

Comparing the Affectiva iMotions Facial Expression Analysis Software with EMG

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People's faces display emotions, informing others about their affective states. In order to measure facial displays of emotion, Electromyography (EMG) has widely been used, requiring electrodes and technical equipment. More recently, emotion recognition software has been developed that detects emotions from videos. However, its validity and comparability to EMG is unclear. The aim of the current study was to validate the Affectiva Affdex emotion recognition software by iMotions for happy, angry and neutral faces and to compare it to EMG. Twenty participants displayed these facial expressions while videos or EMG were recorded. Findings show that happy and angry expressions can reliably be detected by the software and by EMG, while neutral faces are more often falsely identified as negative by EMG than by the software. EMG and software values correlate highly. In conclusion, Affectiva Affdex software can reliably identify emotions and its results are comparable to EMG findings.

Keywords: Displays of Emotion; EMG; Emotion Recognition Software; Affectiva; Validation

Introduction

Identifying which emotion somebody is experiencing is a crucial skill, facilitating social interactions. In a laboratory context, facial emotion expression can be measured using Electromyography (EMG, Fridlund & Cacioppo, 1986; Van Boxtel, 2010). EMG measures muscle activity using electrodes placed on the skin surface. Different muscles become active in response to different emotions. In particular, the zygomaticus major muscle reliably becomes active during displays of happiness (smiles), while the corrugator muscle is related to angry facial expressions (Dimberg, 1982; Tan et al., 2012). Activity of corrugator and zygomaticus can be used to differentiate positive and negative emotions from others, with particularly corrugator activity clearly demonstrating emotions of negative valence (Tan et al., 2012). Therefore, many EMG studies focused on measuring the activity of these two muscles in response to happy and angry faces (Dimberg & Lundquist, 1990; Dimberg

& Söderkvist, 2011; Dimberg & Thunberg, 1998; Dimberg, Thunberg, & Elmehed, 2000; Hofman, Bos, Schutter, & van Honk, 2012; Otte, Habel, Schulte-Rüther, Konrad, & Koch, 2011). For example, this technique has been used to study voluntarily controlled compared to automatic facial reactions to emotional stimuli (Dimberg, Thunberg, & Grunedal, 2002), responses to unconsciously perceived emotional faces (Dimberg et al., 2000), effects of perceived fairness on mimicry (Hofman et al., 2012) and neural mechanisms involved in facial muscle reactions (Achaïbou, Pourtois, Schwartz, & Vuilleumier, 2008). Research also investigated individual differences in muscle responses, e.g. due to gender (Dimberg & Lundquist, 1990), empathy (Dimberg, Andréasson, & Thunberg, 2011; Dimberg & Thunberg, 2012) and anxiety of individuals (Kret, Stekelenburg, Roelofs, & De Gelder, 2013). In summary, EMG is an established method, widely used to study displays of emotions.

However, more recently, novel software solutions have been developed that compute emotions displayed by faces from video recordings of the face. Software includes e.g. EmoVu (Eyevis, 2013), FaceReader (Technology, 2007), FACET (iMotions, 2013) and Affectiva Affdex (iMotions, 2015). To investigate the suitability of this software for research, it needs to be verified whether it (1.) reliably detects emotions and (2.) is comparable to previously established methods like EMG. The reliability of the Affectiva Affdex software has already been confirmed in a preliminary study by Taggart, Dressler, Kumar, Khan, and Coppola (2016), who demonstrated reliable emotion recognition by the software. However, its comparability with EMG remains unclear. Other face emotion recognition software (FaceReader) has been validated by comparing the software computations for happy and angry expressions with EMG results (D'Arcey, 2013). D'Arcey (2013) correlated FaceReader scores with EMG measures of the zygomaticus and the corrugator muscle to investigate comparability. Based on this validation method, the aim of the current study was to validate the Affectiva software by directly comparing it to EMG.

Participants are faster at producing a facial emotion and show stronger responses if they view a face displaying the same emotion (Korb, Grandjean, & Scherer, 2010; Otte et al., 2011). Therefore, in the current study, participants were instructed to imitate an emotional facial expression (happy, angry, neutral), while equivalent face stimuli were presented to them. Muscle responses to emotional faces can begin to occur as early as 300-400 ms after exposure (Dimberg & Thunberg, 1998), and therefore were measured starting from the initial presentation of the face for a 10 second period. As responses can be stronger on the left side of the face (Dimberg & Petterson, 2000), EMG was sampled from this side.

