Università degli Studi di Padova

DEPARTMENT OF GENERAL PSYCHOLOGY

HUMAN INSPIRED TECHNOLOGY RESEARCH CENTRE

PHD COURSE IN BRAIN, MIND AND COMPUTER SCIENCE XXXIV CYCLE:

LIE TO ME: PROCESSING AND DETECTION OF SPONTANEOUS AND POSED EMOTIONAL FACIAL EXPRESSIONS

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"*I hardly heard what he said. I could not take my attention away from hisface.*

For me, the human face is the most important subject of the cinema."

Ingmar Bergman

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Synopsis

In social interactions, looking at others' faces, everything changes if the emotionsdisplayedare perceived as genuine or not genuine. For instance, a genuine (i.e.,spontaneous) positive emotion might promote social interaction, while a not genuine (i.e., posed or fake) emotion might promote avoidance. Thus, to ensure successful social interactions, we must appropriately understand the distinction between genuine and not genuine emotions. Surprisingly, the genuineness ofemotions is a topic still ambiguous and virtually unexplored so far. How can we distinguish spontaneous from posed emotional facial expressions? How do they differ in their kinematics? Is it possible to distinguish them automatically? To date, it is still unknown which features or facial movements candifferentiate genuine from posed emotions. State of the art about emotional lie detection reported significant variability and inconsistency among the results. Moreover, changing perspective, from the observer point of view, how do peopleimplicitly react to genuine or fake emotions? Do individuals process differently spontaneous and posed emotional facial expressions? If so, is it possible to findspecific neural correlates of genuineness in the processing of genuine and posedemotions? How different the cortical activity is during the visual perception of these two categories of emotions. How the same emotional expression can beimplicitly perceived according to the authenticity of the facial expression shownis a question still unsolved. Critically, the emotions conveyed by faces classically used as emotional stimuli in the research on emotions are not genuine. The genuineness of emotional facial expressions is topic has been surprisingly under-investigated. The current dissertation aims to respond to the following questions, exploring both how genuine and not genuine emotions can be discriminated, and how individuals perceive and react to them. In particular, the second and third chapter of the work will focus on emotional lie detection through machine learning models and kinematics analysis respectively. In the fourth chapter, for the first time, EEG Time-Frequency analysis will be used to compare the perception of genuine and posed emotional facial expressions. This project has relied on anew set of emotional stimuli (first chapter) created ad hoc for these purposes, where genuine emotions were elicited in the volunteers with the aim to createa strong correspondence between emotion felt by the participants and emotion perceived by the observers. Finally, in the last part of the dissertation, the implications and applications of the results are discussed in light of the stateof the art of lie detection, psychology and neuroscience of emotions, and the Artificial Intelligence field.

Chapter 1- Padova Emotional Dataset of Facial Expressions (PEDFE): a unique dataset of spontaneous and posed emotional facial expressions

1.1. Abstract

Facial expressions are among the most powerful signals for human beings to convey their emotional states. Indeed, emotional facial datasets represent the most effective and controlled method of examining humans' interpretation of and reaction to various emotions. However, the scientific research on emotion mainly relied on static pictures of facial expressions posed (i.e., simulated) by actors, creating a significant bias in emotion literature. This dataset tries to fill this gap, providing a considerable amount (N=1458) of dynamic, spontaneous (n=707) and posed (n=751) clips of the six universal emotions from 56 participants. Furthermore, pictures displaying frame by frame the temporal dynamic of the expression, are also available for each clip. Notably, all stimuli were validated by 122 human observers. Hit rates for emotion and genuineness, as well as the mean, standard deviation of genuineness, and intensity perception, are provided for each clip.

Keywords: facial expressions, genuine emotions, posed emotions, emotion dataset

1.2. Introduction

Facial expressions represent an innate and automatic behavior component of emotional and social communication (Darwin, 1872; Jack et al., 2016; Motley and Camden, 1988; Zloteanu et al., 2018). Emotional facial expressions, in particular, have a communicatory function that conveys specific information to the receiver (Andrew, 1963; Darwin and Prodger, 1998; Ekman et al., 1969; Jack et al., 2012; Jack and Schyns, 2015). For example, an expression of happiness through a smile in response to a particular behavior, increases the probability that the action will be repeated in the future, differently from an angry or sad face (Motley and

Camden, 1988). In this sense, the nature and the interpersonal function of the emotional facial expressions signal a feeling (or an intention) that predicts different social outcomes (Darwin, 1872; Ekman, 1972). It is precisely for this reason that knowing what another person feels, accurately deciphering what someone is trying to communicate, is extremely important in day-to-day social interactions (Johnston et al., 2010). However, the great variability of facial expressions makes this task very hard. In fact, emotions conveyed by faces can change under several parameters. We can display different varieties of expressions: some intense and sustained, while others are subtle and fleeting (Ambadar et al., 2005). One of the highest level and critical communication features is related to the perception of authenticity of the emotion expressed (Lu et al., 2020; Rooney et al., 2012). In fact, we can express emotions spontaneously, triggered by real circumstances (i.e., “event elicited")(Dawel et al. (2017). For example, someone might be scared because he is genuinely afraid of a snake or be sad because of the loss of a loved one. Conversely, we can deliberately feign or pose emotions in the absence of a congruent underlying context in order to receive adaptive advantages. These expressions reject the strategic intent of the sender in the absence of felt emotions (Ekman and Rosenberg, 2005). For example, pretending to be sad can be a useful strategy to take advantage of a perceiver's reciprocal kindness or compensatory behavior in response (Reed and DeScioli, 2017). The endogenous nature of emotional experiences (i.e., genuine or posed) completely changes the observer's perception and reaction. In social interactions, perceiving others' emotional reactions as genuine might promote social interaction and increase the expresser's trustworthiness (Reed and DeScioli, 2017). For example, Johnston et al. (2010) showed how genuine (or spontaneous) smiles make perceivers more cooperative than posed smiles. In psychotherapy, therapists' genuineness, authenticity, and honesty promote to enhance their credibility, which is essential for promoting therapeutic alliance and patients' trust (Dowell and Berman, 2013; Jung et al., 2015; Lu et al., 2020; Schnellbacher and Leijssen, 2009). Furthermore, in movies, the perception of realism in the actor's performance may promote a more emphatic mechanism and a more emotional contagion of the perceivers (Rooney et al., 2012). From a neuropsychological point of view, it has also been argued that genuine and fake emotions may recruit different components of emotional contagion (Manera et al., 2013). For example, there is evidence that genuine smiles are associated with the experience and physiological activations of positive emotions, while faked ones with the experience and physiological activation of negative emotions (Davidson et al., 1990; Ekman et al., 1990; Soussignan, 2002). Despite this evidence, to the best of our knowledge, only two recent studies used spontaneous facial expressions so far (Kunecke et al., 2017; Vergallito et al., 2020). Virtually all the previous research investigating facial expressions have focused on posed (or fake) emotions (Dawel et al., 2017; Tcherkassof et al., 2013), raising serious doubts about the ecological impact of these stimuli (Barrett et al., 2019; Russell, 1994; Tcherkassof et al., 2013; Wallbott, 1990; Wallbott and Scherer, 1986; Zuckerman et al., 1976). Spontaneous/genuine and posed/fake emotional expressions differ in their temporal and morphological characteristics, such as duration, intensity, and asymmetry (Cohn and Schmidt, 2003; Ekman, 1997; Sato and Yoshikawa, 2004; Valstar and Pantic, 2010; Wehrle et al., 2000; Yoshikawa and Sato, 2006). Indeed, posed emotions display stereotypical and exaggerate facial configuration that is rarely met in real life (Barrett et al., 2019). On the other side, spontaneous emotions in real life are usually less intense, more subtle, and more difficult to detect (Dawel et al., 2017; Tcherkassof et al., 2013). As a result of the strict focus on prototypical posed facial expressions, it is evident that researchers may have underestimated the considerable differences between spontaneous and posed emotional facial expressions. It is thus still not known whether our knowledge of processing of emotions conveyed by faces is biased by the fact that studies have been conducted using stimuli displaying stereotypical emotions. This important bias makes unknown whether the results on emotions perception from faces so far available within the scientific literature are driven by the (un)conscious perception of the non-authenticity of the perceived emotions. Even more importantly, it is not known whether results obtained using posed emotions are generalizable to genuine emotions. These research questions are still unanswered also because the scientific community is still devoid of a validated dataset of stimuli including both genuine and posed emotions from the same actors. Although some datasets including genuine and posed emotions seem to be present in literature (please see Krumhuber et al. (2017) for a review), their usefulness is limited as the emotions expressed are not genuine as elicited by methods that limited the spontaneity of the subjects' facial displays (e.g., subjects were aware of the aim of the studies, thus creating a barrier in the elicitation of spontaneous emotions) (Cheng et al., 2018; Kulkarni et al., 2018; Novello et al., 2018). In addition, some of them are not validated (Cheng et al., 2018; Kulkarni et al., 2018), or they are displayed only through static pictures (Dawel et al., 2017; Novello et al., 2018). The current work aims to enrich the future research of emotions providing the scientific community with a new dataset of emotional stimuli conveyed by faces, that includes a considerable amount of both spontaneous and posed emotional facial expressions of the six basic emotions. We called this dataset Padova Emotional Dataset of Facial Expressions (PEDFE). The contributions of the current research are multiple: first, PEDFE includes a considerable number of emotional clips for both spontaneous and posed emotions. The same emotion is displayed genuinely and posed for each participant, allowing a direct comparison (i.e., intra-subject and between-subject) between these two ways to express the emotional facial expressions. Second, the elicitation protocol uses a multimodal sensorial perception to elicit emotions as natural as possible, avoiding any restrictions or influences by the researcher (please see the paragraph "Dataset Creation"). To the best of our knowledge, the current emotion elicitation protocol has more tasks (i.e., 15) than the other reported methods. Third, all stimuli were validated by asking subjects to rate each clip according to the emotion, genuineness, and intensity of the facial expression perceived. It implies an essential step in creating emotional datasets that most of the datasets displaying genuine and posed emotions neglected. Last, PEDFE qualifies as the first spontaneous dataset displaying only the face, removing all distracting variables from the background (e.g., hair, clothes, color of the background, and so on), and providing several advantages in research (Davies et al., 1994; Minami et al., 2018; Tsao and Livingstone, 2008; Xu et al., 2017).

1.3. Dataset Creation

1.3.1. Participants selection procedure and compliance with ethical standards

Fifty-seven participants, aged between 20 and 30 years, took part in the experiment. Participants were randomly assigned to one of the two settings (please see Section 1.3.2). The sample was enrolled using an advertisement on the University Website and were compensated for their participation. Participants signed an informed consent before the beginning of the experiments. After reading this informed consent, they were still unaware of the purpose of the study and were unaware of being filmed. The participants were informed that they had the right to quit the experiment and withdrew their consent at any time. At the end of the session, participants were debriefed, and the study's real aims were revealed. They were also told they were recorded. One participant withdrew her consent, and her clips were permanently removed from the database. The experimental procedure and the emotional elicitation protocol submitted to the participants and described in the following paragraphs were approved by the Ethics Committee of the University of Padua (Protocol number: 2917). The participants' video recordings were included in the database only after they signed a written consent to use their videos for research purposes.

1.3.2. Experiment setup

The aim of the experimental procedure was to record spontaneous (i.e. stimulus elicited) emotions of participants while they watched emotional video or were performing simple tasks. For this reason, participants were left alone in an experimental room to decrease the possibility that embarrassment and social inhibition could affect the spontaneity of expressed emotion, impacting on the overt manifestation of emotions. The doors and windows were kept shut during the entire protocol to avoid external interference and allow participants a more in-depth emotional excursion during the tasks. Participants were set about one meter in front of a Lenovo ThinkPad T490. As it is known that awareness of the experimental aim can interfere with the spontaneity of overt emotional expression (Happy et al., 2015; Sebe et al., 2007), participants were unaware of the purpose of the experiment. For this reason, a cover story was created. In particular, participants were told they have to rate emotional valence of the videos, as already did for a previous study (Happy et al., 2015). They were also told that, in order to accurately assess emotions, they had to try to get immersed in the viewing experience and feel free to experience their emotions. Moreover, subjects were allowed to sit at their ease without any other restrictions inside the experimental room to avoid possible suspects or limit the emotions' naturalness. The same protocol was submitted in one of the two following modalities in order to enrich the database with different viewing angles. The first setting was created based on the well-known assumption that awareness of being filmed might impacts on spontaneity of overtly expressed emotions. Thus, in this first setting, a hidden camera placed at the right room's top angle was used. Participants were thus totally unaware of being recorded, preserving the emotional reactions' spontaneity. The clips were recorded with a AW-HE40HWEJ–Panasonic at a distance of at least 2 meters, with an angular size of 20°, varying in accordance with the head movements of subjects. The second setting was thought with the aim to create video depicting the participants on a frontal view. For this reason, in the second setting, a Logitech C920 HD Pro Webcam, Full HD 1080p/30fps, was placed at the top of the computer screen used for the tasks. In this setting, to preserve the subjects' expressions' spontaneity, participants were told that the recording was necessary to study the eye movements and pupil dilatation while performing the valence rating task. The two experimental setups guarantee more options to the experimenter who will use the emotional stimuli by having the same emotions (both spontaneous and posed) with a front and a lateral view (see Fig. 1.1).

a) First setting (b) Second setting

Fig. 1.1 : Examples of fear expressions for the two settings.

1.3.3. Emotion elicitation procedure

Spontaneous emotional reactions were elicited with a multimodal protocol. Emotions were mostly triggered by watching emotion-inducing videos, which resulted to be the most effective stimuli for evoking emotional responses (Carvalho et al., 2012). The clips were selected from different stimuli that have been used for similar studies (Rottenberg et al., 2007), and from other sources such as international films, commercial spots, and YouTube clips. The length of the clips did not exceed 5 minutes according to the recommended size of the emotional video (Rottenberg et al., 2007). The emotions were not only elicited through passive elicitation by watching emotion-inducing videos. For example, anger was also triggered by using a rage game, well-tested stimuli to provoke anger, in which the emotion was elicited as a result of the encoder actively engaging with the game (Sneddon et al., 2011). Indeed, the typology of these games was designed to make the task very difficult to purposely increase a high level of frustration and anger to the players. As, in pilots trails, we found that anger is often repressed, we provide participants with a desktop punching ball. Finally, as olfactory stimuli can reliably elicit disgust and have been resulted in very efficiently in previous studies (Hayes et al., 2009a, Zhang et al., 2016), an unpleasant odor was presented to the subject to induce a disgusting feeling.

The spontaneous emotion elicitation protocol is summarized in Table 1.1. Notably, more stimuli were chosen per emotion to enhance the probability of eliciting the target emotion and collecting more samples of clips displaying the same emotion for each subject. For example, in sadness, we used five tasks to trigger and collect sad facial expressions. This choice was due to the peculiar characteristics of sadness, which is associated with loss of muscular tone and a focus on inner thoughts and feelings (Ekman and Friesen, 2003; Izard, 1991) that make sadness more difficult to detect. The number of tasks used to elicit sadness as well as in other emotions and, in general, the size of the multi-modal elicitation protocol was thus extended to increase the chances to stimulate and collect more emotional facial expressions as possible from the same participant. The order of tasks from 1 to 14 was randomized across the subjects. After the end of each task, participants were asked to identify the emotion they experienced within the six basic emotion and neutral. They were also given the possibility to report if they felt an emotion that was not included within the six basic ones. Furthermore, besides identifying the emotion felt, they were also asked to rate how much the emotion they felt was genuine on a Likert scale ranging from -7 to +7 where -7 corresponded to “completely not genuine" and +7 corresponded to “completely genuine", according with previous literature (Dawel et al., 2017). Finally, participants rated the intensity of the emotions experienced during the tasks on a scale ranging from 0 (None) to 9 (Strong) (Dawel et al., 2017). When the multimodal emotion elicitation protocol was successfully concluded, participants were asked to pose the six basic emotions multiple times, modulating the intensity of the posed emotions.

1.3.4. Video extraction

One of the authors (AM), a certified Facial Action Coding System (FACS) coder, extracted the facial expression of emotions present in the recorded videos. The clips' selection was made considering both the FACS's criteria (Ekman et al., 1978) and participants' self-reports.

FACS is a widely used protocol for recognizing and labeling all visually discernible facial movements, called Action Units (AUs). In addition, the manual proposes a list of possible combinations of AUs which are typically associated with emotions expressions (Ekman et al., 2002). The current method was used to reliably and accurately extract the emotional facial expressions shown by participants. In other words, the clips were selected only if the emotional expression (e.g., happiness) matched FACS criteria (e.g., AU6+12) and participants' self-report (e.g., they declare to have experienced happiness with a high level of genuineness). In the case in which multiple emotions were induced (e.g., happiness and surprise), the emotional facial expressions associated were both selected if the self-reports and facial changes of participants were in accordance with the emotions elicited. Conversely, if participants reported having felt constrained and not natural in the emotional experience (e.g., a score of -4 on the genuineness scale), all the expressions associated with the task were removed. Likewise, if participants showed a facial expression associated with an emotion (e.g., a scowl that may reject anger), the facial change was not selected if participants did not report to have experienced anger. In fact, a scowl is not always a cue of anger but could instead reject confusion or concentration. This strict procedure aims to reduce the selection of facial expressions that do not convey authentic and spontaneous emotions. Each clip was cut from the onset point (i.e., the first frame when the expression is visible) to the apex (i.e., the period during which the movement was held at the highest intensity reached) of the emotion. Additionally, if the same emotion(s) was repeatedly elicited in a task, the related expressions were selected multiple times as much as the number of times participants spontaneously expressed the emotion(s) reported, in order to increase the number of clips included in the nal dataset and provide more trials of the same emotion for each participant. Lightworks (https://www.lwks.com/), a non-linear editing system (NLE) for editing and mastering digital video, was used to extract the emotional clips' perfect range frame.

