Posed and spontaneous smile assessment with wearable skin conductance measured from the neck and head movement

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***Abstract*—Electro-Dermal Activity (EDA) and head movement have been shown to correlate with felt affect. Given the easiness to measure them, they are suitable as a wearable affective assessment tool. Arguably, autonomic affective responses such as EDA are less affected by volition than the production of other embodied cues of affect such as facial expressions. Moreover, head movement has been shown as a reliable source of information about the intention behind a facial expression. Therefore, we explored the feasibility of using EDA measured from the neck and head movement to make inferences about the nature of facial expressions, in particular, smiles. EDA was measured simultaneously from the hand and the neck of participants displaying spontaneous and posed smiles. Our results show that both measurement locations are highly correlated. Furthermore, EDA signals carry information about the spontaneity of the measured smiles, as shown by a classification accuracy of about 90%. Finally, head movement turned out to be rather revealing, with classification accuracy reaching about 99%.**

***Index Terms*—Affective computing, sensing, skin conductance, head movement, smile genuineness**

I. Introduction

Affective assessments are relevant in several application domains, including user and customer experience mapping [1], [2], and tracking affective therapy results [3], [4]. Among the different representations of affect, the circumplex model of affect [5] seems the most suitable for continuous measurement because it represents multiple emotion labels in two dimensions. These dimensions are valence and arousal. Valence refers to the degree of pleasantness, ranging from negative to positive. Arousal refers to how awake, alert, or activated a person feels. Both valence and arousal can be mapped to embodied affect responses.

Embodied behavior has long been considered an alternative to measuring emotion [6]. Early theories on emotion processes suggested that changes in our body states create the subjective feeling of an emotion [7], [8]. These embodied states include facial expressions of emotion, autonomic changes, and body movement. Whilst facial expressions are a good predictor of the valence [9], other autonomic physiological changes are associated with arousal [10]. Furthermore, behavioral cues such as head and body movement also carry information about the affective state of the person [11], [12]. These can be combined in a wearable which can provide information about facial expressions and their nature.

According to the Basic Emotion Theory (BET), several prototypical facial expressions of emotion are believed to be hardwired and mapped to a specific felt emotion as a result of natural selection [13], [14]. However, facial expressions can also be produced voluntarily, and they are often used to provide misleading information about the wearer's emotional state [15]–[17]. Moreover, facial expressions can also be used as a social signaling tool with several functions. In particular, smiles are not only an expression of joy. They also communicate reward, affiliation, and dominance [18], and they can be used as a polite greeting [19].

The lack of coherence between facial expressions and the experienced emotion encourages the use of multimodal systems to assess affective experience. In other words, identifying facial expressions of emotion alone might not be enough to fully understand affective experience. As arousal is one of the components of affect, it might prove useful to determine whether a smile spontaneously represents enjoyment, or if it is voluntarily posed as a social signal. Arguably, autonomic affective responses are less affected by volition than the production of facial expressions of emotion, and they co-occur with felt emotion [10], [20]–[23]. Moreover, head movement has been shown as a reliable source of information about the intention behind a facial expression as humans leak their intentions through body language [12].

Autonomic responses include Electro-Dermal Activity (EDA) or Skin-conductance (GSR). EDA carries important information for affective assessments [1], [24]. The EDA signal includes both tonic components (Skin Conductance Level-SCL) and rapid phasic components (Skin Conductance Responses-SCR) that result from sympathetic neuronal activity [23], [25], [26]. EDA is consistently regarded as an indicative of cognitively or emotionally mediated motor preparation. EDA responses might be expected to occur before spontaneous facial behavior has been initiated [10] as they also happen without the interference of volition [27]. An increase of EDA is usually observed in emotions other than non-crying sadness, acute sadness, contentment, and relief [10]. Thus, the presence

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of EDA responses might hint to positive affect co-occurring with an smile. Additionally, negative emotions are usually associated with more prominent autonomic responses than positive emotions [20]. This suggests that EDA responses might differ depending on the experienced valence, even though they are present in both positive and negative emotions.