The current study investigated whether the Affectiva software can identify different facial expressions (smile, brow furrow) and emotions (joy and anger vs. neutral) as efficiently as EMG, by testing

participants once with EMG and once with a video recording, later analysed with Affectiva software. We expected greater absolute Affectiva scores for the happy than the neutral or angry value in the happy condition and greater scores for the angry than the neutral or happy value in the angry condition. We further expected significant correlations between EMG and iMotions measures. The full study was preregistered with the Open Science Framework (doi: [osf.io/75j9z](https://doi.org/10.31233/osf.io/75j9z)) and all methods and analyses were conducted in line with the preregistration unless noted otherwise.

In addition to these planned analyses, we conducted an exploratory test to investigate the accuracy of Affectiva for video recordings in which participants are wearing electrodes, covering parts of their facial muscles. To combine multiple measures, it might be desirable to be able to simultaneously use Affectiva software and EMG. However, the EMG electrodes cover muscles, possibly making it more difficult for the software to recognize emotions. Therefore, in one condition we simultaneously recorded EMG and Videos, to investigate whether Affectiva software can still reliably identify facial emotions when these are partially covered up with electrodes.

Methods

Participants

Twenty students between 18 and 29 years (mean age = 21 years, $SD = 2.6$, 17 female) from the University of Göttingen and the HAWK Göttingen participated in return for course credit. The sample size was based on previous research (Dimberg, 1982; Otte et al., 2011). All participants were right handed, had normal or corrected to normal vision (only contact lenses, no glasses) and no neurological or psychiatric disorders according to self-report. Five additional participants were tested but excluded due to not fulfilling the original inclusion criteria (2), technical failure (2), or because they did not complete the full study (1).

Task design and Stimuli

Three types of facial expressions were recorded from the participants (happy, angry and neutral) using a video camera and EMG electrodes respectively. The task was implemented in PsychoPy (www.psychopy.org) and consisted of two blocks, the order of which was counterbalanced between participants. Facial expressions of participants were recorded with a C922 Pro Stream Webcam (Logitech) during both blocks. In addition, one of the blocks included a facial electromyogram (fEMG) recording. Participants were asked to position their face between the two bars of an adjustable headrest to ensure a central position of the face during recordings. The experimental task for the participants was to imitate the emotions of 60 faces of the Karolinska Directed Emotional Faces (KDEF) database, which were presented in a randomized order. The stimuli consisted of 20 happy, 20 angry and 20 neutral facial expressions. Gender was counterbalanced between conditions (happy, angry and neutral) with 10 female and 10 male faces in each condition. Images were edited to the same format with Adobe Photoshop CS6 by matching luminance across images and applying a grey mask rendering only the facial area visible. The task started with a short, written introduction after which the participants could proceed by pressing the space button. During each trial, a fixation cross was presented for 5s, followed by the stimulus being presented for 10s at the centre of the screen. Participants could take a short break after a sequence of 20 stimuli had passed.

iMotion Affectiva

Videos were recorded in intervals starting from stimulus onset until stimulus end (10 sec). Videos were imported in iMotions Biometric Research Platform 6.2 software (www.imotions.com; note that due to an update this is a more recent software version, than originally preregistered) and analyzed using the Affectiva Affdex facial expression recognition engine. Emotion

probabilities were exported for all 60 stimuli per subject.

fEMG recording and pre-processing

The fEMG was recorded from 10 electrodes during one of the two blocks. All data were recorded with a Biosemi ActiveTwo AD-box at a sampling rate of 2048 Hz. The skin around electrode placement sites was cleaned with a soft peeling and an ethanol solution to enhance electrical contact between skin and electrode. Electrodes were prepared with electrode gel (Signagel) before the arrival of the participant. Electrodes were attached at the left side of the face using bipolar placement as suggested by Fridlund and Cacioppo (1986). For measuring *Zygomaticus major* activity, a line joining the *cheilion* and the *preauricular depression* was drawn with an eye pencil. The first electrode was placed midway along this line and the reference electrode was placed 1 cm inferior and medial to the first. To measure *Currogator supercilli* activity, an electrode was placed directly above the brow and the reference was affixed 1 cm lateral and slightly above the first. Alternative reference electrodes were attached behind both ears above the mastoid. The two ground electrodes were placed 0.5 cm left and right from the midline directly below the hairline. Two electrodes were attached to the *Orbicularis oculi* (1 cm below right border of the eye and 0.5 cm inferior and lateral to the first) to measure eye blink artefacts.