Table 1.1: Multimodal protocol for Spontaneous and Posed emotion elicitation. Tasks are pre- sented in this table in the same order they were presented to participants.

Task	Emotion	Activity	Description	Lenght
T1	Sadness	Watch a VIDEO: Death of Mufasa, from the Lion King [1]	The clip displayed the saddest part of the movie, when Mufasa dies because of Scar, and the touching reaction of Simba.	02:42 min
T2	Sadness	Disney Pixar Up[2]	The scene where Ellie and Carl are shown. Their relationship is being shown as time passes from their wed- ding to Ellie's death.	04:21 min
T3	Sadness	"Giving without expecting anything in return is the best communication"[3]	Spot for Telecom in Thailand. The story is about kindness rewarded over the course of 30 years.	03:08 min
T4	Sadness	"Love is a gift"[4]	It's a short film about a man counting down the days to Christmas so he can continue his yearly tradition sparked by a tragic moment from the past.	02:25 min
T5	Sadness	"Edeka 2015 Christmas Commercial"[5]	Edeka's holiday commercial reminds people of the important things in life in a tragic piece of storytelling.	01:30 min
T6	Surprise	The Invisible Gorilla[6]	An experiment in Change Blindness.	01:00 min
T7	Happiness	When Harry met Sally	This is a classic and funny part to a very good movie. The restaurant/deli scene where Sally fakes an orgasm to prove a point.	02:46 min
T8	Surprise	Colour Changing Card Trick[7]	An experiment in Change Blindness.	02:43 min
T9	Anger	Flappy Bird[8]	A so-called "Rage game", namely a game while gaming and can't accom- plish your goal whatever that is, and you get random from your lack of suc- cess.	05:00 min
T10	Fear	Scare Jump[9]	A so-called jump scare, namely a game intended to scare the audience by sur- prising them with an abrupt change in image, co-occurring with a frightening sound.	04:00 min
T11	Anger	Abused dog in a metro	The clip showed the abuse of a dog, beaten by his owner on a public metro.	03:00 min
T12	Fear	Scare jump horror clip	A classic horror clip aimed to scare participants with frightening scenes and spectral sounds.	02:28 min
T13	Disgust	Pimples squeezing[10]	Disgusting huge and ingrown pimples are squeezed in the clip.	05:00 min
T14	Disgust	Stinky potion	A solution characterized by an un- pleasant smell that causes a strong re- action of disgust.	01:00 min
T15	-	Simulation Session	Participants were asked to pose each emotion as authentic as possible for 30 seconds each, trying to change their in- tensity.	06:00 min

1.4. Results

PEDFE contains clips and static pictures of 56 participants, displaying subtle to full-blown elicitation of different emotions. Overall, the number of emotional clips is 1731 (the exact number clips for each emotion and category are provided in (see Fig. 1.2), whose duration varies from 0.1seconds(s) to 23.5 seconds(s).

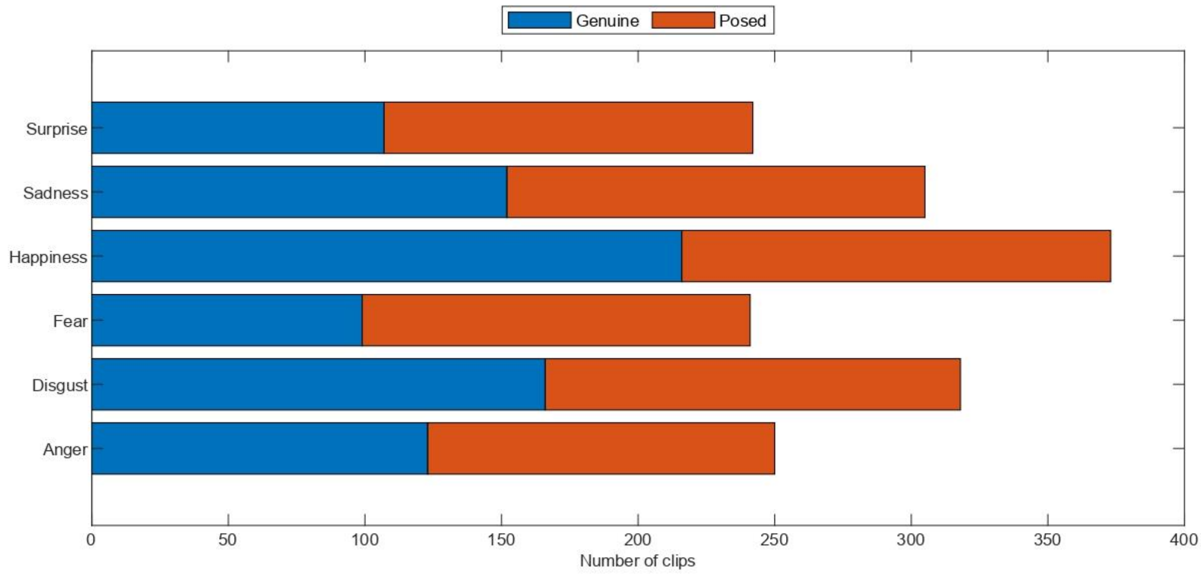


Fig. 1.2: Number of clips before the Validation, divided for emotion and type.

More precisely, the duration of the facial expressions varied in accordance with the emotion displayed. For example, sad clips last longer (M = 5:35s; SD = 2:92s) than other emotions such as happiness (M = 2:89s; SD = 1:25s), disgust (M = 2:81s; SD = 1:33s) or anger (M = 2:92; SD = 1:38) because of the gradual evolution of sadness over a longer timeframe. Conversely, emotions like surprise (M = 1:94s; SD = 1:04s) or fear (M = 1:86s; SD = 0:92s) emerged and disappeared faster, lasting a few seconds at the most (Ekman and Friesen, 2003) The considerable number of clips (i.e., 1731), as well as the self-reports given by participants, revealed the effectiveness of the elicitation protocol (please see Fig. 1.3, Fig. 1.4). In fact, most participants reported, on average, to have experienced the emotion that the elicitation tasks aim to do (except for Task 3). This was also confirmed by the intensity reported for each task, rejecting from medium to very high intensity (for the disgust tasks). Furthermore, the genuineness distribution rating revealed the spontaneity and genuineness of the emotional expressions displayed by participants. However, as expected and already reported in similar studies (Happy et al., 2015), the elicitation and recording of facial expressions occurring spontaneous emotional experiences is empirically not easy (Tcherkassof et al., 2013). Indeed, the emotional induction varied according to the subjective perception and sensitivity of the participants. For example, Task 1 ("The Lion King") was reported as very sad by most of the subjects, while a few experienced fear or anger. Yet, in Task 11 (“Abused dog in a metro"), most participants revealed to have experienced anger. However, others reported sadness, surprise, or even no emotions (i.e., neutral). Likewise, the intensity of the emotional excitement perceived varied across the tasks and between the subjects. Importantly, the intensity reported in self-reports is not predictive of the emotional expressions shown. For example, even though fear is reported as the second emotion per high level of intensity, the number of the clips is relatively low compared to other emotions (e.g., happiness).

Moreover, not all subjects display the entire range of emotions. While happiness and disgust were easy to induce (see Fig. 1.1), other emotions such as fear and anger were challenging to elicit (possible theoretical interpretations for these results are provided in the section 1.6).

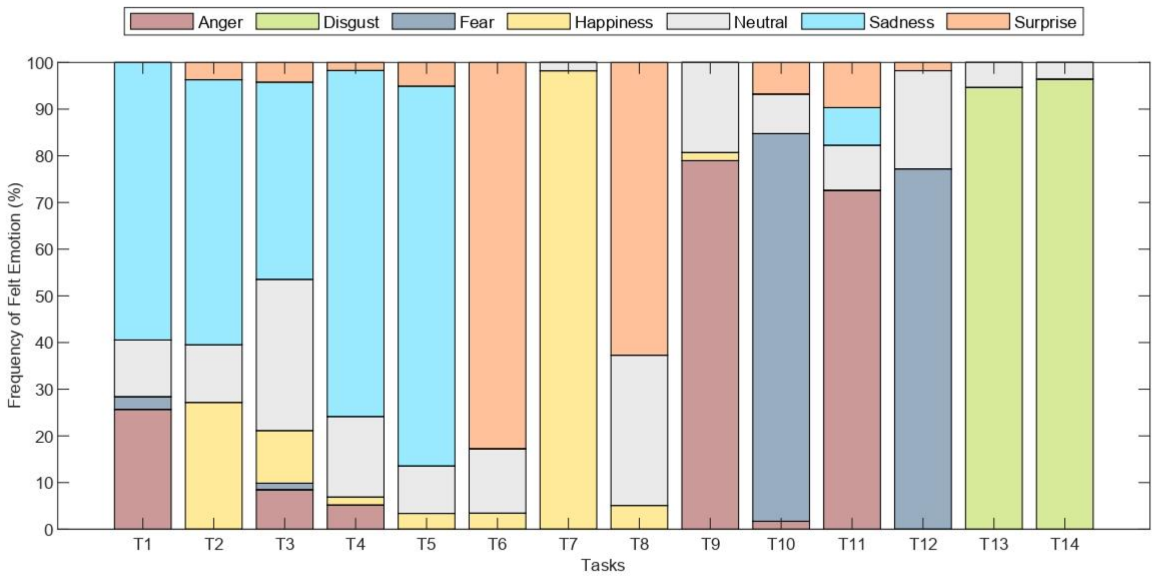


Fig. 1.3: Emotion distribution from self-report for each task

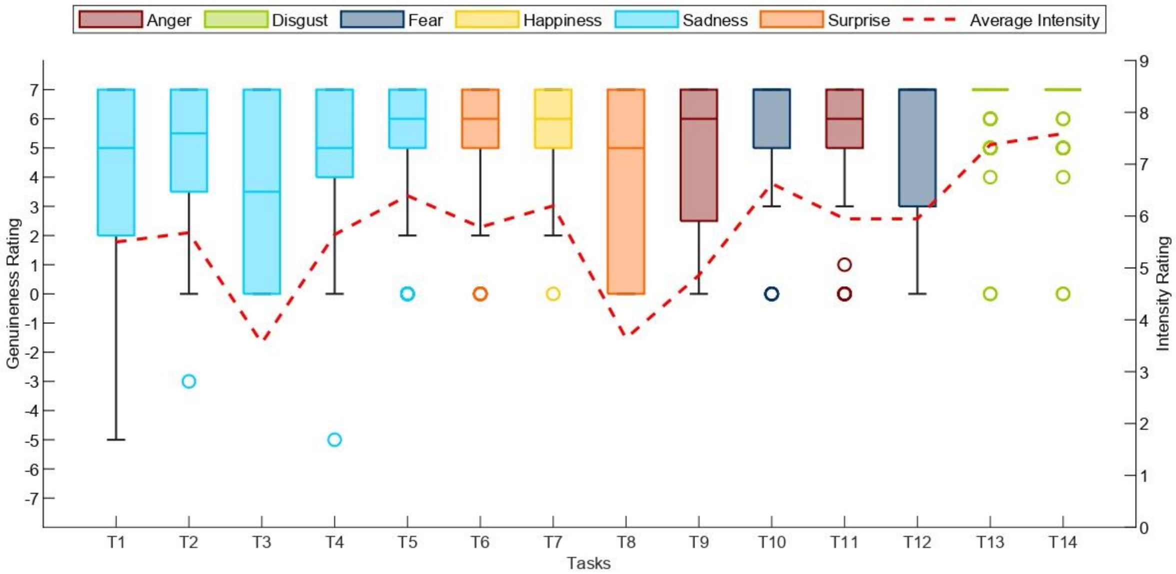


Fig. 1.4: Genuineness and Intensity rate distribution for each task. The boxplots of participants' ratings are provided for the fourteen elicitation conditions. At the end of each boxplot, the horizontal lines indicate the lower quartile of the responses, while the open circles represent the participants detected as outliers in the boxplot. The red dotted line indicates the average intensity reported in each task.

1.5. Validation

1.5.1. Participants

Being the number of stimuli very high (N = 1731), they were split into four independent blocks, each of them including approximately 400 stimuli. Each rater was randomly assigned to one block. A total of 122 participants were recruited for the validation study, matched for age (Mean=25.3; SD=2.47) and gender (Male=58 ; Female=64), resulting in each block being validated by 30 independent raters. A further 29 subjects did open the link to the rating task but never started it (i.e., 23.8% drop-out). Of all 122 participants, 98 (80.3%) completed the entire rating, while 24 raters (19.7 %) did not. Among these, 25% (6 out of 24) completed more than 70% of the questionnaire. The rest of participants (18 out of 24) partially rated the validation (23.8% on average), and their data is included. Participants were all graduate students at the University of Padova (Italy). The majority of the participants were recruited through the institute's participant pool. Others were recruited from online University discussion forums.

1.5.2. Procedure

The Validation Procedure was sent online to participants' email addresses using Qualtrics software (http://www.qualtrics.com). Participants were shown short clips displaying facial expressions of anger, disgust, fear, happiness, sadness, and surprise from the PEDFE. After each of the emotional clips, participants were asked to categorize the emotion, and the type of expression (i.e., genuine or fake) displayed. Last, participants evaluated how intense the emotions looked at them. The validation was conducted according to Dawel et al., 2017. The emotion recognition was measured with a fixed-choice question, with all the six presented emotions plus "neutral" and "none of the above" options (Frank and Stennett, 2001).
Thus, participants indicated which emotion label best described the displayed expression. Per the emotion category, we calculated the \hit rates" by dividing the number of accurately recognized emotions by the total number of displays for that emotion. The emotions' genuineness was rated with a 15-points Likert scale, ranging from -7 (completely fake) to 7 (completely genuine). The neutral midpoint "0" corresponded to "I do not know". In other words, all the ratings above "0" indicated a genuine perception of the emotion. Likewise, scores below "0" indicated a fake perception of the emotion shown. This method implicates different advantages. First, it allowed us to assess the ratings in absolute terms (i.e., genuine or fake). Second, it provided information regarding the gradient of genuineness perceived by raters (e.g., +7 indicates that the emotion was perceived as genuine without any doubt by the observer, a different gradient from a score of +1, very close to "0"). Doing so, we calculated the "hit rate" of genuineness by dividing the number of accurately recognized emotions as genuine or fake by the total number of displays. Simultaneously, the Mean and the Standard

Deviation (SD) of the gradient of genuineness were also calculated. Last, participants rated the intensity perception of the emotion shown on a scale of 0 (none) to 9 (strong). The mean and SD of these parameters were calculated. The questionnaire took about 2 hours and 30 min to be completed. However, participants were strongly suggested to divide the questionnaire into three days (i.e., 45 minutes of task per day).

1.5.3. Validation results

The “hit rate for emotion" was adopted as the main exclusion criteria for the original 1731 clips. In fact, all the clips recognized with a "hit rate for emotion" less than 30% were removed from the entire dataset, obtaining 1458 emotional clips (i.e., 707 spontaneous and 751 posed) in total (please see Table 1.2). Notably, on average, regardless of genuineness (i.e., spontaneous or posed), all the emotions were categorized with an accuracy of 78.6%, ranging from 58.01% (for fear) to 93.66% (for happiness). As expected, happiness is the best labeled emotion (both for spontaneous and posed expressions). Conversely, fear is the worst in accordance with the literature that reveal lower recognition rates of fear than the other basic emotions (Roy-Charland et al., 2014). Further analyses were run in order to investigate if the cause of the low accuracy rating of fear was due to the misclassification with the surprise. To do this, we calculate the number of times the emotion was categorized as a surprise for each clip. Results confirmed that, on average, fear is labeled as a surprise 29.76% of the time (SD 19.71%). Additionally, to evaluate if the intensity perception of the emotional expressions affects the emotion's discrimination, we conducted the Pearson correlation test. Importantly, the hit rate seems to be moderately affected by the intensity of the emotions expressed ($r = 0:44$, for 1458 items), in particular for anger expressions ($r = 0:67$ for 166 items). The correlations between hit rate per emotion and intensity are reported in Supplemental Material 1.A for each emotion. For what concerns the hit rate for the genuineness categorization, the global accuracy is stable across all the emotions (i.e., 62.51%), ranging from 60.22% (for disgust) to 65.25% (for fear). More precisely, genuine emotions were categorized better (i.e., 71.92% on average) than the posed ones (i.e., 53.65% on average), regardless of the emotion displayed (please see Fig. 1.5). Chi-squared test among all the binary responses extract by raters for each emotional stimulus confirmed the significant effect of the type of the stimuli (i.e., spontaneous or posed) on the hit rate of genuineness for each emotion with a $p < 0.00001$. In particular, anger $\chi 2$ $(1;N =1:4662)$ =

100:65, disgust $\chi2$ (1;N = 1:7719) = 221:97, fear $\chi2$ (1;N = 1:4049) =164:53, happiness - 2(1;N = 1:10876) = 376:52, sadness $\chi2$ (1;N = 1:6619) =172:65, and surprise $\chi2$ (1;N = 1:5823) = 100:94. In other words, people tended to classify posed emotions as genuine more often than they classify genuine as posed (please see Fig.1.5). Differently from the hit rate for emotion, these results are completely unrelated to the intensity (r = 0:11, for 1458 item) or the emotion (r = 0:06, for 1458 item) expressed. A theoretical explanation of these results is provided in section 1.6.