EDA is also suitable as a wearable affective assessment tool due to the easiness to measure it [22], [28]. While previous studies have tested different EDA electrode placements [29], it is yet to be explored whether EDA can be used to make inferences about the coherence of felt affect and facial expressions of emotion. In this work, EDA was recorded as a measure of arousal, as well as head movement measured with an Inertial Measurement Unit (IMU). Head movement is hypothesized to increase accuracy when distinguishing posed from spontaneous smiles. Previously this was assessed using Computer Vision (CV) only [12], [30], head-worn sensor measurements are yet to be tested. Moreover, we explored the feasibility of using affective-induced EDA response assessment measured from the neck, compared to that from the hand. Measuring EDA from the neck for such assessments would make it easier to combine this arousal measure in other head-worn wearables that detect valence through facial expressions such as [31]–[33].

The contributions of this paper are the following:

- Show that it is possible to use neck EDA as an alternative to hand-measured EDA for dynamic affective judgments.
- Assess the feasibility of using EDA to make inferences about the spontaneity of a smile.
- Compare EDA response peaking (SCR component) with respect to the onset of a smile. We hypothesize that EDA peak timing would differ depending on whether the smile was elicited by felt affect or emitted with a cognitively prepared social intention. Cognitively emitted smiles might also cause a delayed EDA response due to the facial feedback hypothesis [34].
- Confirm the usefulness of head movement features in the assessment of smile spontaneity, in particular when measured with an IMU.

II. Related work

Smile genuineness has been assessed mainly through the morphology and dynamic features of the smile itself. For this purpose, CV is the most widely used technique. The use of spatial patterns achieved about 90% accuracy in the task of distinguishing posed from spontaneous smiles [35]. Dynamic features based on lip and eye landmark movements tailored to different age groups yielded an identification accuracy up to 92.90% [36]. Other algorithms using spatio-temporal features as identified by restricted Boltzmann machines achieved up to 97.34% accuracy on the UvA-NEMO database, and 86.32% in the Spontaneous vs. Posed Facial Expression (SPOS) database [37]. On the other hand, Electromyography (EMG) is also suitable for studying the dynamic differences between posed and spontaneous expressions of emotion [30], [38], [39]. A wearable approach using distal EMG with spatial and magnitude feature analysis allowed to distinguish spontaneous from posed smiles for the camera with an accuracy of about 74%. By employing spatio-temporal features, the accuracy reached about 90% [40]. This accuracy was maintained for posed smiles emitted in presence of negative affect, but only for subject-dependent models. With subject-independent models, the accuracy dropped to chance level [41].

Head movements have also been used to assess the nature of a smile using CV only. The direction of correlation among smiles as determined from the FACS Action Unit (AU) 12, head movement using a cylindrical head model, and direction of gaze may discriminate between facial actions with similar morphology but different communicative meaning. For example, lip-corner displacement and head pitch were negatively correlated as predicted for smiles of embarrassment, while a positive correlation may be typical of smiles of enjoyment [11]. Furthermore, the use of a cylindrical head tracker with head and shoulder movement features added useful information to facial features in the task of distinguishing posed from spontaneous smiles [12].

Both facial features and head movement have been shown to carry information about the meaning of a smile. However, the relationship between EDA and affect during posed and spontaneous smiles is yet to be investigated. Moreover, whilst EDA is typically measured from the hand, several studies have assessed the nature of EDA signals measured from different parts of the body. An exploration of 16 different body locations for EDA measurements showed that EDA activity is most responsive in feet, fingers and shoulders [29]. This suggests that the feet would be the best place to measure EDA given the high density of eccrine sweat glands on the soles [42], and the unobtrusiveness of the recordings. Indeed, the assessment of skin conductance on the lower limbs has been previously discussed as effective to assess different situations such as seizure detection [43], [44]. Despite the feet and ankles being a promising placement, it would be more convenient to combine EDA and other measurements, such as facial EMG and Plethysmography (PPG) measured from the earlobe, in a single wearable to assess the nature of facial expressions. Therefore, a more suitable measurement location would be the area around the shoulders. Currently, there is only one study known to us which has described EDA measurements from the neck [29]. However, they only reported examples of the signal and mean correlations. Therefore, we explored the validity of this location for measurement of EDA dynamic changes. Additionally, EDA has been related to involuntary affective reactions [10], [20], [24], [27].