Data was processed with Brain Vision Analyzer 2.1 (Brain Products GmbH, Munich Germany). The following steps were conducted for each subject separately. A high-pass filter at 20 Hz and a low-pass filter at 400 Hz were applied. The *zygomaticus major* and *currogator supercilli* channels were re-referenced to their respective reference electrode to remove common noise between bipolar channels. The resulting data was rectified and segmented into three emotion-specific segments (happy, angry and neutral), which consisted of 20 epochs of 1200 ms respectively, starting 200 ms before stimulus onset. Segments were averaged per subject

and the mean amplitude between 0 and 1000 ms after target onset was exported.

Procedure

This study was approved by the local ethics committee of the Institute of Psychology at the University of Goettingen. After arrival, the participant was seated in an electromagnetic shielded chamber and provided written informed consent as well as relevant personal information. Participants were shortly briefed about the process of electrode attachment and then prepared for fEMG recording directly before the fEMG trial. After the fEMG setup was complete, the electrode offset was checked and adjusted to below 30 mV. Participants were instructed to imitate the displayed facial expressions. Each block lasted approximately 20 minutes.

Results

Confirmatory analyses

A difference value was calculated separately for the happy, the angry and the neutral trials. This value was computed from the results of the iMotions analysis and the fEMG results using the following equations: a) $\frac{\text{joy} - \text{angry}}{\text{joy} + \text{angry}}$, b) $\frac{\text{smile} - \text{brow furrow}}{\text{smile} + \text{brow furrow}}$ and c) $\frac{\text{Zygomaticus amplitude} - \text{Corrugator amplitude}}{\text{Zygomaticus amplitude} + \text{Corrugator amplitude}}$. One-tailed tests were used for all analyses, as hypotheses were directional; however, note that this did not make a difference for the significance of results in the current study.

Correlations between the Affectiva values and the EMG were computed, showing a significant correlation of the EMG measures with the difference score for Affectiva Smile and Brow furrow values, $r(60) = .761, p < .001$, and the difference score for Affectiva Joy and Anger values, $r(60) = .789, p < .001$ (Figure 1).

Furthermore, for each expression condition (happy, angry, neutral) separate one-sample-t-tests were computed to investigate whether each of the difference scores (joy/angry; smile/brow furrow,

zygomaticus/corrugator) differs from zero. Regarding the Affectiva Software, difference scores were significantly positive in the happy condition for both the smile/brow furrow, $M = 0.97, CI = [0.92, 1.02], t(19) = 40.81, p < .001$ and the joy/anger score, $M = 1.00, CI = [0.9996, 1.00], t(19) = 8837.84, p < .001$. They were significantly negative in the angry condition, for both the smile/brow furrow, $M = -0.88, CI = [-1.08, -0.68], t(19) = -9.13, p < .001$ and the joy/anger score, $M = -0.80, CI = [-1.00; -0.59], t(19) = -8.25, p < .001$. They did not differ from zero in the neutral condition for both the smile/brow furrow, $M = -0.24, CI = [-0.64, 0.16], t(19) = -1.24, p = .116$ and the joy/anger score, $M = -0.24, CI = [-0.57, 0.08], t(19) = -1.55, p = .069$. Regarding EMG, scores were also significantly positive in the happy, $M = 0.63, CI = [0.44, 0.81], t(19) = 7.08, p < .001$, and significantly negative in the angry condition, $M = -0.79, CI = [-0.83; -0.74], t(19) = -34.41, p < .001$, but they were also significantly negative in the neutral condition, $M = -0.43, CI = [-0.55, -0.32], t(19) = -7.71, p < .001$.