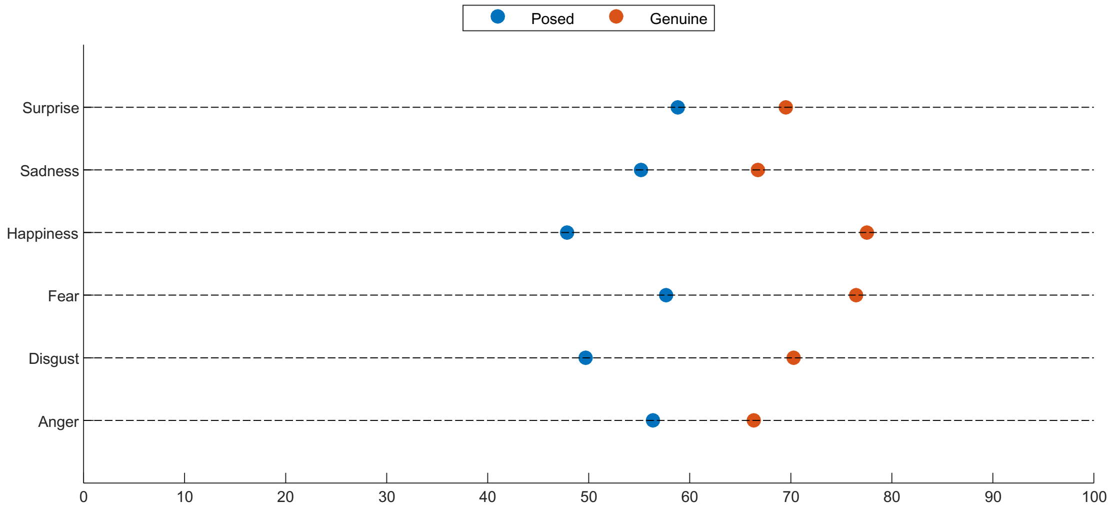


Fig. 1.5: Genuineness Hit rate for each emotion.

1.5.4. Video enhancement for Machine Learning applications

After all the emotional facial expressions were rated from the entire validation, the clips were submitted through different video processing steps. These phases aim to obtain clips containing only the face of the participant, removing everything that did not strictly concern facial expression. First, the clips were processed using OpenFace (Baltrusaitis et al., 2016).

OpenFace is a face detection software based on deep neural networks that we used to extract for each clip frame containing only the face of the subject (i.e., the background was removed, see Fig. 1.6).

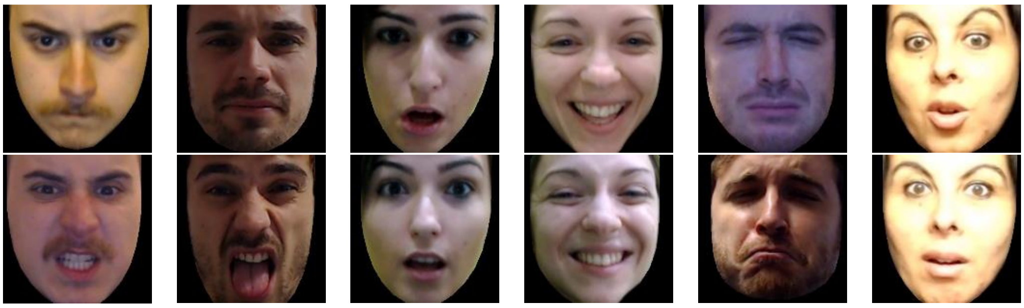
Fig. 1.6: Clip pre and post production

The size of each frame is fixed and was manually set to 300 x 300 pixels, meaning that all the extracted faces were resized to fit these constraints. In addition, OpenFace provides bidimensional coordinates of 68 facial landmarks for each frame. To maintain the native dimension of the faces, in order to avoid stretched images, we leveraged the coordinates of the landmarks to resize the frames of each clip. In particular, the maximum difference among x-coordinates and y-coordinates per frame was extracted. We then calculated the median value among all the frames of a clip, obtaining the native size of each face. Finally, we resized each frame of a clip to the corresponding native size, and we padded the frame with black pixels, obtaining new clips of 854 x 480 pixels (see Fig. 1.7). Moreover, for each clip, the pictures captured frame by frame displaying the emotions' temporal dynamics are also provided, except for the clips "5 dg 1" and "30 dg 1" that were successively removed due to the low quality of the recordings. The pictures were included in the dataset available to the scientific community as they can be beneficial to researchers to investigate the course of the emotional expression as well as the various degrees of intensity of the emotions (e.g., from neutral to mid to high intensity) with static pictures. Of note, the kind of emotion expressed by the participant, the genuineness and intensity of emotions felt are obviously not affected by the video enhancement procedure. Researchers who will use these videos should be cautious in generalizing the results of validation to these videos.

Table 1.2: Total number of clips included in PEDFE, followed by their respective hit rates.

	TOT	POS	GEN	HR Emo TOT (%)	HR Emo POS (%)	HR Emo GEN (%)	HR Type TOT (%)	HR Type POS(%)	HR Type GEN (%)
Anger	166	90	76	64.88	69.30	59.64	60.92	56.36	66.33
Disgust	305	149	156	84.48	87.10	81.98	60.22	49.69	70.28
Fear	156	93	63	58.01	53.95	64.01	65.25	57.66	76.47
Happiness	370	156	214	93.66	93.42	93.84	65.02	47.85	77.53
Sadness	251	132	119	71.09	73.57	68.35	60.66	55.18	66.74
Surprise	210	131	79	78.70	85.44	67.52	62.84	58.81	69.51
ALL	1458	751	707	78.61	79.51	77.66	62.51	53.65	71.92

Note. TOT: Total number of clips; GEN: Number of Genuine clips; POS: Number of Posed clips; HR Emo TOT: Emo- tion Hit rate for the total number of clips; HR Emo POS: Emotion Hit rate for Posed clips; HR Emo GEN: Emotion Hit rate for Genuine clips; HR Type TOT: Genuineness Hit rate for the total number of clips; HR Type POS: Genuineness Hit rate for Posed clips; HR Type GEN: Genuineness Hit rate for Genuine clips.



(a) Anger *(b)* Disgust *(c)* Fear *(d)* Happiness *(e)* Sadness *(f)* Surprise

Fig. 1.7: Peak intensity images of genuine (first row) and posed expressions (second row) of the six emotions included in PEDFE.

1.6. Discussion

So far, the emotions conveyed by faces classically used as emotional stimuli in the research on emotions are not genuine. Thus, to date it is still unknown whether our actual knowledge on perception of emotions conveyed by faces is biased by the unconscious perception of the non-authenticity of the emotion expressed and thus, if results achieved so far could be generalized to the perception of authentic, more ecological, expressions. The current work aims to provide the scientific community with a new dataset of emotional facial expressions including both spontaneous (i.e., genuine) and posed emotions from the same actor and validated by independent raters. Genuine emotions were elicited using an innovative multi-modal elicitation strategy, that allowed us to select the most effective strategy for each emotion's peculiarity. In the final dataset, which includes 707 spontaneous and 751 posed emotions, facial expressions of the six basic emotions are displayed both in dynamic clips and static pictures. As expected, some emotions such as fear and anger were more challenging to elicit than others (e.g., happiness or disgust) and, as a consequence, the number of stimuli included in the dataset varies according to the emotion expressed. For example, PEDFE contains 370 clips of happiness expressions and "only" 156 of fear and 166 of anger. This finding is perhaps not surprising, considering that fear and anger are known as the most difficult emotions to elicit (Rottenberg et al., 2007). The reason why anger is difficult to elicit might be because anger requires a high level of personal engagement to be experienced (Zupan and Babbage, 2017). The vision of clips and the rage game used in the elicitation protocol might have not triggered high levels of anger in all participants. As with regard of fear, this emotion was in some participants expressed through a passive freezing reaction (Lojowska et al., 2018; Roelofs, 2017), which was translated in a subjective experience of fear in the absence of facial movements. This made the detection and recognition of fear by means of facial clues harder.

In addition, stimuli aiming to elicit both anger and fear often cause a blend of negative emotions, such as disgust and sadness in the case of anger, or tension and anxiety in the case of fear (Rottenberg et al., 2007).This likely contribute to the expression of mixed emotions, not surviving to the stringent selection strategy we adopted, consisting in matching the emotion subjectively felt by the participants (rating), with the emotions expressed and codified by a certified FACS expert. This of course contributed to the relatively low number of clips. In general, regardless of the emotion considered, the collection of spontaneous expressions in an experimental setting is not easy because of a trade-off between ecological reactions and methodological restrictions (Sneddon et al., 2011; Tcherkassof et al., 2013). To make sure that participants' emotional facial expressions were natural and spontaneous, no restrictions (e.g., movements, eye gaze, the intensity of the expressions) were given to participants. This unavoidable compromise made it impossible to match the number of genuine and posed emotions perfectly. Furthermore, the great variability among the participants' sensitivity affected the expressions of emotions both between subjects and within the same subject (i.e., in expressing spontaneous and posed emotions). However, this limitation offers, at the same time, an ecological set of spontaneous facial expressions, providing emotions that differ under different features, such as the intensity of the expression, eye gaze, head movements.

Another contribution comes from the elimination of the background. Indeed, all the incidental features such as hair, clothes, the color of the setting room that may influence emotional expression perception were removed from the background of the stimuli. In other words, only the face on a black screen was portrayed in the clips. A further significant benefit of the isolation of the background concerns the automatic detection of the emotional facial expressions and the face. Indeed, many face recognition algorithms require prior segmentation and alignment or faces, failing with non-uniform background. Isolating the face from the background can help the algorithms align the face to a standard template and improve facial expressions' accurate detection (Tsao and Livingstone, 2008). Future users should however be aware that the independent raters validated the original clips and not the modified ones. However, future users could still benefit from the rater of genuineness and intensity of the felt emotions from the original actors. Notably, all stimuli were validated by human observers. The normative data obtained are in line with the typical finding in expressions databases (Langner et al., 2010; Palermo and Coltheart, 2004). More precisely, the hit rate for emotion is, on average, more than 93% for happiness and ranging from 64.88% to 84.48% for the other emotions. The only exception is fear, where the hit rate for emotion is 58.01%. However, it is noted how fear is easily mistaken for a surprise (Ekman, 1976; Ekman and Friesen, 1971; Rapcsak et al., 2000; Wang and Markham, 1999). The low level of accuracy in fear was indeed due to this typical tendency. In general, the emotion accuracies are moderately correlated with the intensity of the emotion perceived as reported in section Supplemental Material 1.A. In other words, the more intense the emotion is expressed, the higher is the accuracy rate for the emotion, in accordance with the literature of emotions. It is known how low intensity reduces labeling accuracy, affecting the observers' ability to detect whether an expression is shown because of insufficient physical information in the face (Barrett et al., 2019; Dawel et al., 2017; O'Reilly et al., 2016). Different from the hit rate for emotion, the accuracy of the hit rate of genuineness is on average 62.51%, highlighting the inability of humans in (emotional) lie detection. In fact, it is known that people (both untrained observers and professional experts like psychologists) are unable to recognize deceit in emotional displays, in particular, if they have to rely on visual cues only (Bartlett et al., 2006). Several studies demonstrated how people tend to perform not far from the chance level when asked to detect such behaviors (Levine et al., 1999; Porter and Ten Brinke, 2008; Porter and ten Brinke, 2010; Porter et al., 2012; Vrij, 2008; Bond & De Paulo, 2006). Furthermore, this problem is amplified by people's tendency to believe that the person with whom they are speaking is honest, regardless of whether or not that person is lying or being untruthful (Levine, 2014; McCornack and Parks, 1986). This mechanism called truth-bias belongs to human nature to believe and weakens its ability to detect deception. This was also confirmed in the validation of PEDFE, where the hit rate for the genuineness of posed emotion (i.e., when participants should have classified emotions as posed to respond correctly) is on average 53.65%. Conversely, the hit rate for the genuineness of genuine emotion (i.e., when participants should have classified emotions as genuine to respond correctly) is 71.92%. Also note, these results do not change according to the intensity of the emotion expressed. In other words, the intensity of the expression does not improve the accurate detection of spontaneous and posed emotional facial expressions differently for the hit rate for emotion.

1.7. Conclusion

This paper presents a new dataset of facial expressions displaying spontaneous and posed emotions. PEDFE contributes a unique source of ecological stimuli, providing 1458 dynamic clips and the pictures frame by frame of each stimulus. The significant number of emotions included in PEDFE, offers an excellent choice and a vivid picture of the variability in emotional expressions permeating real-life situations. Furthermore, the normative data give insight into the perception of emotional facial expressions by human observers. PEDFE may be an invaluable resource in different fields of study, such as psychology and analysis of non-verbal behavior, affective computing, and emotional lie detection. Future works will aim to enrich the dataset with new participants and more complex emotions.

Chapter 2- Inter-individual variability in the detection of spontaneous and posed emotional facial expressions

2.1. Abstract

Facial expressions are the most effective and reliable indicator of emotional states. However, people are adept at modulating and falsifying their emotional expressions according to their needs. To date, several attempts have been made to discriminate spontaneous (i.e., genuine) and posed (i.e., fake) emotions automatically. Unfortunately, the results obtained so far revealed significant variability and inconsistency in state of the art. The great inter-individual variability in the facial displays makes, indeed, impossible the detection of universal deceptive cues in the emotional expressions. In the current research, we developed a framework for the automatic detection of spontaneous and posed emotional facial expressions from clips. We applied the developed framework in two scenarios with the aim to classify the genuineness of emotional expressions ad hoc for each user (i.e., single case scenario) and investigate the relevancy of inter-individual variability in the emotional lie detection (i.e., group level scenario vs single case scenario). Results revealed that Machine Learning models achieved high accuracies in genuineness discrimination (84.4% accuracy on average) when capitalized for a single user specifically. Contrarily, the same approach obtained an average accuracy of 67.0% if trained and deployed on all the users generically. Finally, the implications and applications of the results are discussed in light of the state of the art of lie detection, psychology of emotions, and the AI field.

2.2. Introduction

The social sharing of emotions is a psychological phenomenon that explains the tendency to recount and share emotional experiences with others (Rime, 2009, Rime et al., 1998, Rime et al., 1991). Humans'nature to share emotions de- rives from different reasons such as obtaining help, care, or support, drawing attention, getting closer to someone, facilitating social interactions, and so on (Rime, 2007, Rime et al., 2020). In the last decades, the easy use of social media started to dig deeper and deeper down into society's brain stem, catalyzing the human tendency to widespread every aspect of their lives (Wang and Pal, 2015, Vermeulen et al., 2018, De Choudhury and Counts, 2012, Boychuk et al., 2016, Waterloo et al., 2018). The current social media platforms promote emotional self-expression, inviting users to post their positive and negative emotional expressions online regularly (Waterloo et al., 2018). TikTok, for example, is one of the fastest-growing social media platforms in the world, which allows users to share their personal content. According to the latest statistics, 689 million people are monthly active users. Among them, 55% upload their own videos displaying feelings, reactions, and emotions (https://www.oberlo.in/blog/tiktok-statistics). What we see on the social platforms are genuine emotions or something posed? Social media platforms are also a theater where everyone may fake their feelings. In fact, many people on social media do not display genuine emotions for a number of reasons, namely: increase or appease their followers, present idealistic self-representation, regulate their emotions by sharing their feelings, and so forth (Vermeulen et al., 2018, Bailey et al., 2020). Consequently, it is common to see fake (altered) facial expressions of emotions on social media. Many users may pose their emotional reactions, may hide their inner feelings, or overreact to scenarios they create through their social media profiles. It is human nature to lie. Therefore, how can we distinguish spontaneous emotional reactions from a posed ones? It is well known how people are completely unable to recognize deceit in emotional displays, in particular, if they have to rely on visual cues only (Bartlett et al., 2006), thus in the absence of a real context (like in social media). Several studies demonstrated how people tend to perform not far from the chance level when asked to detect such behaviors (Porter and ten Brinke, 2010, Porter et al., 2012, Vrij, 2008). Most advanced machine learning and computer vision analysis focused on the difference between the activation and the kinematics of the muscle movements, also called Action Units (AUs) (Ekman et al., 1978), in spontaneous and posed facial expressions (please see Jia et al., 2020 for a review). This method origi- nates from Ekman's theories (Ekman and Keltner, 1997, Ekman and Friesen, 1986), which identified six basic emotions characterized by a specific facial configuration in their display: happiness, sadness, anger, disgust, surprise, and fear. Previous research's aim was to identify the keystone about the emotional lie detection in facial displays, identifying a "common pattern" in detecting spontaneous and posed emotional facial expressions. Different features were investigated to discriminate spontaneous and posed emotions automatically. For example, spontaneous smiles seem to have a slower onset speed and larger duration than posed ones (Guo et al., 2018, Schmidt et al., 2006, Schmidt et al., 2009, Krumhuber et al., 2007). Conversely, onset and offset speeds tend to be greater in posed smiles than the genuine counterpart (Schmidt et al., 2006). Other features were also considered in the detection of spontaneous and posed facial displays, such as intensity (Krumhuber and Manstead, 2009, Krumhuber et al., 2009), symmetry of both sides of the face (Ekman, 2003, Guo et al., 2018), or the degree of irregularity (i.e., number of pauses or discontinuous changes in the phases of the expressions) of the emotional expressions (Hess and Kleck, 1990, Guo et al., 2018). However, although several studies have reported promising detection accuracy on specific datasets (i.e., intra-dataset testing scenario), the performance can vary widely using the dame detection method with different databases (Jia et al., 2020). Indeed, the generalization and the improvement of these models is a problem still unsolved so far (Jia et al., 2020). The machine learning models used so far yielded great variability among the results, lack of robustness of the models, and keep resulting controversy in the literature (Guo et al., 2018, Jia et al., 2020). Consequently, to date, there is still skepticism about the interpretability and applications of the results obtained. The weak consistency among the results may be due to the higher inter-individual variability in the facial displays of emotions (Holberg et al., 2006, Sangineto et al., 2014, Wehrle and Kaiser, 1999, Duran et al., 2017). In Holberg et al. (2006), the inter and intra-variability of the subjects were measured in controlled smiles. The results showed how inter-individual variability achieved up to 60% whereas the intra-variability was constant at 10%. Likewise, Golland et al. (2018) investigated the facial muscle activity during elicited emotional experiences by means of EMG. The relative results showed how the corrugator activity evidenced substantial differences and individual variability between the subjects. The poor performances may be thus due to the fact that the datasets used for training models do not adequately take into account the real-world scenarios variability, an effect called dataset bias effect (Khosla et al., 2012). This could explain why the accuracy of these models drastically drops in real-world situations with spontaneous expressions (Sangineto et al., 2014, Duran et al., 2017). The previous analyses are in fact based on averaged values of subjects, an approach that may be called group level scenario (i.e., user-independent), and do not consider the specific individual variations (Holberg et al., 2006). This bias is particularly important considering that different factors such as gender, age, culture, morphological appearance strongly affect the way in which emotions are exhibited (Grossard et al., 2018, Sangineto et al., 2014, Folster et al., 2014, Cordaro et al., 2018, Wang et al., 2019). Previous works on facial expression analysis have proved that person-specific models are advantageous in comparison with generic ones (Sangineto et al., 2014). Accordingly, it would be an understatement to neglect the inter variability among the subjects in favor of a generalist approach. Facial displays are not identical for different subjects, and perhaps even each person does not have a unique expression for the same emotion (Sadeghi et al., 2013). In the current study, we made a step forward, trying to identify a specific pattern in the genuineness of the emotional displays for each subject (different from the previous group level scenario). In other words, Machine learning (ML) models were used to detect a unique fingerprint of genuineness singularly for each user. Moreover, a comparison with a more generic approach (i.e., group level scenario) that neglects the specificity of the subjects' emotional displays in favor of an ensemble method was also provided.