III. Data set

EDA was measured from two locations along with elicited spontaneous and emitted posed smiles during presentation of both positive-valenced and negative-valenced stimuli as described in [41], [45].

A. Participants

41 participants took part in the study (19 female, average age = 25.03 years old, SD = 3.83). This research was approved by the Institutional Ethical Committee of the University of Tsukuba with review code 2017R176. All the participants provided written informed consent at the beginning of the experiment, and verbal consent at the beginning of each experimental block.

B. Experiment design

The experiment had several blocks. In the first block, "Spontaneous Block" (S-B), naive participants watched 10 s of raindrops video as baseline, followed by three videos generally perceived as funny, lasting 30 s each. The aim was to elicit spontaneous smiles. Afterwards, the participants answered the AffectGrid [46] to self-report their affective state after watching the stimuli. Next, the participants video-coded their own facial expressions by reporting whether it was a smile or not, and whether they thought it was spontaneous or posed. The second block, "Neutral Block" (N), was aimed to reduce the positive affect previously elicited. In the third block, the participants were asked to pose a smile for the camera during approximately 5 s as practice for the fourth block. In the "Posed Block" (P-B), the participants were requested to make similar facial expressions as they did when they watched the first video, for a contest. In the contest, another unknown person would have to guess the nature of the produced smiles. The participants were asked to do their best to win against the evaluator. The P-B stimuli video consisted of 18 IAPS pictures [47] with likeability scores between 4.0 and 5.0, presented every 5 s. Therefore, smiles during the P-B were considered posed. Finally, participants replied to the AffectGrid. After that, they video-coded their facial expressions similarly to the S-B. The video-coding was done with the Dartfish V3.2 software.

C. Measurements

EDA was measured from both the left hand index and ring fingers, and from the neck. Head movement was measured with two Inertial Measurement Units (IMU, Shimmer3 GSR+) placed on the back of the head with the aid of a circlet (Fig. 1). Video of the participant's facial expressions was recorded with a Canon Ivis 52 at 30FPS. All stimuli were presented in a Philips B-line 240B4 24 inches monitor with a resolution of 1920 x 1200 pixels. All sensors were synchronized to the start of the stimuli. A MSi GP602PE230 Laptop was used to present the stimuli and to control the triggers to synchronize all devices. The Shimmers were connected via Bluetooth to this Laptop. Additionally, the stimuli laptop was connected via USB to a custom hardware circuit. This circuit received wireless signals from a remote controller used by the experimenter to start the stimuli. Simultaneously to the stimuli start, one LED attached to the circlet above the right ear was lighted to mark the facial videos, and a software trigger was inserted using a local host UDP connection to a custom recording software developed in C# using the C# Shimmer API.

Fig. 1. *Wearables to gather data.* From left to right, the usage of the Shimmer3 GSR on the hand, and the Shimmer3 GSR integrated on an EMG wearable to measure skin conductance from the neck.