To investigate absolute value differences between conditions, dependent sample t-tests were used to investigate differences between conditions (e.g. Zygomaticus amplitude in the happy condition was compared to the negative and neutral condition, equivalent analyses were computed for the values of Corrugator amplitude, joy score, anger score, smile score and brow furrow score respectively). Descriptive statistics are displayed in Table 1, showing that the emotion measured through each respective measure showed the highest values on this measures, e.g Zygomaticus amplitude was highest in the happy condition, while Corrugator amplitude was highest in the angry condition but low in the happy and neutral condition. Dependent sample t-tests confirm this overall pattern, with the emotion measured by each respective measure significantly differing from the other two emotions, while the other two emotions did not differ from one another (Table 2). Note that the only exception from this pattern was the Zygomaticus score which was also significantly higher in the angry than the neutral condition.

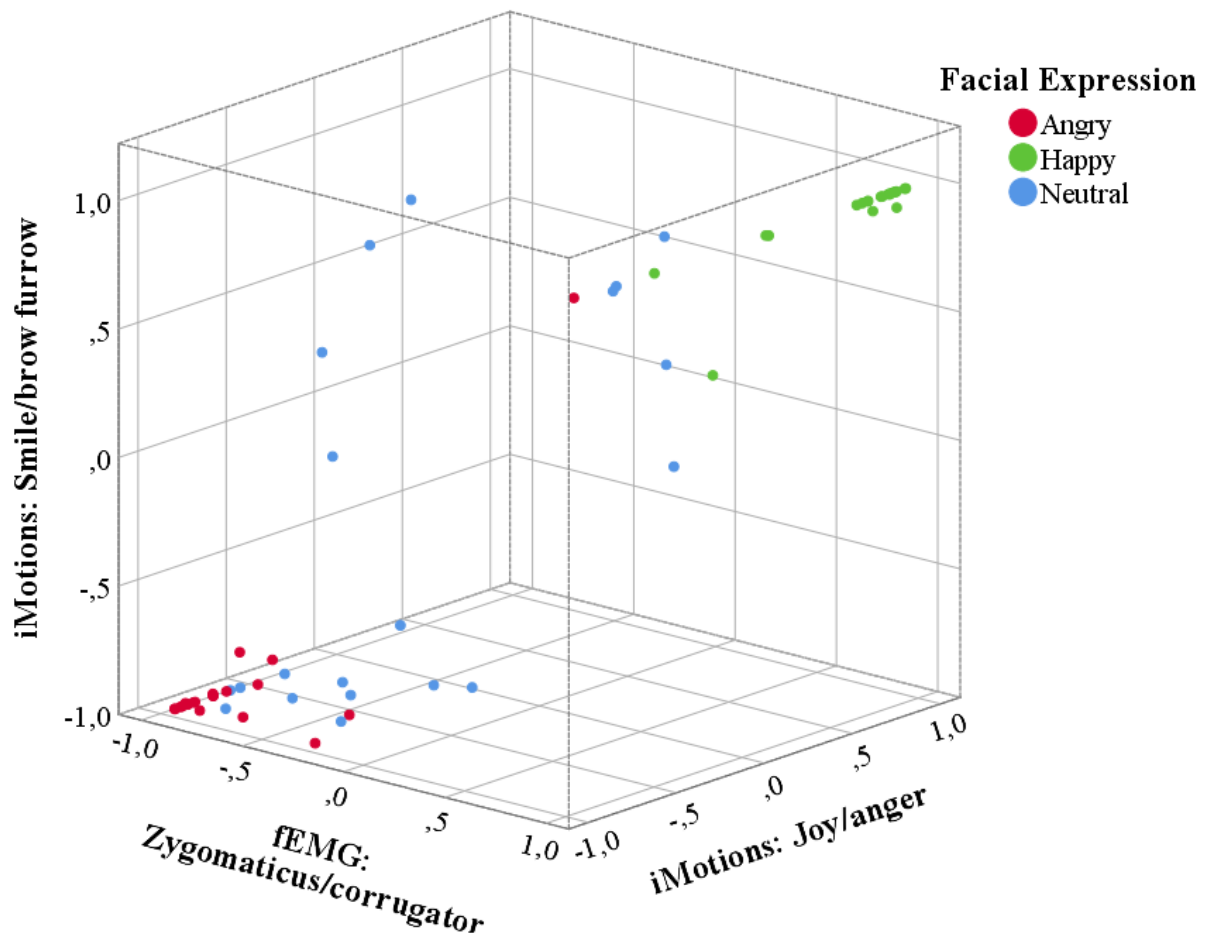


Figure 1. Scatter plot of difference scores.