2.3. Methods

In other words, Machine learning (ML) models were used to detect a unique fingerprint of genuineness singularly for each user. Moreover, a comparison with a more generic approach (i.e., group level) that neglects the specificity of the subjects' emotional displays in favor of an ensemble method was also provided. In the current section, the framework used for the prediction of posed and spontaneous emotions is described. In Fig. 2.1 the steps followed in our approach are depicted. In particular, 4 main steps have been identified:

1) **Stimuli:** Clips displaying spontaneous and posed facial expressions of the six basic emotions (i.e., happiness, sadness, anger, fear, surprise, disgust) were used for the current study. Stimuli were taken by PEDFE (Miolla et al., 2021), a new emotion dataset containing, for each subject, different clips of the same emotion, both in spontaneous (S) and posed conditions (P). Overall, 56 subjects display a total of 1729 clips (S:863, P:866), and more precisely 373 of happiness (S:216, P:157), 305 of sadness (S:152, P:153), 250 of anger (S:123, P:127), 241 of fear (S:99, P:142), and 242 surprise (S:107, P:135). For an extensive description of the dataset, please see (Miolla et al., 2021). The

dataset was divided into training (i.e., posed or spontaneous labeled clips) and test sets (i.e., unlabeled clips). Sets' size and composition depends on the configuration considered (i.e., group level or single case) and is discussed in detail in Section “Application Scenarios”;

2) **Data processing:** The Facial Action Coding System (FACS) represents the gold standard to detect and describe every single facial appearance accurately, also note as action units (AUs, Ekman et al., 1978). To automatically extract AUs from the set of emotional stimuli (AUs Activation Detection), all the videos were processed using OpenFace (Baltru_saitis et al., 2016). OpenFace, as far as we know, is the best state-of-the-art free software for AU extraction. It estimates the activation level of 17 AUs for each frame, providing two metrics: binary (active/non-active with predetermined threshold) or continuous (it assumes a value between 0 and 5, where 0 corresponds to inactive and 5 to maximum activation). A total of 136 features per video were extracted from the metrics provided by OpenFace (Feature Extraction). More precisely, 5 groups of features were calculated for each AU, as reported in Table 2.1;

3) **Model Generation:** Five binary Machine Learning models were trained on different groups of features and validated to select the best model/feature configuration for the prediction of posed and spontaneous emotions. In particular, Support Vector Machine with RBF kernel (SVM RBF), linear Suppor Vector Machine (SVM Linear), Ridge classifier (RC), Decision Tree (DT), and Random Forest (RF) were used as prediction models. A 5-fold cross-validation was applied to select the best combination of features. Further, hyper-parameters were varied by using the grid search on all five considered classifiers. Specifically, for SVM RBF C was varied among [10^{-2}; 10^{-1}; 10^{0}; 10^{1}; 10^{2}], and in the range [10^{-3}; 10^{-2}; 10^{-1}; 10^{0}; 10^{1}]. For SVM Linear C was varied in 10^{-2}; 10^{-1}; 10^{0}; 10^{1}; 10^{2}]. For both the SVM models a Standard Scaler was applied to normalize the input. α parameter for RC was tested in the range [10^{-2}; 10^{-1}; 10^{0}; 10^{1}; 10^{2}]. For DT the max depth was varied in the range [2; 3; 4; 5]. Finally, for RF number of estimator were set in [20; 50; 100; 500], and the max depth was varied in [2; 3; 4; 5];

Feature Group	Description	Formula
Activation	Average and standard deviation of AUs'intensity	$Mean_i = \frac{1}{N}\sum_{n=0}^{N-1} AU_i(n)$ $SD_i = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1} (AU_i(n) - Mean_i)^2}$
Normalized Activation	Normalized average activation and normalized standard deviation of the AU activation per frame	$NMean_i = \frac{1}{N}\sum_{n=0}^{N-1} \frac{AU_i(n)}{\sum_{k=1}^{45} AU_k(n)}$ $NSD_i = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1} \frac{(AU_i(n) - NMean_i)^2}{\sum_{k=1}^{45} AU_k(n)}}$
Duration	Activation duration of the AU normalized on frames number	$Dur_i = \frac{1}{N}\sum_{n=0}^{N-1} AAU_i(n)$
Speed	Average and standard deviation of the changes in AU activity	$SMean_i = \frac{1}{N}\sum_{n=0}^{N-1} AU_i(n+1) - AU_i(n)$ $SSD_i = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1} [(AU_i(n+1) - AU_i(n)) - SMean_i]^2}$
Entropy	Average dispersion of AU activity across subsequent frames	$Ent_i = \frac{1}{N}\sum_{n=0}^{N-1} \lvert AAU_i(n+1) - AAU_i(n)\rvert$

Table 2.1. Groups of feature extracted from OpenFace output leveraging the Action Units (AUs) and the Activated Action Units (AAUs) activity. Where *i*,k ∈ 1,2,4,...,45 are variables ranging over the action units, and n ∈{0,...,N} is the frame number.

4) **Predictions:** Selected model and group of features are used to perform the prediction on the testing clips.

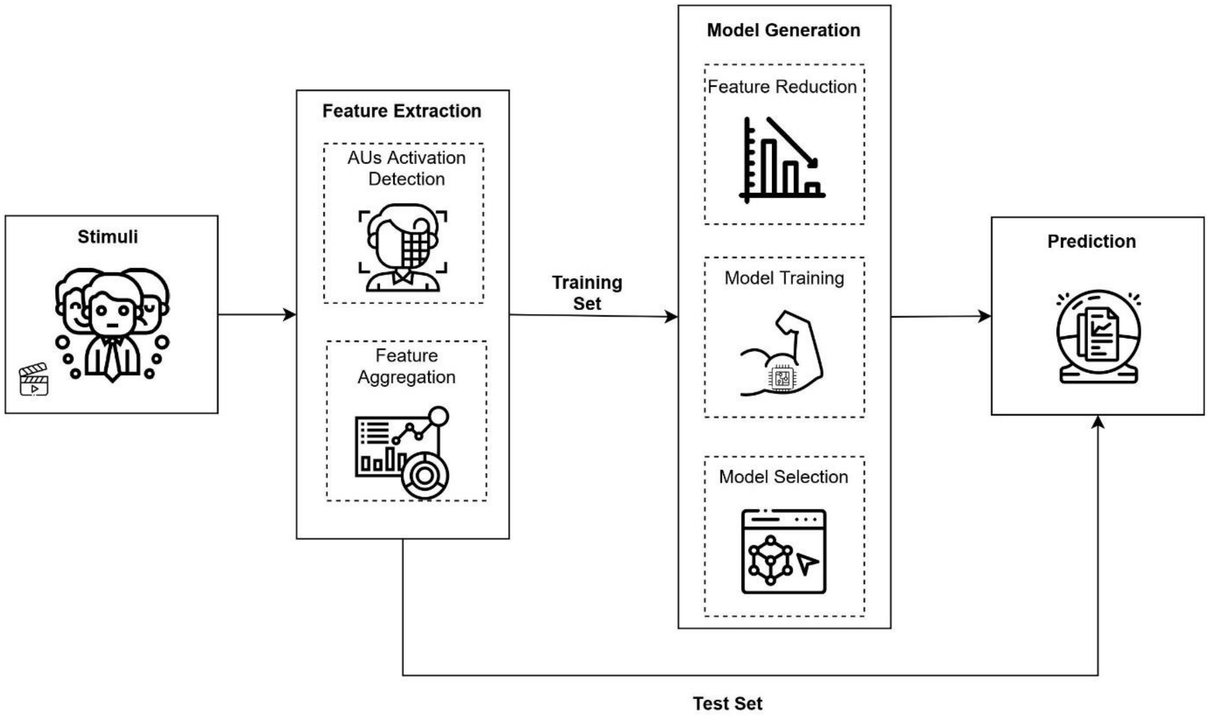


Fig.2.1. Framework for the automatic detection of spontaneous and posed emotional facial expressions.

2.3.1. Application scenarios

The significant amount of clips, as well as the several samples for the same subject and for the same emotion, allowed us to use two main analysis scenarios: group level and single case. These two scenarios were applied in order to investigate how the role of the intra-individual variability affects the detection of spontaneous and posed emotional facial expressions in automatic classification.

- **Group level scenario:** The group level scenario intends to identify a common (deception) cue to detect each emotion's spontaneous or posed facial expressions. This scenario assumes that the proposed approach is applied to an unknown subject (i.e., the subject is not present in the training set). To simulate this scenario, all the subjects were used for training the models except one used for testing (i.e., the unknown subject). This procedure was looped for each subject included in the dataset to avoid information leaking from the tested subject. In other words, no previous information (i.e., clips) about the tested subject are available in the training phase. In particular, a nested cross-validation (CV) was implemented. The outer loop consists of a leave-one-out CV per subject, while the inner loop consists of a group 5-fold CV used in the Model Generation phase for model validation, model selection, ad feature selection (please see Fig. 2.1.). This procedure was repeated for each emotion separately, generating a total of six models (i.e., one for each emotion).

- **Single case scenario**: The single case scenario aims to classify the genuineness of emotional facial expressions of a specific subject based on its already known emotional displays. In other words, the previous information (i.e., clips) of the subject was used for training the models in order to classify the genuineness of a new clip of the same subject. The application of the following scenario is twofold: first, to identify a fingerprint of genuineness in the emotional facial expression of each user; second, to investigate the impact of the inter-individual variability among the users' emotional displays. Contrarily to the group level scenario, all the clips of the specific user (i.e., previous information) were used to train the models except one used for testing (i.e., the subject's unknown clip). This procedure was looped for each clip of the subject by using a nested CV per clip. In particular, in the outer loop, a leave-one-out CV per clip was performed, while in the inner loop, a 5-fold CV was implemented for the Model Generation phase. Subjects with less than 20 clips were excluded from the analysis for lack of sufficient information in the training phase of the models.

2.4. Experimental results

The experimental results obtained in the group level scenario, yielded an overall accuracy of 67.0%. In particular, for anger was obtained an accuracy of 62.4%, for disgust 61.7%, for fear 67.4%, for happiness 65.4%, for sadness 69.9%, for surprise 75.5%. In this scenario, RF resulted the most selected model, followed by SVM Linear (see Fig. 2.5a). A significant improvement was obtained in the single case scenario, where an overall accuracy of 84.4%

was achieved. Specifically, the following accuracies were obtained for anger, disgust, fear, happiness, sadness, and surprise respectively: 90.1%, 82.2%, 84.6%, 81.7%, 89.8%, 83.2%. Different from the first scenario, SVM RBF resulted the best model for the majority of the users, followed by RC (see Fig.5b). The significant improvement in the genuineness classification can also be noted for each emotion singularly (see Fig. 2.2).

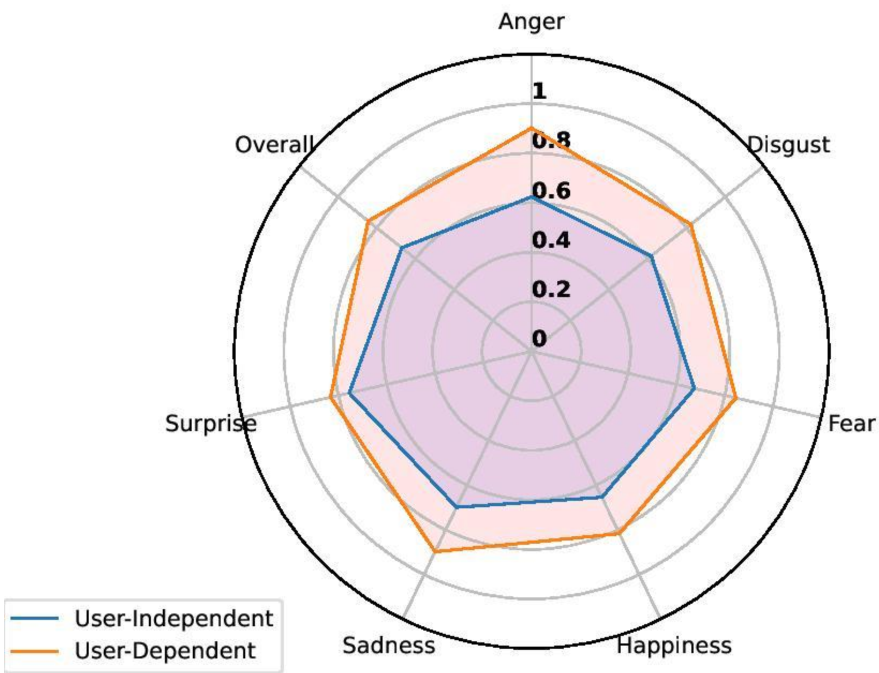


Fig.2.2. Accuracy detection in Group level and Single case scenario across all the emotions. Each axis of this circular radar graph represent the emotions investigated while the y axis inside the graph reflects the accuracy expressed as decimals.

In particular, the Single case scenario increased the performances by 27.7% for anger, 20.5% for disgust, 17.2% for fear, 16.3% for happiness, 19.9% for sadness, 7.7% for surprise, with an overall improvement of 17.4%. A further investigation was conducted by analyzing the differences in the classification for each user in both scenarios. The radar graph displayed in Fig. 2.3 confirmed the enhancement of performances in the genuineness classification for every single user.

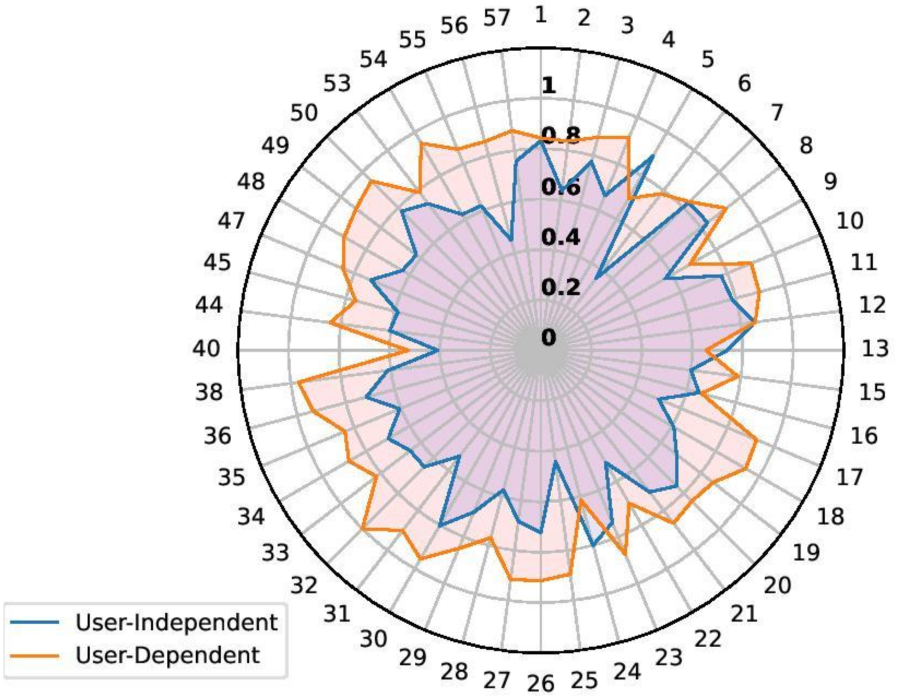


Fig.2.3. Accuracy detection in Group level and Single case scenario across all the subjects on average for all the emotions. Each axis of this circularradar graph represent the number of the subject while the y axis inside thegraph reflects the accuracy expressed as decimals.