D. Data

According to the Affect Grid self-report (Fig. 2), valence scores were significantly higher in the spontaneous block than in the posed block ($F(1{,}64) = 11.47$, $p < .01$, $\eta_p^2 = 0.64$). This suggests that the producers felt more positive in the spontaneous block, and that they had to smile in the posed block even if they had slightly negative feelings. On the other hand, self-reported arousal did not differ among the experiment blocks ($F(1{,}64) = 0.50$, $p > .05$, $\eta_p^2 = 0.22$). According to their own video coding, 272 smiles were elicited from 32 participants. 127 were spontaneous (mean per producer = 3.54, SD = 3.32), and 145 were posed (mean per producer = 3.10, SD = 1.97). Besides the participants own video coding, two independent raters labeled the videos. They coded for the start frame and the duration of every facial expression. They labeled each expression as a smile, or another facial expression; and as a posed or spontaneous expression. Additionally, they labeled the involved FACS Action Units (AU) [48]. Smiles were often a display of AU6 and/or AU12. However, the smile label was not assigned every time these AU occurred. When judging whether participants were smiling or not, the Fleiss Kappa indicating the agreement between the two coders and the participants own video-coding was 0.57. However, the agreement fell to 0.13 when the task was to determine whether the displayed expressions were posed or spontaneous. Therefore, both experimental design and self-reported video-coding were considered when establishing the ground truth labels. 127 smiles were categorized as ground-truth-labelled 'spontaneous' as they occurred in the spontaneous block and were self-reported as spontaneous. 145 smiles occurring in the posed block and self-labeled as posed were assigned the 'posed' smile ground-truth label. For the EDA analysis, two participants were excluded due to excessive artifacts in the EDA signals. For analyses dependent on the smile number, 17 participants who had no or only one smile in one of the two classes were excluded. This situation occurred for several reasons: (1) the positive videos were so pleasant that the participants had a long lasting smile during the whole 1.5 minutes of the S-B, and given the instructions they also mimicked

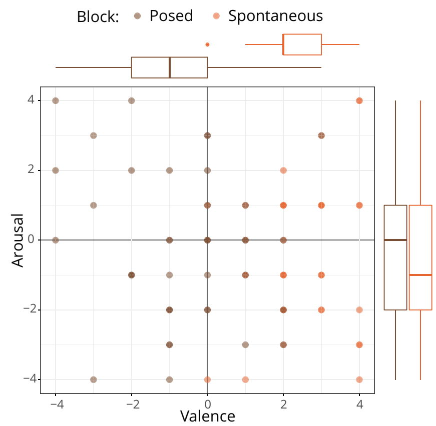

Fig. 2. *Self-reported Affect Grid values per block.* Participants (n = 41) felt more positive in the spontaneous block. In the posed block, they had to smile even if they had slightly negative feelings. Self-reported arousal did not differ among the experiment blocks.

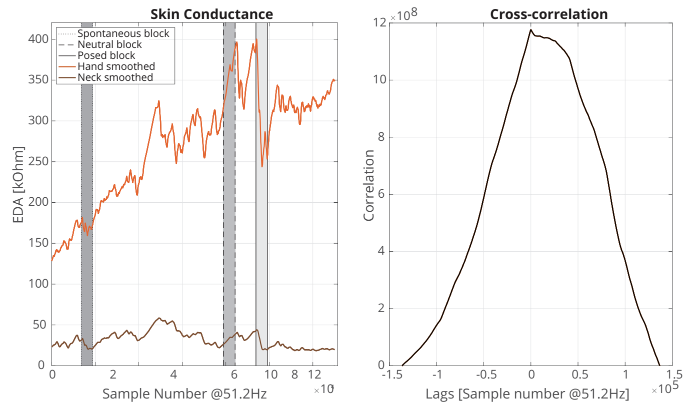

Fig. 3. *Skin conductance from the hand and neck.* The skin conductance measured from participant 41 is shown in the figure. There are similar trends in both measurements. The magnitude of the neck EDA is much less than for the hand. Gray zones represent the spontaneous, neutral, and posed experimental blocks, respectively. On the right, the cross-correlation between the neck and hand measurements is shown. The highest peak at zero lag suggests that there were no delays in the changes of both signals.

