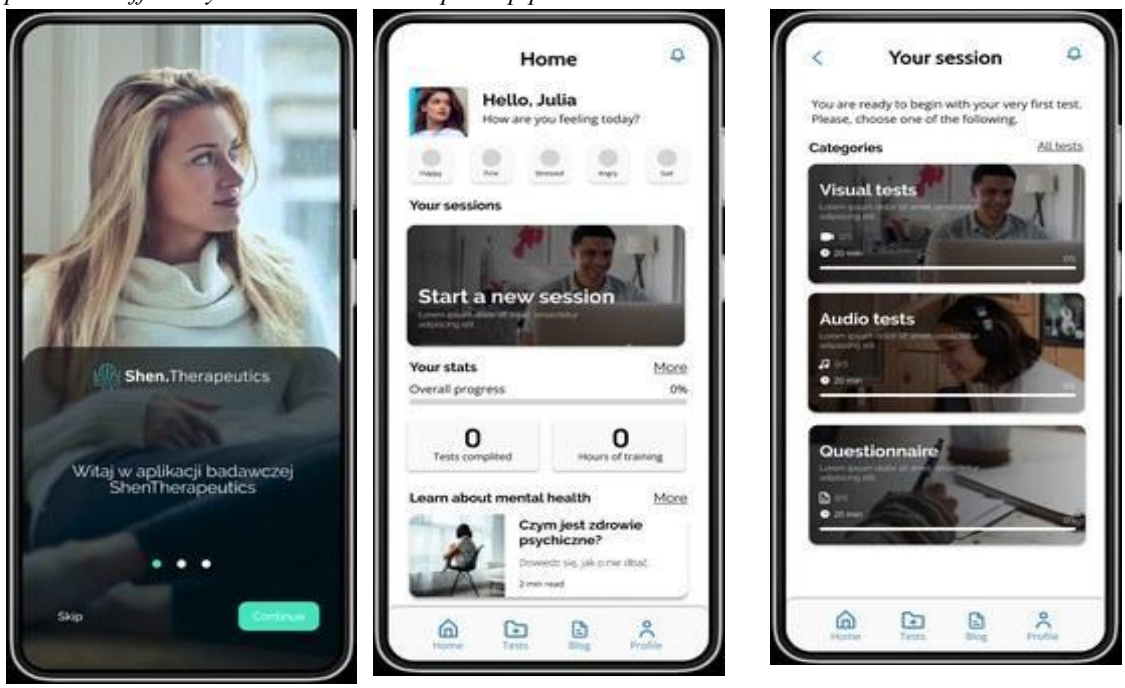


3.2 Stage 2: Remote Data-Collection Application

A mobile application was developed to enable the protocol in distributed settings. After a facial calibration step, participants complete three parts: (Part 1) 4–6 emotionally valenced video clips from the Emotional Movie Database (EMDB; Carvalho *et al.,* 2012), rated on the Self-Assessment Manikin (SAM) scale; (Part 2) expressive reading of affectively loaded sentences from the Affective Norms for Polish Short Texts (ANPST; Imbir, 2016); and (Part 3) a structured voice interaction with open-ended social scenario questions.

An optional IPIP-50 Big Five personality inventory is administered at session close. Facial video is recorded throughout each part and processed by the optical pipeline described in Stage 1.

Figure 5. *Screenshots of the remote data-collection application. Left: onboarding screen. Centre: home screen with session statistics. Right: session screen with test category selection (visual tests, audio tests, questionnaire). Facial video recorded throughout each part is processed offline by the FLAME-based optical pipeline.*



3.3 Stage 3: Real-Time Portable Prototype

The third stage integrated the validated optical pipeline into a portable device for real-time use in interview scenarios. The system performs per-frame FLAME mesh fitting, continuous keypoint tracking, FACS descriptor extraction, and emotion inference over a sliding temporal window, all in real time. The prototype was built into a portable case housing a laptop computer and two industrial cameras with LED illumination (Figure 6), enabling transport between locations.