Our framework showed an increase in the overall accuracy between Single case and Group level scenarios for 94% of the users. Analyzing each emotion (see Fig. 2.4) for the 90\% of the users, the prediction accuracy improved for anger genuineness classification. Sadness, fear, and disgust showed an improvement in 87%, 85%, and 83% of the users, respectively. Finally, surprise and happiness reported an improvement in 76% and 75% of users.

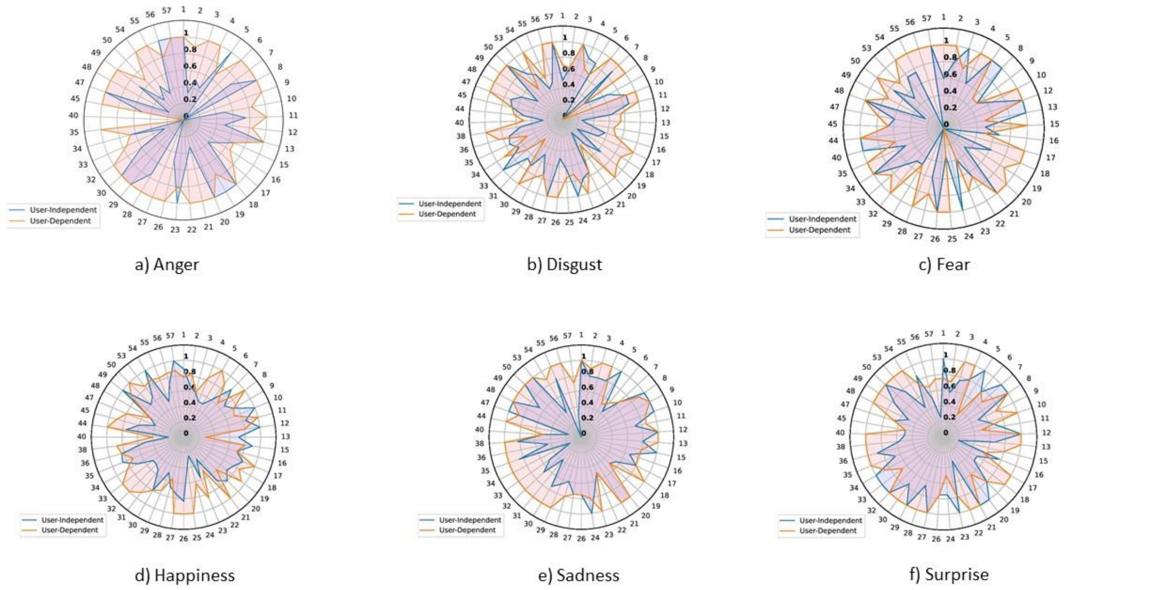


Fig.2.4. Accuracy detection in Group level and Single case scenario across all the subjects for anger(a), disgust(b), fear(c), happiness(d), sadness(e),and surprise(f) respectively. Each axis of this circular radar graph represent thenumber of the subject while the y axis inside the graph reflects the accuracyexpressed as decimals.

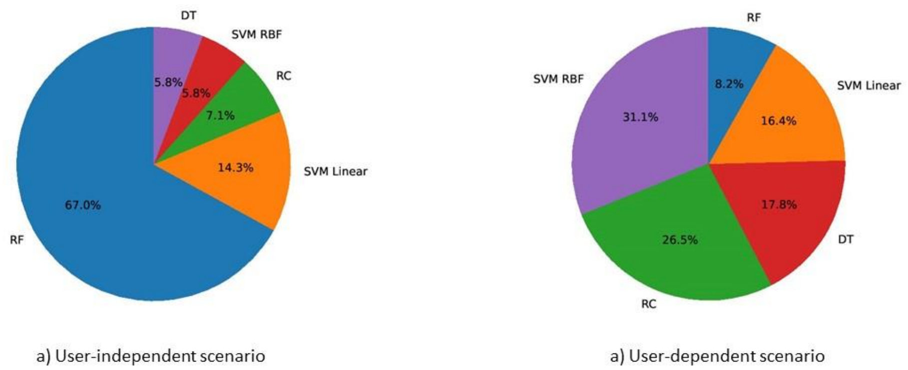


Fig.2.5. Frequency of selected models in our framework per scenario.

2.5. Discussion

In the current paper, Muscle Movement (Action Units) based ML models were used to automatically discriminate spontaneous and posed emotions. More precisely, five binary machine learning models were adopted in two different settings, namely Group level and Single case scenario. In the first setting, a leave one out nested CV per subject was used across the whole dataset of clips, recursively and randomly subdividing training, validation, and test set for each emotion regardless of the subject's identity displayed in the clips. The Group level approach was used to identify the common differences between spontaneous and posed emotions with no regard to the inter-individual variability of the subjects that performed the emotional facial expressions. Contrarily, in the second setting, a leave one out nested CV per clip was used singularly for each subject, thus splitting training, validation, and testing set only across the clips of the subject regardless of the emotion displayed. The following approach was used in order to take into account the potential inter-user variability in the emotional display. The results were of particular interest as they revealed a significant difference between the two approaches even though the same models were implemented on the same features. In particular, the Group level approach achieved on average 67.0% of accuracy. In contrast, the Single case approach performed with a 84.4% accuracy, reaching up to 90.1% accuracy for sadness emotion. The comparison of the performance between the two scenarios, highlights the significant differences across all the subjects' emotional displays. The general framework spontaneous vs posed emotions used in the Group level scenario was partially able to identify a keystone about the emotional lie detection in facial displays. However, the current analysis totally neglected the individual variations in the emotional displays, causing a drop in the performances if compared to the second approach. In fact, the same approach gained an overall 17.4% improvement if adopted singularly for each subject, and thus if they were specialized ad hoc for each user without trying to generalize a unique facial patterns to every user (i.e., Single case scenario). The implications of the following research are relevant on multiple levels. First, concerning the emotional lie detection applications, it seems that it would be more reliable to focus on detecting the unique deceptive cues for each subject instead of identifying a common rule to discriminate spontaneous and posed emotional facial expressions generally. In other words, the significant inter-individual variability in people's emotional display may underestimate the intra-individual differences between spontaneous and posed emotional displays of each subject. Consequently, it may seem that, despite some similarities (detected with 67% accuracy by Group level scenario), each subject tends to have a specific strategy or deception fingerprint that discern spontaneous from posed emotions. This factor may partially explain the inconsistent results obtained so far in the automatic detection of the genuineness of emotional facial expressions (Jia et al., 2020, Guo et al., 2018, Luke, 2019, Jupe and Keatley, 2020). Second, these results remarked the higher inter-individual variability in the facial displays of emotions, already highlighting in previous studies (Holberg et al., 2006, Sangineto et al., 2014, Wehrle and Kaiser, 1999, Duran et al., 2017). In other words, the valuable differences and individual variability between the subjects reflected in different characteristics (e.g., gender, age, morphological traits, and so on (Grossard et al., 2018, Sangineto et al., 2014, Folster et al., 2014, Cordaro et al., 2018, Wang et al., 2019) was revealed to be an essential factor to be considered. Third, these results are particularly interesting also in relation to the universality of emotions (i.e., basic emotion approach) proposed by Ekman (1992[a]). The basic emotion theory claims the existence of prototypical facial configurations for some given emotion categories (i.e., basic emotions, Ekman, 1992b, Ekman and Cordaro, 2011). For example, according to the theory, the facial core configuration of anger is typically reflected by furrowing the brows, widening the eyes, and tightening the lips. Additionally, some variants may involve the opening of the mouth or include the narrowing of the eyes only (Ekman et al., 2002). According to that, it would be possible to read people's emotional states universally, and, more important, it would be possible to discriminate spontaneous from posed emotions basing on temporal (e.g., onset time of the expression), and morphological cues (e.g., reliable muscles, Ekman and Rosenberg, 1997, Mehu et al., 2012). As a consequence of that, the models used should have been able to generally discriminate spontaneous and posed basic emotions across all the subjects, without any concern about the significant potential variability in the emotional displays. However, the Group level approach partially confirmed a common pattern between all the subjects. In fact, even though it is possible to find a slight similarity in the emotional deception for all the individuals included in the dataset, the intra-individual analysis (i.e., Single case approach) was revealed to be more accurate and precise than the general approach (e.g., Group level approach). In other words, albeit same inter-subjects similarities found by ML models, our results yield significant differences between subjects. These results align with the recent theories of emotions that refuse the universality of emotional facial displays. In particular, other scientific frameworks suggest that the facial configurations of emotions may vary substantially across different people and situations (Barrett et al., 2019). In particular, the behavioral ecology view (BECV) proposes that facial expressions are flexible tools that mute change over time for cultural or natural reasons and may cause diversity across people (Crivelli and Fridlund, 2019). This could explain why the Single case approach outperformed the generic Group level approach. However, it is fair to assert that these results may also depend on the simplicity of the models and features used that are not able to generalize to all people's emotional displays (i.e., Group level scenario) like in the Single case scenario. Finally, the importance of the intra-individual variability is also relevant in relation to the use of the recent emotion recognition software that claim to be able to read emotions in people based on their facial expressions (e.g., Affectiva.com, 2018; Microsoft Azure, 2018). These API systems aim to generalize their predictions in the open world, neglecting the intra-individual variability among the emotional displays. Different bias already emerged in the performance of the machine learning algorithms used, such as the gender or the age of people (Howard et al., 2017, Kim et al., 2021, Klare et al., 2012). The current results provide additional proof about the variety in the emotional displays, both in spontaneous and posed emotions, raising further doubts about the methodology used in emotional facial recognition. Additionally, the current research restates the necessity of a methodology based on the single user, emphasizing the significant differences among the individuals, and abandoning the idea of a collective and equal emotional facial display. Nonetheless, the findings of this study have to be seen in the light of some limitations. The sample size used for the analysis is composed of only 56 subjects. Moreover, the features extracted are limited to the descriptive statistics of action unit movements and do not consider dynamic and temporal elements (e.g., onset, offset time, asymmetry, acceleration). Finally, only five models were used in the current research. Other models may be revealed more effective and accurate in the same task. Therefore, the empirical results reported herein should be interpreted and considered with caution. Future studies are needed to address the generalization of these results.

2.6. Conclusion

The automatic genuineness detection of emotional facial expressions is a topic still debated and controversial in the state of the art of lie detection. In the current paper, ML models were used to predict the genuineness of emotional facial expressions in general and specifically for every single user. The framework used was revealed to be a promising approach to apply in future research, and highlighted how inter-individual variability could be a significant factor to consider. Finally, the related findings were discussed in light of the state of art of lie detection, psychology of emotions, and artificial intelligence.

Chapter 3- Unmasking the face: the kinematics of spontaneous and posed happiness

3.1. Introduction

With its 43 muscles, the face is capable of making more than 10.000 combinations of facial expressions. However, even the smallest line, the slightest movement on our face, can affect the way we communicate our thoughts, intentions, and feeling (Jack & Schyns, 2015). In each emotion, indeed, there is a broad family of possible expressions, including different variations such as timing, intensity, facial muscles involved (e.g., in the upper or lower face), asymmetry of the face, synchrony of movements, and so forth (Ekman, 2009). A single chance in the above parameters may lead to differences in genuine (i.e., spontaneous) or fake (i.e., posed) emotions' morphological configurations.

Both untrained observers and professional experts (i.e., psychologists) are completely unable to recognize these subtle changes in emotional displays, in particular, if they have to rely on visual cues only (Bartlett, 2006). Several studies demonstrated how people tend to perform close to the chance level when asked to detect such behaviors (Bond & DePaulo, 2006; Porter et al., 2012; Porter & Ten Brinke, 2008; Vrij, 2008). This result is also due to the people's ability to modulate, suppressing, or falsifying their emotional expressions because of display rules or personal needs (Ekman & Friesen, 2003; Etcoff et al., 2021; Reed & DeScioli, 2017; Zloteanu & Krumhuber, 2021).

Among the various emotions, happiness is the most effortless facial expression to fake deliberately (Ekman et al., 1988). The smile, indeed, is often used in social-day interactions also in the absence of felt happiness. People frequently smile for multiple reasons, such as conveying enjoyment and positive feelings or reflecting politeness and affiliation (Calvo et al., 2013; Ekman & Friesen, 2003). In addition, a smile of happiness is also used to qualifier or mask (i.e., cover or conceal) a negative emotion that is truly felt, namely: anger, fear, contempt, or nervousness (Ambadar et al., 2009; Ekman et al., 1988; Maringer et al., 2011;

Niedenthal et al., 2010). As a result of this, it becomes of crucial importance to discriminate between genuine and non-genuine smiles.

Previous research focused on the appearance change produced by the zygomatic major muscle as the primary marker to detect genuine and deliberate smiles (Ekman, 1992; Ekman et al., 1988, 1990; Frank et al., 1993). The zygomatic action in smiles stretches the lip corners up at an angle towards the cheekbones, pulling the cheeks upward and narrowing the eye-opening (i.e., AU 6 according to the Facial Action Coding System, (Ekman, 2002). It had been argued that according to the genuineness of smile, crow's-feet wrinkles beyond the eye corners were produced—the so-called Duchenne marker (Duchenne & de Boulogne, 1990). The Duchenne maker was considered a spontaneous reflection of happiness or positive affect. Conversely, the smiles where the eye muscle movement is lacking was considered fake or non genuine-Non-Duchenne (Ekman, 1992; Ekman et al., 1988, 1990; Frank et al., 1993). However, an increasing amount of evidence demonstrated how the Duchenne marker is not a reliable sign of an emotional lie. It, in fact, could also be produced voluntarily by participants in the absence of genuinely felt happiness (Gunnery et al., 2013; E. G. Krumhuber & Manstead, 2009; Schmidt et al., 2006, 2009).

More recent studies focused on more dynamic features such as the total duration, the onset and offset time (how long the expression takes to appear or disappear), the amplitude (i.e., intensity), and the asymmetry of facial expressions. For example, genuine smiles seem to last longer and tend to have a more prolonged onset and offset than posed smiles (Guo et al., 2018; E. Krumhuber & Kappas, 2005; Schmidt et al., 2006, 2009). Moreover, the amplitude of posed smiles appears to be greater and perceived more intense than genuine smiles (Guo et al., 2018; Schmidt et al., 2006, 2009). However, even though some features seem to be stable across the studies, others, such as the face's asymmetry, the frequency, or the AU sequence recruited in genuine and posed smiles, keep resulting controversy in the literature (Guo et al., 2018).

The discrepancy of the results may be due to the different factors. First of all, the strategy used to fake the emotions strongly affects the perception and detection of facial expressions in line with previous evidence (Guo et al., 2018; Zloteanu et al., 2018, 2020). Indeed, emotions can be deliberately performed by either mimicking the facial display of another individual (i.e., Mimic method, Ekman, 2007), recalling memories of affectively-congruent episodes (i.e., Stanislavski, Hull, 1985), or improvising according to the one's own beliefs (i.e., Improvised). Each strategy differs from the others in terms of facial change appearance, thus yielding contradictory and misleading results in the literature (Namba et al., 2017; Zloteanu et al., 2020). Second, the lack of objective tools used to investigate the dynamic characteristics of expression, such as timing, smoothness, asymmetry, synchronization of different facial parts (Frank et al., 2009). The extensive use of qualitative manual coding by trained observers, indeed, lacks precision and is prone to different biases (Ancillao et al., 2016; Fasel & Luettin, 2003; Linstrom, 2002; Matsumoto, 1990; Vimercati et al., 2012). Moreover, the accuracy and reliability of the recent computer vision and pattern recognition methods, albeit achieved good performance in the facial landmark and action unit recognition, need to be enhanced and further verified (Baltrusaitis et al., 2018; Guo et al., 2018). This is even more true for challenging tasks, such as detecting the subtle and veiled difference between genuine and posed temporal emotion dynamics. Notably, these methods are also affected by the variety of conflicting ideas regarding the definition of dynamic parameters in the phase of feature extraction, causing inconsistencies in the literature (Guo et al., 2018). All these elements contribute to the unreliability of the state of art about emotional lie detection.

To the best of our knowledge, this is the first time in which a 3D-optoelectronic system is used to analyze facial motion kinematics between genuine and posed emotions. This method is remarkably accurate in the quantitative capture of facial motion, outperforming the canonical 2D computer vision system (Ancillao et al., 2016; Linstrom, 2002; Vimercati et al., 2012).

As a result of this, it is still unclear how genuine and posed happiness differ according to their kinematics properties, requiring the need for more sophisticated 3-dimensional space to expand our understanding of how facial displays unfold over time and space.

3.1.2. Aims

In this study, for the first time, the most accurate methodology (Ancillao et al., 2016; Linstrom, 2002; Vimercati et al., 2012) based on a 3D-optoelectronic system is used to analyze the subtle kinematics difference between genuine and posed happiness in order to disambiguate the inconsistent state of the art of emotional lie detection. More precisely, we hypothesized that:

1st Hypothesis: facial motion should differ between spontaneous and posed emotional expressions, on a wide range of parameters

2nd Hypothesis: the lower part of the face should be more informative than the upper part of the face during facial expressions

3rd Hypothesis: quantitative analysis should also reveal differences in the left and right sides of the face

3.2. Methods

3.2.1. Participants Ethic statement

The experiments were approved by the Ethics Committee of the University of Padua (No 3580), in accordance with the Declaration of Helsinki (Sixth revision, 2008). All participants signed their informed consent in writing prior to the beginning of their experimental session.

3.2.2. Participants

20 participants, aged between 20 and 30 years, were recruited for the experiment. The sample was enrolled through advertisements on the University Website and were compensated for their participation. Participants signed an informed consent before the beginning of the experiments. The participants were informed that they had the right to quit the experiment and withdrew their consent at any time. At the end of the session, participants were debriefed, and the study's aims and hypothesis were revealed. The experimental procedure and the happiness elicitation protocol submitted to the participants and described in the following paragraphs were approved by the Ethics Committee of the University of Padua.