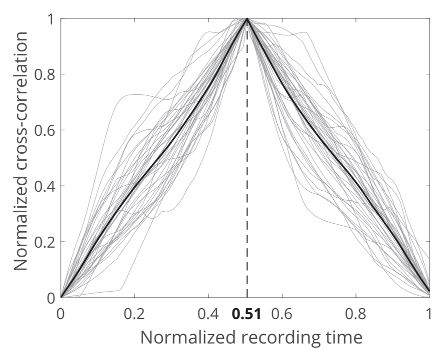

Fig. 4. *Cross-correlation of skin conductance from the hand and neck.* The plot shows the normalized cross-correlation between hand and neck skin conductance per participant in gray (n = 39), and the average of the cross-correlations in black. The maximum peak close to 0.5 means that the lag between them tends to zero. A triangular cross-correlation shape suggest auto-correlation. Therefore, we can assume the EDA signals from neck and hand are equivalent.

one long lasting smile in the posed block; (2) participants mentioned that sometimes a posed smile transformed into a spontaneous one when they thought about the irony of having to smile at the conflicting stimulus images, resulting on their posed smiles not being labelled as "posed"; and (3) the stimuli during the S-B was not funny enough to elicit an overt smile, thus, following the instructions, participants did not smile in the P-B either.

IV. Analysis and Results

A. Equivalence of skin conductance measurement location

The skin conductance measured from both the neck and the hand of each participant was first smoothed by using a 100 ms sliding window overlapping each sample. Then, a Savitzky-Golay Filter with a 1st order polynomial and 1001 samples as frame length was used to smooth the signal. The Savitzky-Golay Filter parameters were selected by visual inspection. The selection criterion was to remove motion-related artifacts in the EDA signal. Pre-processed EDA responses mildly fluctuated with the stimuli blocks. Hand EDA changed more than neck EDA. Hand EDA displayed typical tonic and phasic changes. On the neck EDA, phasic changes were about four times smaller in magnitude (Fig. 3). Nevertheless, cross-correlation between EDA hand and EDA neck signals during the whole experiment per participant showed strong correlations between these signals for all subjects (n = 39, Fig. 4). The peak centered at 0.51 is equivalent to zero lag, which suggests auto-correlation of the two signals. In other words, we can treat them as equivalent.

B. Mean EDA per experimental block

The mean EDA per experimental block was checked to rule out block effects. In addition to the pre-processing described in the previous section, the tonic component of the EDA was removed by subtracting the two coarsest coefficients from a Discrete Cosine Transform from the original signal [28]. Afterwards, the EDA mean of the 10 s baseline before each experimental block was subtracted from the rest of the EDA signal of the block. Fig. 5 shows the paired baseline-corrected EDA means per measurement location (n = 39). A Bonferroni-corrected Wilcoxon paired test indicated that the differences between the mean EDA during the spontaneous and posed blocks are not significant for both hand (V = 477, p = 0.23), and neck (V = 482, p = 0.2) locations. This is in line with the self-reported arousal. Participants did not report one block being more arousing than the other (Fig. 2).

C. EDA co-occurrence to posed and spontaneous smiles

Two types of analyses were performed to investigate the differences between EDA events co-occurring with posed and spontaneous smiles. First, the differences in the SCR responses per smile type and electrode location were explored relative to the smile onset to assess if EDA activity precedes facial behavior or not (section IV-C1). Second, the potential of using the data gathered to automatically distinguish spontaneous

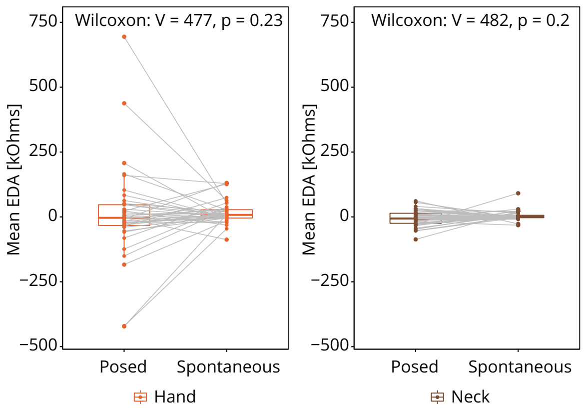

Fig. 5. *Mean EDA per block per participant (n = 39).* The means of EDA Magnitude per block after baseline correction are not different from each other. This is in line with the self-reported arousal, independently from the measurement location. Locations are indicated in color. The left plot corresponds to hand-measured EDA, and the right one to neck.

from posed events using a predictive model was investigated (section IV-C2).