Figure 6. *The portable real-time prototype device. Left: industrial cameras mounted in the housing. Centre: complete device in portable case form factor. Right: internal camera module with LED illumination. One operator manages the device while the participant sits in front of the camera array.*

4. Results and Discussion

4.1 Stage 1: Cross-Modal Correlation Results

Table 1 reports grand-mean Pearson r values between optically derived and EMG muscle signals, averaged across all five sessions (n = 4 for FRONT due to the pilot session using the PLATY channel). Table 2 shows per-session values.

Table 1. *Grand-mean Pearson correlation coefficients (r) between optically derived and EMG-recorded facial muscle signals, averaged across N = 5 sessions. Temporal alignment includes per-stimulus lag correction (±0.25 s). † FRONT is n = 4 (session 11 used a Platysma channel; that session's PLATY r = 0.45 is excluded from the FRONT mean but is reported in Table 2).*

Muscle	N	r (mean ± SD)	r range (min–max)	Interpretation
Zygomaticus major (ZYGO)	5	0.733 ± 0.188	0.41 – 0.84	Strong
Corrugator supercilii (CORR)	5	0.282 ± 0.147	0.18 – 0.46	Moderate
Orbicularis oculi (ORBI)	5	0.239 ± 0.216	0.15 – 0.39	Weak–moderate
Frontalis (FRONT)	4 †	0.239 ± 0.309	−0.03 – 0.45	Variable

Table 2. *Per-session Pearson r values for each muscle channel (alignment-corrected). — indicates the channel was not available or not analysed for that session. * Session 11 FRONT column shows the Platysma (PLATY) channel. ‡ Session 1401 restricted to first 29 stimuli due to a synchronisation drift event in the second half.*

Session	Quality	ZYGO r	CORR r	ORBI r	FRONT r
11 (pilot)	Clean	0.80	0.31	0.15	0.45 *
1400	Usable	0.81	0.39	—	—
1401	Partial ‡	0.79	0.46	—	—
1701	Weak response	0.41	0.18	0.25	−0.03
2000	Clean	0.84	0.27	0.39	0.08

4.1.1 Zygomaticus Major

ZYGO showed the strongest and most consistent optical-EMG correspondence across sessions (mean r = 0.733). Sessions 1400, 1401, and 2000 all yielded r ≥ 0.79, consistent with this muscle's large activation amplitude and high signal-to-noise ratio in both modalities. Session 1701 showed substantially weaker correspondence (r = 0.41). This pattern is best understood not as a pipeline failure but as a

participant-level response amplitude effect: participants who showed clear, broad facial expressions produced strong signal in both EMG and optical channels simultaneously, while subdued reactions reduced SNR in both modalities alike.

This is an expected feature of any correlational study based on naturalistic stimuli and is a known property of emotion-elicitation paradigms using standardised databases such as ADFES — participants differ considerably in the magnitude of their spontaneous responses.

4.1.2 Corrugator Supercilii

CORR showed moderate correspondence overall (mean $r = 0.282$). Higher values were obtained in sessions 1400 and 1401 ($r = 0.39$ and 0.46 respectively), where anger and disgust stimuli reliably activated this muscle. The weaker values in sessions 1701 and 2000 ($r = 0.18$ and 0.27) reflect both lower response amplitudes in those participants and the inherently smaller signal range of the Corrugator relative to Zygomaticus major.

4.1.3 Orbicularis Oculi

ORBI showed the widest spread across sessions, from $r = 0.15$ (session 11) to $r = 0.39$ (session 2000). The optical pipeline uses a regional depressor-supercilii proxy for this channel, as the Orbicularis oculi is challenging to isolate optically given its proximity to the eyelid and lower cheek regions. This structural limitation of the current optical representation likely accounts for the weaker average correspondence relative to ZYGO.

4.1.4 Frontalis

FRONT showed the most variable results across sessions (range: −0.03 to 0.45), with a mean $r = 0.239$ ($n = 4$). The negative value for session 1701 suggests that the Frontalis response for that participant was either absent or occurred in a pattern inconsistent with the optical channel in that session. The pilot session-11 Platysma (PLATY) value of $r = 0.45$ is presented separately as it reflects a different muscle channel.