Exploratory analyses

To explore the reliability of the Affectiva software in trials during which participants were wearing the electrodes, identical analyses were conducted with the difference scores of Affectiva Software computed during the EMG session.

Correlations between the Affectiva values and the EMG were computed, showing a significant correlation of the EMG measures with the difference score for Affectiva Smile and Brow furrow values, $r(60) = .754, p < .001$, and the difference score for Affectiva Joy and Anger values, $r(60) = .686, p < .001$ (Figure 2).

One-sample t-tests showed that difference scores were still significantly positive in the happy condition for both the smile/brow furrow, $M = 0.88, CI = [0.77,$

$0.99], t(19) = 16.69, p < .001$ and the joy/anger score, $M = 1.00, CI = [1.00, 1.00], t(19) = 667.11, p < .001$. They were significantly negative in the angry condition, for both the smile/brow furrow, $M = -0.80, CI = [-0.94, -0.65], t(19) = -11.43, p < .001$, and the joy/anger score, $M = -0.62, CI = [-0.92; -0.32], t(19) = -4.36, p < .001$. However, there now was a significant difference from zero in the neutral condition for the smile/brow furrow, $M = -0.48, CI = [-0.82, -0.13], t(19) = -2.88, p = .005$, though not the joy/anger score, $M = -0.17, CI = [-0.54, 0.20], t(19) = -0.96, p = .176$. To investigate absolute value differences between conditions, dependent sample t-tests were used to investigate differences between conditions, revealing the same pattern as for the Affectiva scores without simultaneous EMG recording (Table 3).

Table 1.

Descriptive statistics for the different outcome measures

Measure		Condition	M	SD	lower CI	upper CI
Affectiva	Anger	Happy	0.00	0.00	0.00	0.00
		Angry	8.88	8.72	4.79	12.96
		Neutral	0.11	0.39	-0.07	0.29
	Brow furrow	Happy	0.60	1.82	-0.25	1.45
		Angry	36.72	29.52	22.90	50.53
		Neutral	1.13	3.42	-0.47	2.73
	Joy	Happy	67.53	27.29	54.75	80.30
		Angry	0.14	0.40	-0.05	0.32
		Neutral	0.20	0.56	-0.07	0.46
	Smile	Happy	69.56	25.20	57.77	81.36
		Angry	0.52	1.42	-0.14	1.19
		Neutral	0.34	0.86	-0.06	0.75
Affectiva (during EMG)	Anger	Happy	0.06	0.23	-0.04	0.17
		Angry	5.30	6.92	2.06	8.54
		Neutral	1.12	3.74	-0.63	2.87
	Brow furrow	Happy	7.35	17.46	-0.82	15.52
		Angry	30.39	27.64	17.45	43.33
		Neutral	8.96	21.42	-1.06	18.99
	Joy	Happy	75.59	16.54	67.85	83.33
		Angry	0.54	1.86	-0.33	1.41
		Neutral	1.46	4.89	-0.83	3.75
	Smile	Happy	77.17	16.71	69.35	84.99
		Angry	1.84	3.62	0.15	3.54
		Neutral	2.31	6.65	-0.80	5.42
EMG	Zygomaticus	Happy	35.18	22.72	24.55	45.81
		Angry	4.48	3.22	2.97	5.99
		Neutral	2.43	0.78	2.07	2.80
	Currogator	Happy	6.18	8.84	2.05	10.32
		Angry	42.41	30.00	28.37	56.45
		Neutral	7.32	4.15	5.38	9.26

Table 2.

Dependent sample t-tests comparing the outcome measures between conditions

Measure	Conditions	t-value	df	p-value	p-value (one-tailed)
Currogator	Happy-Angry	-5.44	19	0.000	0.000
	Happy-Neutral	-0.49	19	0.629	0.315
	Angry-Neutral	5.20	19	0.000	0.000
Zygomaticus	Happy-Angry	6.03	19	0.000	0.000
	Happy-Neutral	6.49	19	0.000	0.000
	Angry-Neutral	2.96	19	0.008	0.004
Smile	Happy-Angry	12.23	19	0.000	0.000
	Happy-Neutral	12.38	19	0.000	0.000
	Angry-Neutral	0.46	19	0.648	0.324
Brow furrow	Happy-Angry	-5.60	19	0.000	0.000
	Happy-Neutral	-1.45	19	0.163	0.081
	Angry-Neutral	5.66	19	0.000	0.000
Joy	Happy-Angry	10.99	19	0.000	0.000
	Happy-Neutral	11.09	19	0.000	0.000
	Angry-Neutral	-0.38	19	0.706	0.353
Anger	Happy-Angry	-4.55	19	0.000	0.000
	Happy-Neutral	-1.27	19	0.221	0.111
	Angry-Neutral	4.60	19	0.000	0.000