1) SCR responses relative to the smile onset per smile type: The relationship between SCR peaks and smile onset was explored by using Nonnegative Deconvolution Decomposition [26]. The number of SCR peaks 5 s before and after each smile onset was extracted with a threshold of 0.01 muS. A 2-factor repeated measures ANOVA on Hand EDA with the number of SCR peaks as the dependent variable and time window and smile type as independent variables, yielded marginally significant results only for time window ($F(1{,}509) = 4.89$, $p = .04$, $\eta_p^2 = 0.04$), with more SCR events occurring before the smile onset than after it. The effect of smile type was not significant ($F(1{,}509) = 1.11$, $p > .05$, $\eta_p^2 = 0.04$) as well as the interaction between time window and smile type ($F(1{,}509) = 0.01$, $p > .05$, $\eta_p^2 = 0.61$). An analogous ANOVA for neck EDA data yielded no significant effects of time window ($F(1{,}509) = 0.45$, $p > .05$, $\eta_p^2 = 0.01$); smile type ($F(1{,}509) = 0.57$, $p > .05$, $\eta_p^2 = 0.04$); and their interaction ($F(1{,}509) = 0.38$, $p > .05$, $\eta_p^2 = 0.01$).

2) Identification of EDA responses during posed and spontaneous smiles: As suggested by [22], [49], a first set of features were extracted from the SCR component pre-processed as described in section IV-B. These included magnitude ratio of the absolute value of the SCR signal and the smile duration; the mean of the first order derivative of the SCR signal per smile; and the number of peaks divided by the minimum smile width. With these features, the amount of available information is reduced by the number of smiles elicited. More importantly, SCR peaks not always coincide with smile behavior. Therefore, the magnitude of the phasic components (SCRs) from the hand and the neck were also considered as feature sets 2 and 3, respectively. Three separate subject-dependent models of posed vs. spontaneous events were trained using a Support Vector Machine (SVM) with a Gaussian Kernel Function in a cross-validation with 70% train, 20% validation, and 10% test data partition. The first model used the first set of features

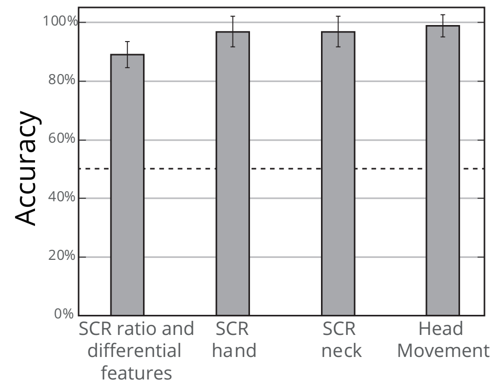

Fig. 6. *Accuracy of identification of posed and spontaneous smiles.* Bar char representing the identification results using hand and neck EDA SCRs, and head rotation features.

for the hand, as it showed more prominent SCRs. The second and the third models used the magnitude of the SCRs from the neck and the hand, respectively. The results are detailed in Fig. 6. SCR dynamic features achieved an average accuracy of 89% (SD = 10%), both SCR hand and neck features achieved mean accuracy of 96% (SD = 6%).