3.2.3. Apparatus

Six infrared cameras (sampling rate 140 Hz), that detected 22 infrared reflective markers (3 mm diameter) applied to the face of participants (see Fig.3.1), were placed in a semicircle at a distance of 1–1.2 meters from the center of the room. Movements were recorded using a SMART motion analysis system (Bioengineering Technology and Systems [B|T|S]). Cameras captured the movements of markers in a 3D space (Figure X1). The coordinates of the markers were reconstructed with an accuracy of 0.2 mm over the field of view. The standard deviation of the reconstruction error was 0.2 mm for the vertical (Y) axis and 0.3 mm for the two horizontal (X and Z) axis.

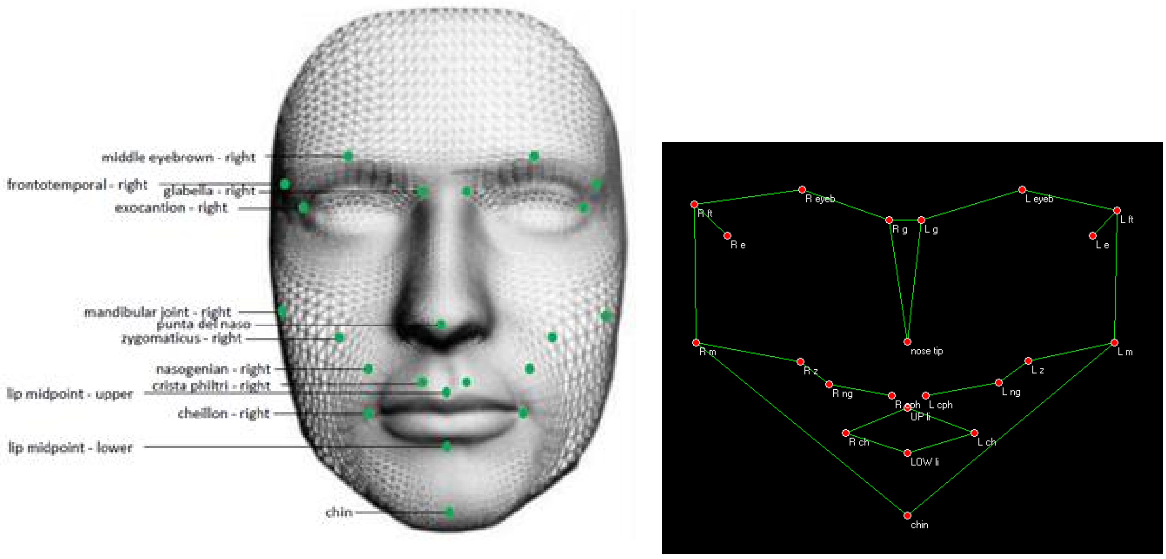


Fig. 3.1. (a) Model of the face: green dots represent key points for the expressions of emotions. (b) 3-D model of the face elaborated by means of the SMART-D tracker system. Each point is defined by the acronym.

3.2.4. Happiness elicitation

Spontaneous happiness was elicited by using emotion-inducing videos. In particular, three clips were used for this purpose, namely an extract from the Italian comedy "Chiedimi se sono felice", an extract of the movie "When Harry met Selly", and an extract from the comedy special "Oh My God" performed by comedian Louis C.K. The length of the clips did not exceed 5 minutes according to the recommended size of the emotional video (Rottenberg et al., 2007). More stimuli were used to elicitate happiness in order to enhance the probability of eliciting the target emotion and collecting more samples of clips displaying happiness for each subject. Similarly to the methodology used in the first chapter, after the end of each clip, participants were asked to identify the emotion they experienced within the six basic emotion and neutral. They were also given the possibility to report if they felt an emotion that was not included within the six basic ones. At the end of the elicitation procedure, participants were asked to pose the happiness multiple times, modulating the intensity of the posed emotion.

3.2.5. Video extraction

The video extraction followed the same procedure of the protocol used in the paragraph 1.3.4. Briefly, one of the authors (AM), a certified Facial Action Coding System (FACS) coder, extracted the facial expression of emotions present in the recorded videos. The clips' selection was made matching both the FACS's criteria (Ekman et al., 1978) and participants' self-reports.

In other words, the clips were selected only if the emotional expression (i.e., happiness) matched FACS criteria (e.g., AU6+12) and participants' self-report (e.g., they declare to have experienced happiness). Each clip was cut from the onset point (i.e., the first frame when the expression is visible) to the apex (i.e., the period during which the movement was held at the highest intensity reached) of the emotion. Additionally, if the same emotion(s) was repeatedly elicited in a task, the related expressions were selected multiple times as much as the number of times participants spontaneously expressed the emotion(s) reported, in order to increase the number of clips included in the nal dataset and provide more trials of the same emotion for each participant. Lightworks (https://www.lwks.com/), a non-linear editing system (NLE) for editing and mastering digital video, was used to extract the emotional clips' perfect range frame.

3.2.6. Data Analysis

Following kinematic data collection, each clip was individually checked for correct marker identification and then run through a low-pass Butterworth filter with a 6 Hz cutoff. The SMARTD Tracker software package (Bioengineering Technology and Systems, B|T| S) was employed to reconstruct the 3-D marker positions as a function of time.

3.2.7. Statistical Analysis

Kinematic data extracted were aggregated in order to investigate the following spatial, speed, and timing dependent measures that were investigated both in the upper and lower face (please see Fig.3.2 for a graphical display):

- **Maximum and Minimum Distances**: the maximum and minimum distance reached by the 3-D coordinates of two points (i. e. corners of the mouth, eyebrows, nose tip – corner of the mouth left and right, nose tip – eyebrow left and right);
- **Delta Distances**: the differences between the highest and lowest values;
- **Maximum and Minimum Velocities**: the maximum and minimum velocities of the 3-D coordinates of two points ;
- **Time to Maximum Velocities**: the time in which two points reach a maximum speed from the movement onset;
- **Time to Maximum Distances:** the time in which two points reach a maximum distance from the movement onset.

Behavioral data were analyzed using Jasp statistical software (JASP 0.14.1, 2020). Data analysis was divided into two main parts: The first one was aimed at testing if facial motion differs between spontaneous and posed emotional expressions; the second one was aimed at testing the differences between the left and right sides of the face during spontaneous and posed emotional expressions

The first part of the analysis consisted in fitting Linear Mixed Effect Models having the two conditions (posed and genuine) as within fixed effects and Individuals as random effects. During the second part of the analysis, A repeated-measures ANOVA with condition (posed and genuine) and side of the face (left and right) as within the subject variables was performed.

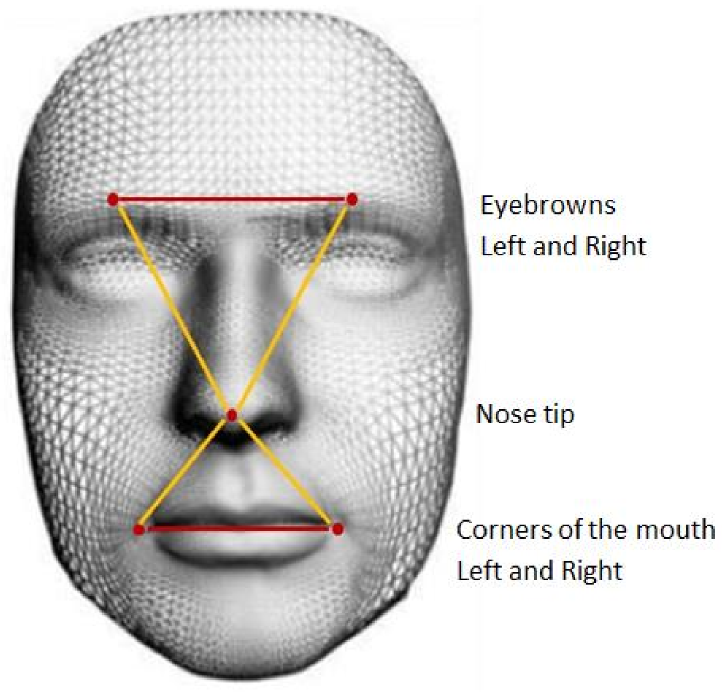


Fig. 3.2: for the sake of simplicity, six relevant facial distances were analyzed: the red dots represent the key point for the expression of emotions and the line segments refer to the six facial distances. The lower and upper parts of the face are indicated through the two red line

segments, whereas the left and right sides of the face refer to the four yellow line segments.

3.3. Results

The lower part of the face - corners of the mouth

The Linear Mixer Models for Happiness revealed an increase of the smile amplitude and speed when the participants perform a posed smile, compared to when they smile spontaneously (see Fig.3.3): MDM= F $_{(1,16)}$ = 17.721; MVM= $p < 0.001$; F $_{(1,16)}$ = 16.966; $p < 0.001$.

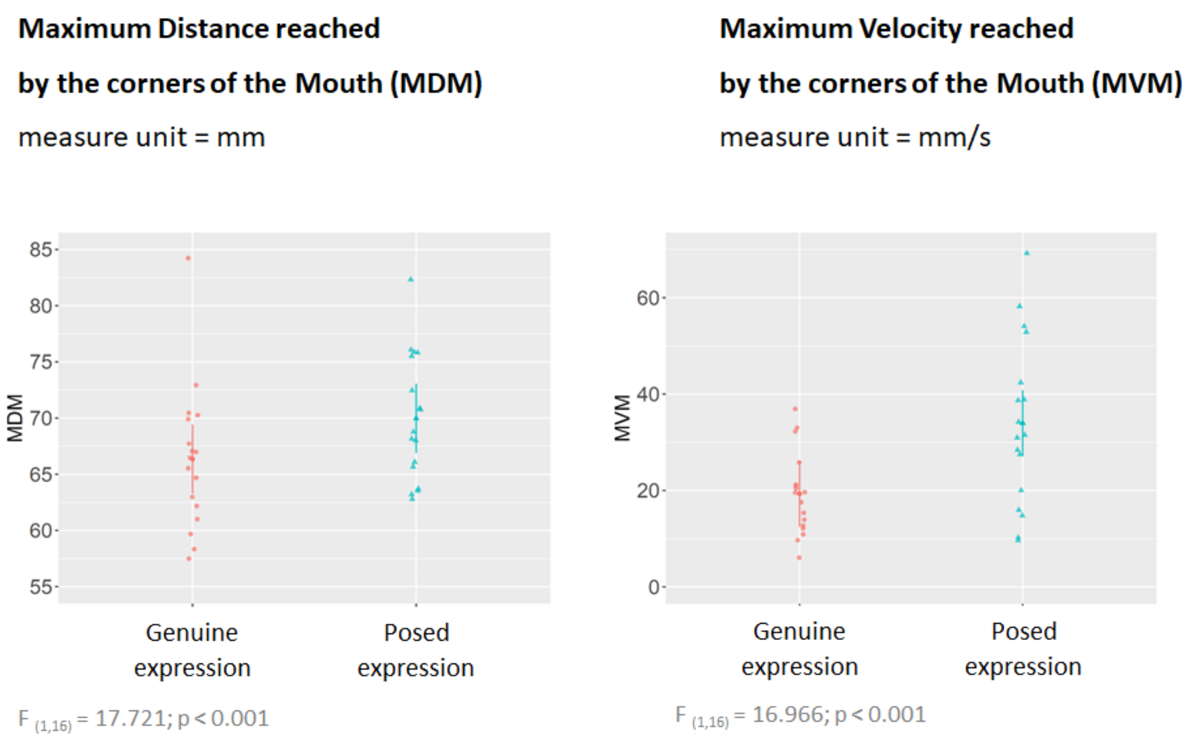


Fig. 3.3. Graphical representation of spatial and temporal components of the corners of the mouth (A) the Maximum Distance reached by the corners of the Mouth (MDM R-L) and (B) Maximum Velocity reached by the corners of the Mouth (MDM R-L) during genuine and posed expressions of happiness.

However, the dependent variables related to the time, specifically the Time to Maximum Velocity of the corners of the mouth and the Time to Maximum Distance reached by the corners of the mouth, did not reveal significant differences through conditions ($p = 0.082$ and $p = 0.325$ respectively). Moreover, a repeated-measures ANOVA for the maximum distances and velocities of the corners of the mouth to the nose tip was run. The analysis revealed a significant main effect of the Condition, whereas the interaction between the Condition and the side of the face was not significant (Fig. 3.4). In accordance with the previous results, the maximum distance related to the lower part of the face is wider and the velocity is higher when the smile is posed (see Fig. 3.3): MDM= $F_{(1, 16)} = 21.440$; $p < 0.001$; $\eta^2_p = 0.573$; MVM= $F_{(1, 16)} = 10.595$; $p < 0.005$; $\eta^2_p = 0.398$.

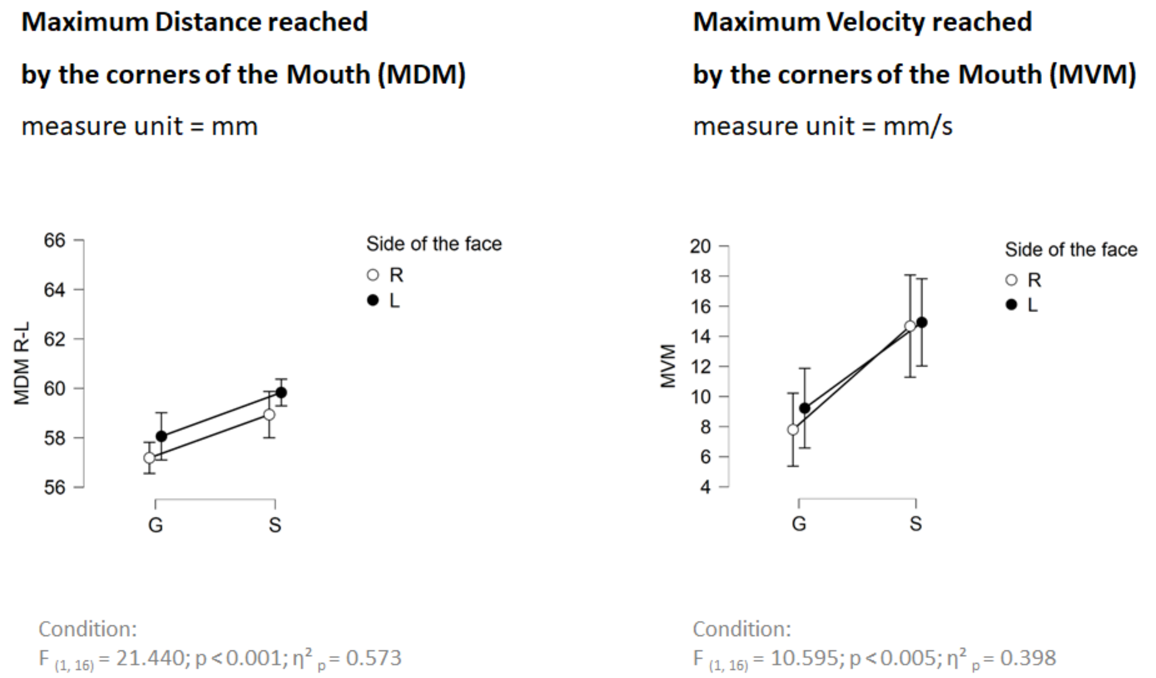


Fig. 3.4. Differences in the maximum distance and velocity between genuine and posed happiness. Graphical representation of spatial and temporal components of the corners of the mouth to the nose tip (A) the Maximum Distance reached by the corners of the Mouth right and left to the nose tip (MDM R-L) and (B) Maximum Velocity reached by the corners of the Mouth right and left to the nose tip (MDM R-L).

The timing-dependent measures (i.e., Time to maximum velocity and Time to Maximum Distance) did not reveal any significant effects in the lower part of the face ($p = 0.240$ and $p = 0.570$).

The upper part of the face - eyebrows

The Linear Mixed Models for Happiness revealed an increase of the Maximum Distance of the Eyebrows when the participants perform a posed smile, compared to when they smile spontaneously (see Fig.3.5): MDE= $F(1,16) = 20.613$; $p < 0.001$. Timing and velocity measure resulted not statistically significant: Max Vel Eyebrows $p = 0.839$ $F = 0.043$; Time to max vel eyebrows $p = 0.622$ $F = 0.253$; Time to max distance eyebrows $p = 0.963$ $F = 0.002$.