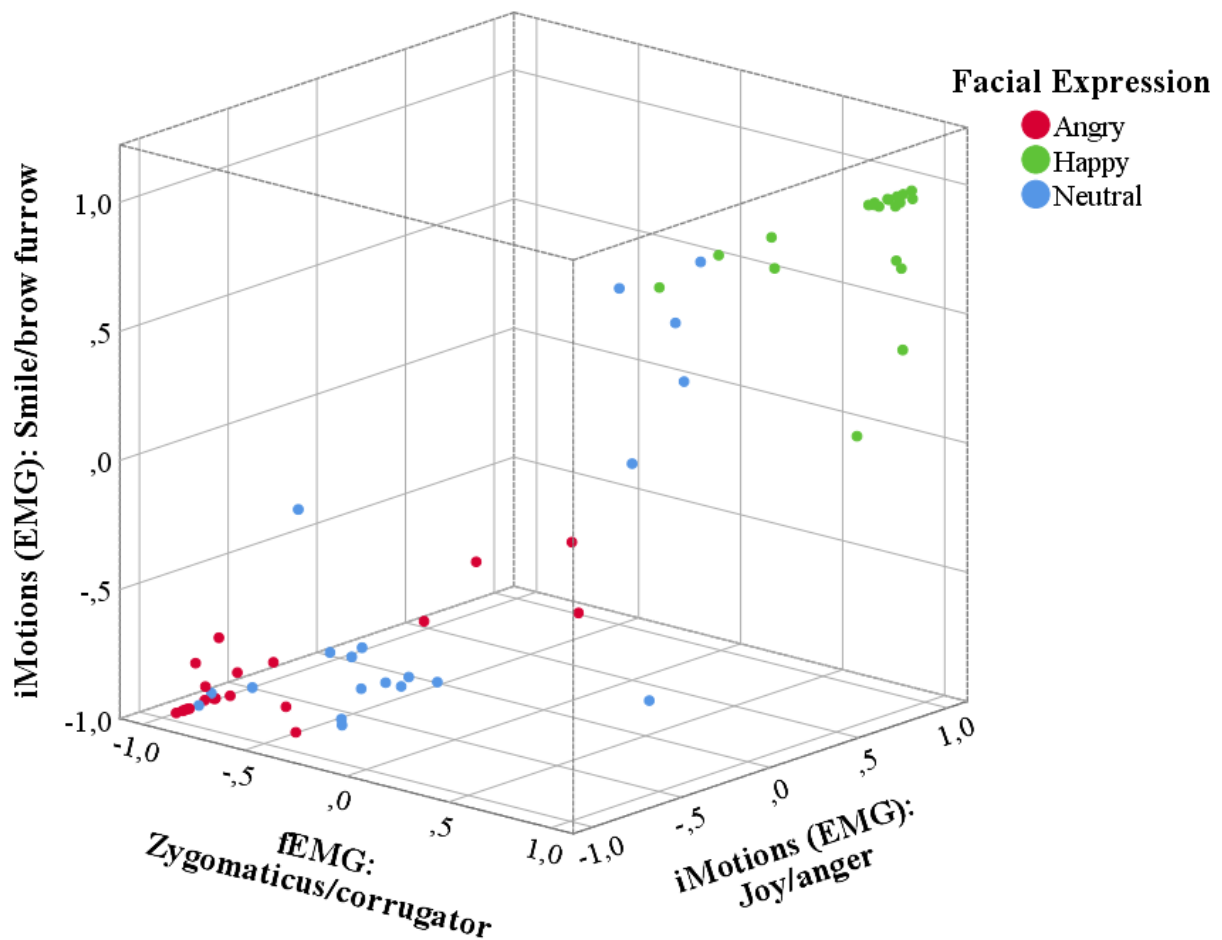


Figure 2. Scatter plot of difference scores for the EMG condition (electrodes attached).