D. Head movement

Head movement was measured with a wearable IMU. An embedded algorithm in the measuring device allowed to estimate its orientation. The calculated quaternion data was smoothed using a Savitzky-Golay Filter with a 1st order polynomial and 301 as frame length. Usually participants kept still during posed smiles, but moved more during spontaneous smiles. This orientation feature data were used to train a SVM to distinguish posed from spontaneous events in a subject-dependent cross-validation with 70% train, 15% validation, and 15% test data partition. The results are slightly better than the ones achieved by measuring EDA (average accuracy of 99%, SD = 4%).

V. Discussion and Future Work

EDA co-occurring with spontaneous and posed smiles was measured from both hands and neck. As expected, the changes on the SCRs matched self-reported arousal levels for both experimental blocks. In this data set, the mean EDA levels were similar in both positive and negative stimuli, probably due to the stimuli mildness. Additionally, both measures from hands and neck are highly correlated with each other in their dynamic changes. This was corroborated by calculating the cross-correlation between the two signals. Nevertheless, EDA on the hands changed more prominently than that measured from the neck. This is probably due to the differences in density of eccrine sweat glands on both locations [42]. Given the different magnitudes, additional processing might be necessary to make these signals equivalent. Possible options include signal normalization, or threshold tuning for each case.

Moreover, EDA, as cue of arousal, was hypothesized to complement the spatio-temporal features characterizing the production of posed and spontaneous smiles. In particular because EDA is less prone to voluntary manipulation. Spontaneous smiles elicited by felt affect might be accompanied with increased affective arousal. Posed smiles emitted with a social signaling intent might lack such arousal changes, or present delayed EDA responses due to the facial feedback hypothesis. Additionally, posed smiles might be used to mask negative affect with distinct arousal changes from positive affect. In our data set, posed smiles were emitted even while watching slightly negative stimuli, so they correspond to the latter type. The results showed that EDA signals carry information about the spontaneity of smiles, as shown by a classification accuracy of about 96%. We tested that these differences were not due to the elicited affect alone. Despite the magnitude differences between neck and hand EDA, both were proven to be suitable for this classification task. Different features were calculated to train a SVM to classify between posed and spontaneous events. Commonly used features such as magnitude, first order derivatives, and peaks per smile have the disadvantage that only one feature can be calculated per smile. This is because the EDA responses are usually delayed and do not happen within the smile samples. In this data set, only eight participants showed enough smiles to perform such evaluation. Hence, the magnitude of the phasic components of the EDA (SCRs) alone was preferred to increase the data available for training and testing. This lead to better performance. Moreover, the results did not find any support for a particular timing of the EDA responses with respect to the smile onset per smile type. Most of the EDA peaks on the hand occurred before the smile onset, regardless of the posed or spontaneous labels. This was expected for spontaneous smiles [20]. In the case of posed smiles, EDA peaks might have anticipated the smiles as some sort of nervousness when deciding when to produce them. Nevertheless, neck EDA did not support these findings. However, we used only one threshold value and one response-window. Further analysis is required to confirm or reject this hypothesis with different parameters and different degrees of arousal.

Future work should also assess whether EDA information can contribute to distinguishing posed from spontaneous facial expressions more generally, and in different settings. We only explored posed smiles used to pose enjoyment during slightly negative stimuli. Other smiles with different signaling intent might have different co-occurring EDA signatures. Moreover, EDA was effective due to the constrained physical activity level and room temperature. Generally, it is difficult to find unique and invariant EDA signatures of emotion due to these confounding factors [10]. Thus, more robust multimodal measures that can work in the wild should be explored. Finally, another limitation of this study is the short duration of the posed and spontaneous blocks. Longer and more varied stimuli might prove useful to elicit more smiles per producer. Additionally, the selected stimuli induced only mild arousal levels. Inducing different levels of arousal would allow to assess the usefulness of EDA in different situations.

As expected from previous research, the head IMU data explained best the differences between the two types of smiles in the predictive model. Participants moved more during spontaneous smiles. In contrast, they moved more in between smiles during the posed block. Since the experimental setup constrained the movements the participants could make, head movements were rather revealing. Further research should investigate whether head movement features can generalize to more ecologically valid setups.

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