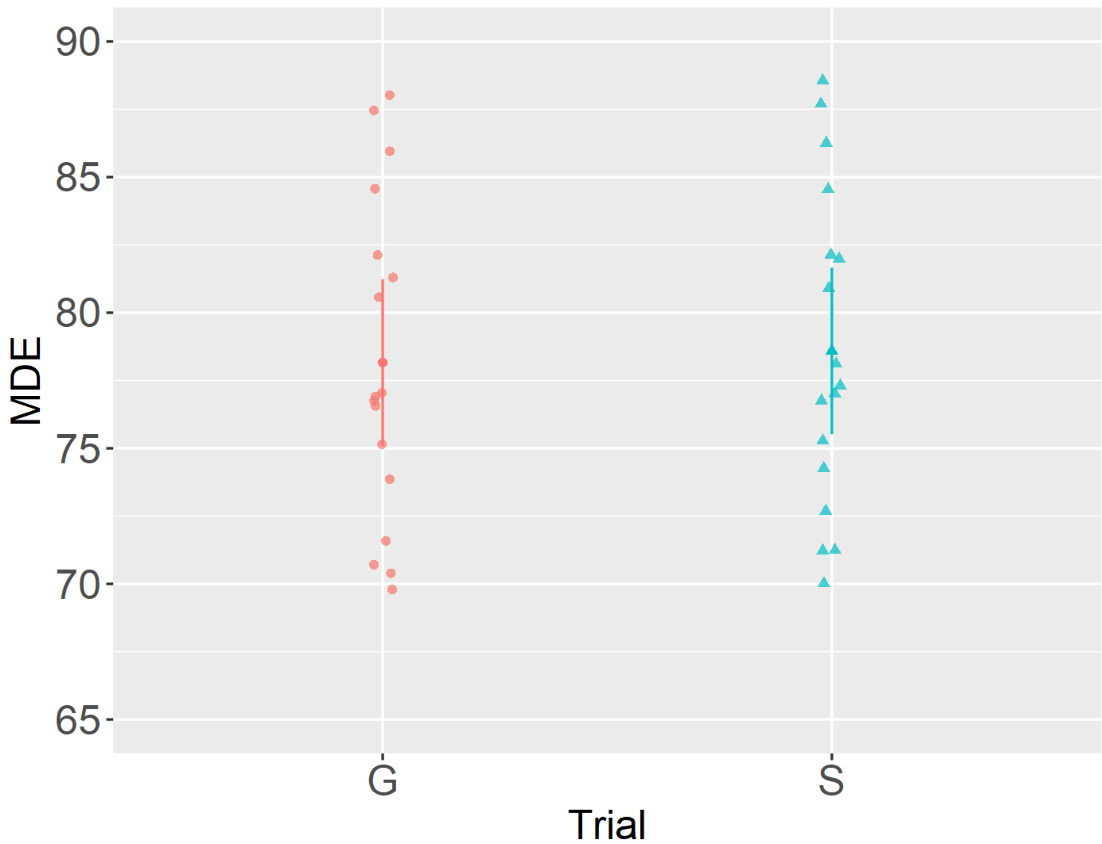


Fig 3.5: Graphical representation of space component: Maximum Distance reached by the Eyebrows (MDE), measure unit = mm.

Moreover, a repeated-measures ANOVA for the maximum distance of the eyebrows to the nose tip was run. The analysis revealed a significant main effect of the Condition, whereas the interaction between the Condition and the side of the face was not significant (Fig. 3.5). In accordance with the previous results, the maximum distance related to the upper part of the face is wider when the smile is posed (see Fig.3.6): MDE= $F_{(1, 16)} = 12.298$; $p < 0.003$; $\eta^2_p = 0.045$.

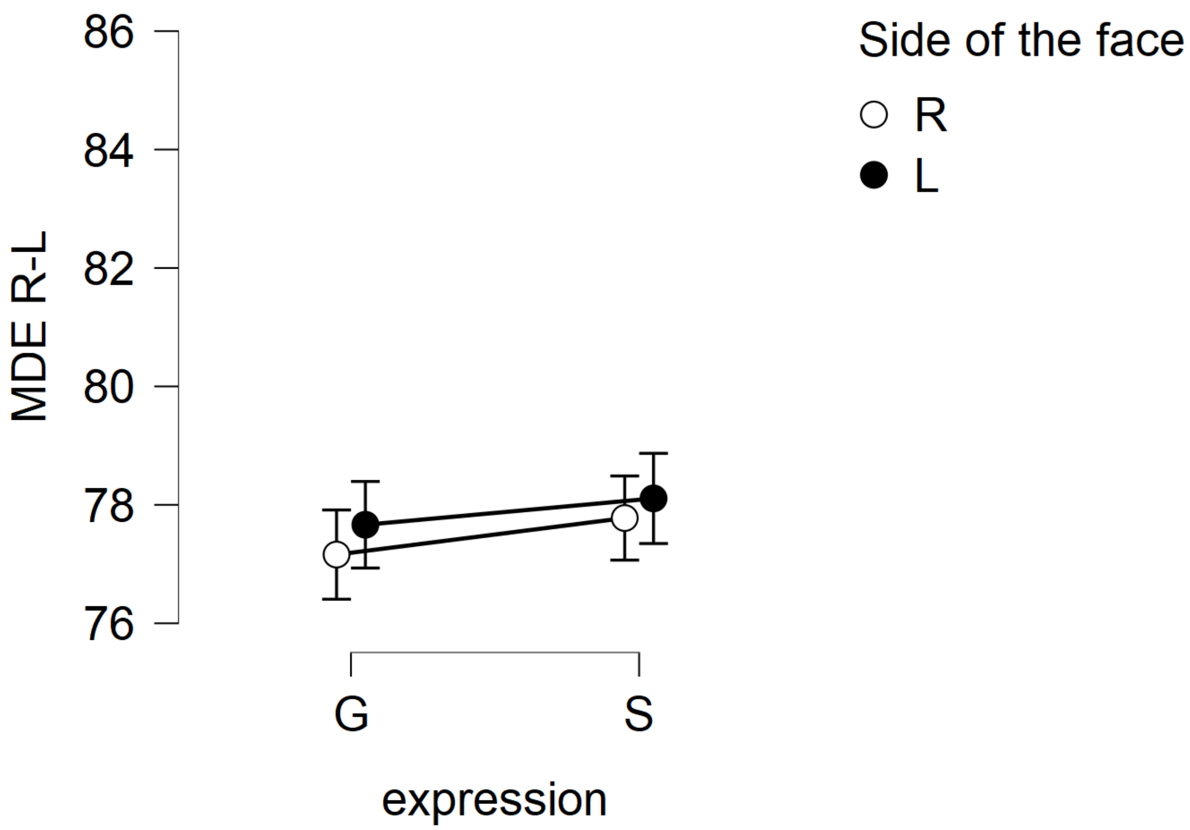


Fig. 3.6: Graphical representation of space component: Maximum Distance reached by the Eyebrows right and left to the nose tip (MDE R-L), measure unit = mm.

Also in the upper part of the face, the timing measures, as well as the velocity dependent measures, resulted to be not statistically significant: Max Velocity Eyebrows $p = 0.836$ $F = 0.045$: Time to max velocity eyebrows $p = 0.390$ $F = 2.047$; Time to max distance eyebrows $p = 0.073$ $F = 3.672$.

3.4. Discussion and Conclusions

For the first time, the 3-D motion analysis was applied to the study of spontaneous and posed dynamic facial expression of happiness to detect subtle movements in terms of space, time, and speed. The aim of this experiment was twofold: first, to investigate whether a genuine expression of happiness differs from a posed one by means of 3-D motion analysis; second, to detect important cues about the distinction between genuine posed expressions, providing new insights and claims in the emotional lie detection field. Results revealed that the mouth widening and the speed of smiles are greater in posed than genuine happiness. No differences were revealed for the timing measures. The findings related to mouth widening and the peak of velocity confirmed the previous notions about the main differences between genuine and posed smiles, where the posed smile yielded greater than genuine smiles (Guo et al., 2018; Schmidt et al., 2006, 2009). Crucially, this effect also translates into speed components (i.e., velocity of the lip corners). Recently, Sowden et al. (2021), using automatic coding, also found a contribution of the of the upper part in spontaneous emotion expression. However, in this research, only the contribution of the maximum distances of the upper part of the face (eyebrow) were found in distinguishing between genuine and posed expressions. Furthermore, recent research has shown that there might be a difference between a felt smile and a fake smile, which could be related to the side of the face (Ross et al., 2016). In this research, this differential contribution of the side of the face did not emerge, but future studies may adopt larger samples to better detect the subtle movements of the two sides of the face. Despite possible limitations of the sample size, this research can be classified as the first study that attempts the use of a 3D-optoelectronic system in the genuineness of emotion detection. Future studies are needed to generalize this methodology to other emotions to accurately investigate the subtle differences in the facial expressions of emotions.

Chapter 4- Detection of genuine and posed dynamic emotional facial expressions using Time-Frequency EEG Analysis

4.1. Abstract

The authenticity of emotional facial expressions may completely change the observer's perception and reaction. However, how the brain extracts the genuineness of emotional expressions is a topic never explored. The literature on emotional perception mainly relied on static pictures or dynamic posed (or fake) emotional facial expressions raising serious doubts about the ecological impact of these results. We compared the perception of genuine and posed emotional facial expressions using time-frequency EEG analysis. The cortical activity of 33 participants was recorded during their perception of three different facial expressions of genuine and posed emotions: happiness, fear, and disgust. Overall, we observed strong differences in both the timing and the topography of the canonical EEG bands. In particular, compared to genuine happiness, posed happiness revealed increased delta and theta power at the onset and offset of the facial expressions over frontal sites. Compared to posed fear, genuine fear elicits an increase in alpha and beta bands followed by an increase in theta activity. Finally, for facial expressions of disgust, we found an early increased theta, alpha, and beta activity for the posed expressions, followed by increased activity in alpha and beta bands during the perception of genuine disgust. Our results support the significant difference between genuine and fake facial expression stimuli and provide new insights into the perception of emotions displayed by faces.

Keywords: Genuine emotions, Posed emotions, Facial expressions, Time-frequency analysis

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4.2. Introduction

Accordingly to Antoine de Saint-Exupèry, a sheep is not simply a sheep: a sheep could be an old sheep, or a sick sheep. In the same way, a face is not simply a face: a face could be a happy face or a fearful face, the face can convey authentic or false emotions. The adjectives we attribute to things make things different. The human face conveys a large amount of information such as identity, gender, age, facial gestures, biographic information, personal traits, intentions, facial expressions, emotions displayed, and so forth (Adolphs & Birmingham, 2011; Dobs et al., 2019; J. V. Haxby et al., 2000; J. V. Haxby & Gobbini, 2011). As a result of this complexity, face perception triggers a cascade of highly connected reactions that conclude in the facial stimulus's holistic perception (Maffei & Sessa, 2021).The leading model of Haxby and Gobbini (2011), based on several years of research into the neural basis of human face perception, suggests that face processing is mediated by a distributed and interconnected system across the brain areas that comprise altogether an integrated perception network (Adolphs & Birmingham, 2011; Grill-Spector et al., 2017; J. V. Haxby et al., 2000; J. V. Haxby & Gobbini, 2011; Ishai, 2008; Maffei & Sessa, 2021; Nguyen et al., 2014; Tsao & Livingstone, 2008). In particular, it is argued the existence of a Core -occipitotemporal visual extrastriate- and an Extended - parietal and frontocentral- network. The first one involves the visual analysis of invariant features critical for identity recognition and the representation of changeable components recruited for facial gesture discrimination, such as facial expressions and eye gaze. The Extended system consists of a tripartite neural network that works in symbiosis with the Core System to extract various types of information from faces (J. V. Haxby et al., 2000; J. V. Haxby & Gobbini, 2011), namely: the representation of person knowledge, action understanding (including gaze and attention), and emotion. Despite acknowledging that face processing relies on a multicomponent and interconnected brain network rather than a specific single brain area, the time-evolving dynamic underpinning emotional facial expressions' perception is still unknown (Dobs et al., 2019; Perdikis et al., 2017). Most experimental studies on facial expression perception have been limited to the use of static pictures displaying the peak intensity of posed (or stereotypical) emotions (Perdikis et al., 2017, Fusar-Poli et al., 2009; Vuilleumier & Pourtois, 2007), such as those developed by Ekman and Friesen (Ekman, 1976). Little is known about the dynamic and changing configurations of morphological features underlying muscle activation, which assume outstanding importance in emotional facial expression perception (Krumhuber et al., 2013). For example, dynamic stimuli increase the identification of emotions, leading to higher arousal and intensity judgments than static stimuli. Dynamic expressions also yield higher response than static expressions in different brain areas, such as FFG, middle temporal gyri, STS, and amygdala, due to the larger flow of information conveyed by facial changes (Arsalidou et al., 2011; Sato et al., 2004; Schultz et al., 2013; Schultz & Pilz, 2009; Trautmann-Lengsfeld et al., 2013). The additional attentional resources recruited for dynamic facial expressions cause an amplitude increase in early posterior negativity (EPN, 200±300ms post-stimulus) and in the late positive complex (LPC, 350±600 ms) (Recio et al., 2011), as well as a more widespread distribution of the Late Posterior Positivity in comparison with the static stimuli (Trautmann-Lengsfeld et al., 2013). Moreover, a recent study by Dyionisis et al.,2017 discriminated natural dynamic stimuli with static and unnatural dynamic stimuli. They found interesting results in the delta and theta PLI (Phase Locking Index) and WP (whole power), and in alpha and beta WP (Perdikis et al., 2017), supporting the idea that the perception of static or dynamic emotional facial expressions is mediated by different networks and distinct mental strategies (Furl et al., 2012; Kilts et al., 2003; Perdikis et al., 2017). In summary, dynamic facial expressions of emotion convey an evolving hierarchy of "biologically basic to socially specific" information over time (Jack et al., 2014). However, it is still not known how does the genuineness (or its lack thereof) of the emotional expression influences the social message perception. Even though the face is the most reliable indicator of the emotional states, and it is evolved as a cooperative social signal to communicate one's genuinely felt emotions to others (Darwin, 1872), it is likewise the deception's best friend. The emotional facial expressions' appearance can in fact be modulated and feigned by people according to personal needs or display rules (DePaulo et al., 1996; Ekman & Friesen, 1975; Kulkarni et al., 2018; Reed & DeScioli, 2017; Vrij, 1995). Recent studies on lie detection revealed how the kinematics of genuine and posed emotion may vary under different parameters such as the temporal and morphological characteristics (e.g., duration, onset, apex and offset time, asymmetry) of the expression (Ambadar et al., 2009; Cohn & Schmidt, 2003; Guo et al., 2018; Krumhuber et al., 2013; Namba et al., 2021; Sato et al., 2004; Schmidt et al., 2006; Valstar et al., 2006; Yoshikawa & Sato, 2006). For example, Genuine smiles of happiness tend to have a slower onset speed and longer onset duration than posed ones (Ekman, 2009; Schmidt et al., 2006, 2009). Likewise, the vertical eyebrow movements in surprise seem faster when someone tries to mimic a surprise expression than someone who genuinely expresses it (Namba et al., 2021). In other words, the dynamic changes of the facial expressions provide significant information to differentiate genuine and posed emotions (Krumhuber et al., 2013). Notably, the endogenous nature of emotional experiences (i.e., genuine or posed) also significantly affects the perception of facial expression (Manera et al., 2013). To date it is still unknown whether our actual knowledge on the perception and processing of emotions conveyed by faces is biased by the (un)conscious perception of non genuineness of the perceived emotions. This topic has been surprisingly under-investigated. Indeed, so far, only few studies on smile investigated the perception of emotion genuineness using behavioral paradigms (Gunnery and Ruben, 2016). Virtually nothing is known about other emotions. Interestingly, there is evidence that genuine smiles are associated with the experience and physiological activations of positive emotions, while faked ones with the experience and physiological activation of negative emotions (Johnson et al., 2010). Furthermore, the method used to feign emotional expressions affect the perceptions of emotional authenticity and several other dimensions (Zloteanu et al., 2020). In a recent study, Zloteanu et al., (2018), showed how Genuine surprise achieved higher ratings of genuineness, intensity, and judgmental confidence than deliberate surprise expressions. With regards with potential neural mechanisms underlying these differences between genuine and posed expressions, it is still unknown which patterns of cortical activity support the different visual perception of these two categories of emotions. Despite preliminary evidences seems to suggest that genuine and not genuine emotions might be differentiated at neural level, these researches have important limitations that prevents to have a clear understanding on how genuine and not genuine emotions are processed: McLellan et al. 2012 conducted an fMRI study on sad and happy expression only, with the limitation that the genuine emotions were not perceived as genuine by the observers; Li et al 2012 conducted a EEG study with the relevant limitation of using stylized pictures of animals as stimuli. Thus, how the same emotional expression (e.g., fear) can be implicitly perceived according to the authenticity (i.e., genuine or posed) of the facial expression shown is a question still unsolved. To the best of our knowledge, this is the first study in which EEG time-frequency analysis is used to fill the gaps in the perception of emotional lie detection.

4.2.1. Aims and Hypotheses of the Present Study

Do healthy individuals process differently genuine and posed emotional facial expressions? If so, is it possible to find specific neural correlates of genuineness in the processing of genuine and posed emotions? This study's main aim is to respond to the following questions, exploring how individuals perceive and react to genuine and not genuine emotions. In this study, we focused specifically on three basic emotions, namely: happiness, fear, and disgust. The facial expressions of surprise were not included because often confused with fear (Kim et al., 2003, 2004; Zhao et al., 2013). The inclusion of surprise would have increased the task's difficulty and reduced the correct number of trials to analyze (please see "Methods"). Sadness was also rejected because of his gradual and extended evolution over time, longer in duration compared to the other emotions taken into account in this study. Finally, facial expressions of anger were not included as, like fear expressions, are considered aversive and threatening stimuli that elicit avoidance, supporting the idea that this emotion communicates a direct threat to the perceivers (Marsh et al., 2005). In other words, it may provoke fear and not anger. The experimental choice to investigate happiness, fear, and disgust only was also adopted to not cognitive overload participants during the task.

The hypotheses of this study are the following:

- For Happiness, it is known that the frontal activity of delta and theta bands is the typical pattern involved in happiness expression perception as well as in cognitive load processes (Güntekin et al., 2019; Güntekin & Başar, 2016). Moreover, state of the art of emotional lie detection confirms that the onset and offset time are the primary cues for happiness's genuineness (Guo et al., 2018; Schmidt et al., 2006). As a result of these considerations, we expect to find increased frontal activity in delta and theta bands at the beginning and at the end of the happiness time-frequency windows, where the cognitive load processes and the difference between genuine and posed happiness are more prominent.