Table 3.

Dependent sample t-tests comparing the Affectiva Scores during EMG testing between conditions

Measure	Conditions	t-value	df	p-value	p-value (one-tailed)
Smile	Happy-Angry	20.23	19	0.000	0.000
	Happy-Neutral	19.07	19	0.000	0.000
	Angry-Neutral	-0.45	19	0.658	0.329
Brow furrow	Happy-Angry	-4.56	19	0.000	0.000
	Happy-Neutral	-1.52	19	0.144	0.072
	Angry-Neutral	4.07	19	0.001	0.000
Joy	Happy-Angry	20.39	19	0.000	0.000
	Happy-Neutral	19.64	19	0.000	0.000
	Angry-Neutral	-1.31	19	0.205	0.102
Anger	Happy-Angry	-3.44	19	0.003	0.001
	Happy-Neutral	-1.35	19	0.194	0.097
	Angry-Neutral	3.07	19	0.006	0.003

Discussion

The current study aimed at validating the Affectiva software by comparing it with EMG concerning its ability to identify the emotions happiness and anger compared to neutral expressions. We expected measures of Affectiva scores to be comparable with EMG measures. In line with our hypotheses, there was a significant correlation between EMG and Affectiva measures. Difference scores between positive and negative measures were significantly positive in happy conditions for all outcome measures (Affectiva joy/anger and smile/brow furrow scores and EMG Zygomaticus/Corrugator scores) and negative in angry conditions. Only in the neutral condition, EMG scores were significantly negative, indicating that there was more Corrugator than Zygomaticus activity. Contrasts between conditions (happy, angry, neutral) in raw scores of the measures confirmed the expected findings, with the emotion that was measured with each respective measure scoring significantly higher than both other emotions, which in turn did not significantly differ from one another, as they scored generally low. The only exception was that the Zygomaticus amplitude was also higher in the negative than the neutral condition.

In addition, we explored whether the Affectiva scores are still reliable when

participants are wearing electrodes. Correlations with EMG scores were again very high. Happy expressions showed significantly positive scores and angry expressions negative scores. However, as for the EMG measures, neutral expressions now received negative scores.

In summary, both EMG and Affectiva Software could correctly identify happy and angry emotions acted out by participants and differentiate them from neutral faces. High correlations show that both methods are generally comparable. Furthermore, our exploratory analysis demonstrated that Affectiva software can still be used on videos of participants wearing electrodes used for facial EMG recording. However, compared to the videos in which participants were not wearing electrodes, the software was now less accurate, considering neutral facial expressions as negative. A previous study correlating FaceReader scores with fMEG, also suggested a tendency of the software to recognize neutral faces as negative – in this case “sad” (Suhr, 2017). However, note that in the current study during the EMG session both EMG and the Affectiva Software considered the neutral expression as negative. Therefore, one alternative explanation is that subjects might just have displayed more negative facial expressions in the EMG condition, leading to negative scores in neutral conditions for

EMG and Affectiva. The same participants completed all conditions, excluding the possibility that inert features of their faces caused the effect. Furthermore, the order of blocks with and without EMG was counterbalanced, excluding the possibility of an order effect. Possibly, the electrodes applied according to standard procedures affect facial expressions, leading to the observed differences. For example, there might be additional tension in the face due to the electrodes placed on the cheeks. In this case, Affectiva software used on videos without electrodes would provide more reliable values than EMG.

The current study focused on the most commonly researched emotions – happiness and anger – by investigating zygomaticus and corrugator responses. Future research could explore other emotions. Furthermore, the current study explicitly instructed participants to display

emotions. Additional research could explore implicit displays of emotion in response to stimuli, to investigate the suitability of Affectiva compared to EMG in recognizing more subtle emotional displays.

In conclusion, the current study showed that the Affectiva software can reliably detect the emotions “happy” and “angry” from faces and distinguish them from neutral expressions. The determined values further significantly correlate with EMG measures, suggesting that both methods are comparable.

Acknowledgements

We would like to thank Hannah Gessler for her help in preparing stimuli and set up, and Fabian Bockhop for assistance during data collection.

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