4.1.5 Electromechanical Lag

The per-stimulus lag search consistently identified a lead of approximately 0.2 s in the EMG signal relative to the optical signal — that is, muscle electrical activation precedes visible skin deformation by roughly 200 ms. This is consistent with the known electromechanical delay in facial musculature (Merletti and Farina, 2016) and confirms that the two modalities are measuring the same physiological event at different points in the causal chain. This finding is methodologically valuable as a calibration parameter for future pipeline configurations.

4.1.6 Proof-of-Concept Framing

The results reported above should be interpreted as proof-of-concept evidence for optical-EMG signal correspondence rather than a definitive validation for high-

stakes deployment. The participant sample (N = 5) is small, stimulus-elicited response amplitudes varied substantially across individuals, and the ORBI channel is limited by its current optical proxy. The strong ZYGO and CORR results in higher-response sessions, and the consistency of the electromechanical lag across all sessions, nonetheless provide meaningful empirical grounding for the approach.

4.2 Stage 2: Remote Application

The remote data-collection application was successfully deployed with a broader participant cohort. All three protocol parts were completed in single distributed sessions. The FLAME-based optical pipeline operated identically in the remote setting, confirming portability of the analytical approach beyond the controlled laboratory.

SAM valence-arousal-dominance ratings provided continuous ground-truth labels for future correlation analysis. Personality inventory data (IPIP-50) are retained for exploratory analysis with larger sample sizes.

4.3 Stage 3: Real-Time Prototype

The portable prototype device operated continuously across 20 consecutive participant sessions without technical interruption. The system produced real-time inference across ten emotion categories: anger, contempt, disgust, embarrassment, fear, joy, neutral, pride, sadness, and surprise.

Operator reports indicated that emotion-related and stress-related signals were the most consistently interpretable outputs, qualitatively consistent with the Stage 1 quantitative finding that ZYGO and CORR are the most reliable optical channels. Two operational limitations were identified: reduced tracking stability during rapid head rotations ($\geq \sim 45°$), and susceptibility to strong directional shadows in uncontrolled ambient lighting.

4.4 Summary

Taken together, the three stages demonstrate that facial muscle activity can be meaningfully estimated from standard video using the FLAME-based optical pipeline, with the strongest correspondence for Zygomaticus major and reasonable correspondence for Corrugator supercilii. Session-level variability is primarily driven by participant response magnitude rather than pipeline breakdown.

The real-time prototype demonstrates technical deployability. The current results constitute a proof-of-concept baseline; expanding to a larger and more diverse participant sample, and improving the optical proxy for Orbicularis oculi, are the primary directions for strengthening the evidence base.

5. Conclusions

This paper presented a three-stage framework for non-invasive facial emotion detection, grounded in concurrent surface EMG validation. Key findings are:

- Optically derived Zygomaticus major signals correlate with concurrent EMG at a grand-mean r = 0.73 across five sessions (range 0.41–0.84). Corrugator supercilii shows moderate correspondence (r = 0.28). Orbicularis oculi and Frontalis show weaker or more variable correspondence, reflecting optical-proxy limitations and participant response variability respectively.

- Session-level variation in correlation strength is primarily attributable to inter-individual differences in spontaneous expression amplitude in response to ADFES stimuli. Participants with subdued reactions show lower SNR in both EMG and optical signals simultaneously, reducing cross-modal correlation. This is an expected characteristic of naturalistic emotion elicitation.

- A systematic electromechanical lead of ~0.2 s is consistently identified across sessions in the EMG signal relative to the optical signal, providing a physiologically grounded calibration parameter.

- The remote application and portable real-time prototype are operationally feasible. The prototype met a basic robustness criterion (20 consecutive sessions without interruption) and produced qualitatively consistent outputs across emotion categories.

Priorities for future work include expanding the validated participant sample, developing an improved optical proxy for Orbicularis oculi, addressing robustness under large head rotations and variable illumination, and conducting a formal fairness assessment across demographic groups. Deployment in high-stakes applied settings will additionally require governance frameworks covering consent, transparency, and data minimisation, as discussed in the companion paper.

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