- The detection of threat (i.e., fear) stimuli is crucial to identify possible dangers in the environment and respond accordingly with adaptive behaviors (Sun et al., 2012). Previous studies have shown a selective oriented processing to fearful stimuli that captures the perceiver's attention to the advantage of other stimuli (DeLaRosa et al., 2014). Posterior theta activity is of particular interest to encode fear stimuli, reflected in increased activity in the amygdala and the CA1 region of the hippocampus (Bienvenu et al., 2012; Pape et al., 2005; Paré et al., 2002; Seidenbecher et al., 2003). Furthermore, fMRI studies show how the perception of greater naturalism of the stimuli might enhance emotion-specific brain activation patterns, such as widespread activation in the parahippocampal gyrus, including the amygdala (Trautmann et al., 2009). Accordingly, we suppose that posed fear expressions are less relevant and significant to the observers' perception. Likewise, we believe that posed fear expressions have less impact on the arousal of participants. Consequently, we expect increased posterior theta activity during the perception of genuine fear compared to the posed one that is gradually more prominent around the apex of the fear expression (i.e., where the maximum intensity of fear is reached).

- Disgust, even though different from fear under several components (Phillips et al., 1997; Woody & Teachman, 2000), can overlap with fear as it is a negative emotion that elicits avoidance and aversion to the perceived stimulus or threat (Woody & Teachman, 2000). The cortical activity of disgust may thus reflect a similar pattern of fear processing and appraisal provoked, yielding increased posterior activity during the perception of genuine compared to posed disgust.

4.3. Methods

4.3.1. Participants

Thirty-four university students with normal or corrected-to-normal vision and no history of neurological or psychiatric illness or substance abuse participated in this study.

One subject was removed from the analysis due to insufficient usable trials (i.e excessive artifact movements). Overall, the remaining participants (19 females and 14 males) had a mean age of 24.9 years (SD= 2.3 years).

The sample size was based on an a priori estimation computed with G*Power 3 software (Faul et al., 2009) which suggested a sample size of 32 participants for detecting a medium effect size of Cohen's d = 0.6 with 90% power (alpha = .05, two-tailed).
The experimental procedure was conducted according to the Declaration of Helsinki principles and after approval of the Ethics Committee of the University of Padua (protocol number: 3234), and a written informed consent was obtained by each participant. Moreover, an informed consent to publish the image from participants was obtained to publish the information/image(s).

4.3.2. Stimuli and procedures

Stimulus materials were taken from the PEDFE set (Miolla et al., 2021), which contains both genuine and posed emotional facial expressions. We selected clips with 27 different actors (9 males, 18 females) matched on the basis of the emotion and genuineness hit rate (for further details, see Miolla et al., 2021) and emotional intensity of their facial expressions (please see Supplementary Material 1 for additional information of stimuli).
Overall, eighteen dynamic stimuli (i.e., nine genuine and nine posed) of Fear, Happiness, and Disgust were selected from the dataset for a total block of 54 stimuli. The order of emotional clips was randomized within the block. The block of stimuli was presented three times (no homologous clip was presented twice within the same block) to reduce the cognitive effort during stimulus elaboration, resulting in a total sequence of 162 stimuli.
Owning to the stimulus's length variability, we adjusted the length of each clip to 4000 ms, extending the duration of the first frame according to the original length of the clip. For example, if a clip lasted 3 seconds, we lengthen the first frame of 1 second to adapt the duration of the clip to 4000 ms. The first frame still preceding the dynamic expression also served as a baseline to exclude possible confounding of reactions to the stimulus person with reactions to emotional displays (de Wied et al., 2006).
Trials were structured in a 1500 ms baseline period in which a fixation point (a white point on a black background) was displayed at the center of the screen, followed by presenting the target stimulus that lasted for 4000 ms (with a display resolution of 1024x720 pixels). At the end of each clip, participants were explicitly asked to correctly identify the emotion, the

genuineness (i.e., genuine or posed), and the intensity of the facial expression displayed. The emotion recognition was measured with a fixed-choice question, with the labels of all the three presented emotions plus "neutral" and "I do not know" options (Frank & Stennett, 2001). The genuineness typology was selected on the basis of a dichotomy choice (i.e., genuine or posed). Last, participants rated the intensity perception of the emotion shown on a scale of 0 (none) to 9 (strong), according to Dawel et al., (2017). The task is represented in Figure 2.1. Prior to EEG recordings, participants familiarized themselves with the overall procedure (training session) with a couple of practice stimuli. Participants were seated comfortably on a chair at a distance of 60 cm from a 17-inch computer screen, on which the expression stimuli were displayed.

The task was implemented using Opensesame 3.1, which results to be particularly effective for reading video files (Mathôt et al., 2012).

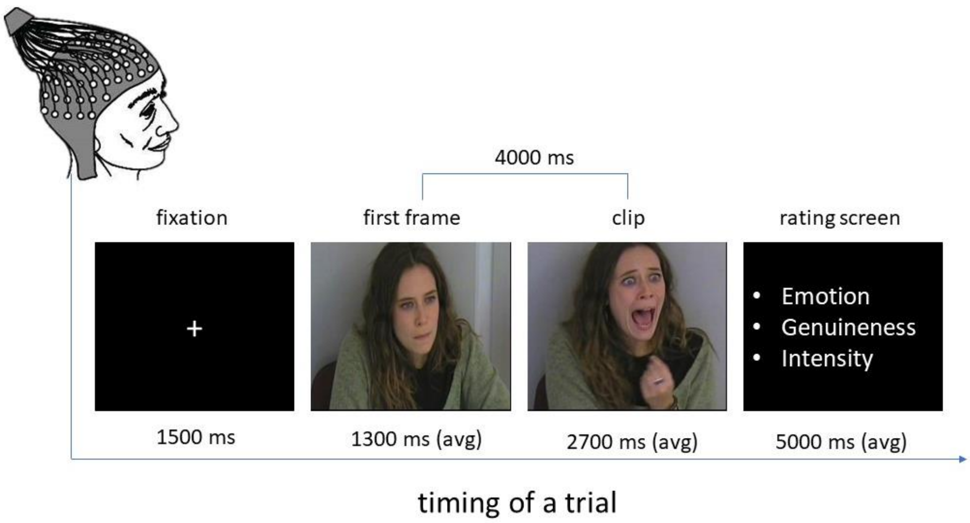

Fig.2.1 Trial structure of the EEG task (an example of a fear facial expressions)

4.3.3. EEG recording and preprocessing

Data were collected continuously from 62 Ag/AgCl electrodes placed on an elastic cap according to the 10-20 system, using a Micromed SD MRI 64 system (Micromed/Treviso, Italy). Data were acquired with a sampling rate of 1024 Hz and using Fcz as online reference. Electrodes impedance was kept under 10 kΩ. Vertical and horizontal eye movements were monitored using two electrodes placed on the external canthus of the right eye and below the left eye, respectively.

Continuous data were high-pass filtered at 0.1 Hz, re-referenced to the average of all channels and submitted to an Independent component analysis (ICA) to identify and discard artifactual components related to eye movements (blinks and saccades) and muscle tension (Delorme et al., 2005). Following ICA-based correction, continuous data were segmented in epochs starting 1500 ms before video onset to 4000 ms after video onset, according to the emotion and the correct identification of the genuineness of the expression. Then, data were low-pass filtered at 80 Hz, and epochs with an amplitude exceeding ± 75 µV in any channel were identified and discarded from the analysis.

The time-frequency representation of the EEG activity was obtained, separately for each condition, convolving the data with a set of complex Morlet wavelets(Bertrand & Tallon-Baudry, 2000), centered on frequencies increasing from 1 Hz to 60 Hz in linear step of 1 Hz and a width of 3 s (expressed in FWHM of the gaussian taper). Finally, the time-frequency representation was normalized over the baseline to derive the event-related spectral changes, and averaged in the five canonical frequency bands (delta = 1-4 Hz, theta = 5-7 Hz, alpha = 8-12 Hz, beta = 13-29 Hz, gamma = 30-45 Hz). The pre-processing was performed in MATLAB using functions from the EEGLab, ERPLab, TBT and Brainstorm toolboxes (*Ben-Shachar, M. S. (2018). TBT: Reject and Interpolate Channels on a Trial-by-Trial Basis. Zenodo. Https://Doi.Org/10.5281/Zenodo.1241518 - Cerca Con Google*, n.d.; Delorme & Makeig, 2004; Lopez-Calderon & Luck, 2014; Tadel et al., 2011)**.**

4.3.4. Statistical analysis

Behavioral analysis. Given that the scoring of the hit rates (i.e., for emotion and genuineness) were calculated by assigning one point for each correct answer and zero points for each wrong, with subjects' scores were modeled with two mixed-effects logistic regression models (the scores are graphically represented in Figure 4.2). The first model was fitted to the hit rate scores for the emotion recognition and included as fixed effect predictor the emotional expression (disgust, happiness, fear) and the genuineness of the expressions, (genuine or posed) and a random intercept to model the repeated measurements across subjects. The second model was fitted to the hit rate scores for the genuineness recognition and included as fixed effect predictor the emotional expression (disgust, happiness, fear) and the genuineness of the expressions, (genuine or posed) and a random intercept to model the repeated measurements across subjects. The effect of each parameter was also calculated through odds ratios, which correspond to the change in the odds given an increase of 1 point in the specific predictor variable (Bland & Altman, 2000). The intensity scores were analyzed by means of a repeated-measures analysis of variance (ANOVA) was conducted for the means of intensity scores given by every single participant for all the stimuli categories (e.g., fear genuine, disgust posed). The "Emotion" (i.e., disgust, happiness, and fear) and the "Genuineness" of the emotions (i.e., genuine or posed) were treated as within-subject factors. The Means and Standard deviations of each category are presented in Table 4.1. The statistical analysis was carried out using the statsmodels package (Seabold & Perktold, 2010) in Python.

Time-Frequency analysis. Statistical analyses were designed to assess the differences in neural activity underpinning the processing of genuine and posed emotional expressions. To accomplish this goal, we employed a mass-univariate permutation-based framework (Groppe et al., 2011; Maris & Oostenveld, 2007). Mass-univariate analyses have gained wide popularity in the neuroscience community due to their flexibility and power compared to classical analytical approach. They consist in performing a statistical test (like a t-test) between two conditions for every point in the electrode x time x frequency space, then iteratively permuting the *within-subject* condition assignment and repeating the test. With a sufficient number of permutations this approach leads to empirically derive the distribution of the test statistic under the null hypothesis of no effect. This null-distribution is then used to perform the statistical inference. Additionally, to address the issues arising from the large number of tests performed, a rigorous control of the multiple-comparisons problem is performed (Maris & Oostenveld, 2007).

In this study we performed, separately for each emotion, the pairwise contrast between the time-frequency representations for the genuine and the posed expressions in the time range between 1500 ms and 3500 ms. We employed 5000 permutations and applied a cluster-based correction for multiple comparisons (cluster-forming threshold = 0.05). In the results section we report the sum of t-statistic and the size of the significant clusters. Statistical analyses were performed in Brainstorm using the interface with statistical functions from Fieldtrip(Oostenveld et al., 2011; Tadel et al., 2011).

4.4. Results

Emotion recognition accuracy. Neither of the two fixed effects (i.e., *Emotion* and *Genuineness*) was significant in the logistic regression analysis. However, the interaction between the two independent variables was found to contribute to the model significantly. The unstandardized Beta weight for the Constant; B=0.973, SE=0.009, z=109.042, p<.0001. The unstandardized Beta weight for the predictor variable; B= (-0.038), SE=0.007, z=-5.157, p<.0001. The estimated odds ratio indicates a decrease of nearly 4% (B=0.963, 95% CI (0.949,0.977) for the *hit rate x emotion* every one unit increase of the predictor variable (i.e., the interaction between *Emotion* and *Genuineness*). In other words, the model indicates that there is no singular relationship between the *hit rate x emotion* scores and the Independent variables (i.e., *Emotion* and *Genuineness*), albeit their interaction significantly affects the dependent variable. In particular, the model suggests that by changing the genuineness of the *Emotion* from Genuine to Posed, the accuracy rates for emotion (i.e., hit rate x emotion) slightly decrease within the emotions (see Fig.4.2.).

Genuineness recognition accuracy. The *Genuineness* and the interaction between the two fixed effects (i.e., *Genuineness* and *Emotion*) were found to contribute to the model. The unstandardized Beta weight for the Constant; B=0.857, SE=0.013, z=65.425, p<.0001. The unstandardized Beta weight for the Genuineness; B= (-0.070), SE=0.016, z=--4.475, p<.0001. The unstandardized Beta weight for the *Emotion***Genuineness*; B= 0.025, SE=0.012, z=2.024, p<.043. The estimated odds ratio indicates a decrease of nearly 7% (B=0.932, 95%

CI (0.904,0.962) and favored an increase of nearly 2% (B=1.025, 95% CI (1.001,1.050) for the hit rate x genuineness everyone unit increase of the predictor variables: *Genuineness* and the interaction between *Emotion* and *Genuineness*, respectively. The model states that the accuracy rates for *Genuineness* (i.e., select if an emotion is genuine or posed) are negatively affected if an emotion is posed (i.e., not genuine), regardless of the *Emotion*. The *Emotion* per se did not reveal significance to the model; in other words, the hit rate x Genuineness does not change significantly among the emotions. In addition, the model suggests that by changing the interaction between *Emotion* and the *Genuineness* categories (i.e., from posed disgust to genuine happiness), the accuracy rates slightly increase within the *Emotions* and *Genuineness* categories (see Fig.4.2.). A theoretical explanation of these results is provided in the section "*Discussion*".

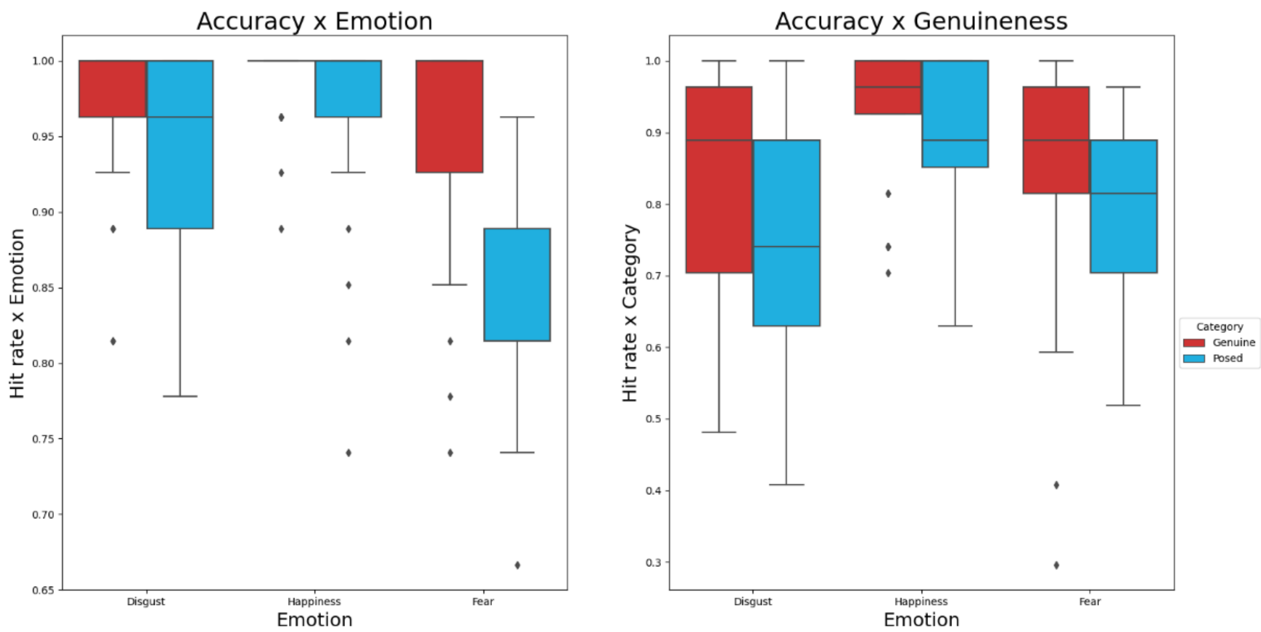

Fig.4.2 Accuracy ratings distribution for the Hit rate x Emotion and Hit rate x Genuineness

Intensity rating. Factorial ANOVA on the intensity scores yielded significant variation between factors (i.e., "Emotion"), $F(2, 195) = 13.7$, $p < 0.001$, and among the factors (i.e., interaction between "Emotion" and "Genuineness"), $F(2, 195) = 6$, $p < 0.003$. The genuineness was not significantly different within the groups ($p > 0.6$). Post hoc Tukey's honestly significant difference (HSD) tests demonstrated that only fear (both genuine and posed) significantly differed from genuine disgust and posed happiness at $p < 0.001$.

Table 4.1. Sample size, Means and Standard deviations of the Intensity ratings for genuine and posed emotions.

Emotion	Genuineness	Participants (N)	Mean	Std
Disgust	Genuine	33	5.17	1.26
	Posed	33	5.86	1.52
Happiness	Genuine	33	5.85	1.21
	Posed	33	4.90	1.69
Fear	Genuine	33	6.51	1.12
	Posed	33	5.55	1.55
Total		198	5.64	1.39

4.4.2. EEG results

Mass-univariate analysis performed on the brain activity recorded during the presentation of Happiness expressions showed a significant negative cluster (*t* sum = 69164 ; size = -182978; p=0.0139). This cluster revealed a reduced power in the delta and theta bands during the processing of the genuine expressions. The topographical distribution of the effect reveals that, for the delta band, the effect was more prominent on fronto-central and occipital sites. For the theta band, the fronto-central effect was sustained over the whole period, while the effect over occipital sites was observed at the beginning and toward the end of the facial display. The topographic representation of the results are presented in Figure 4.3A.

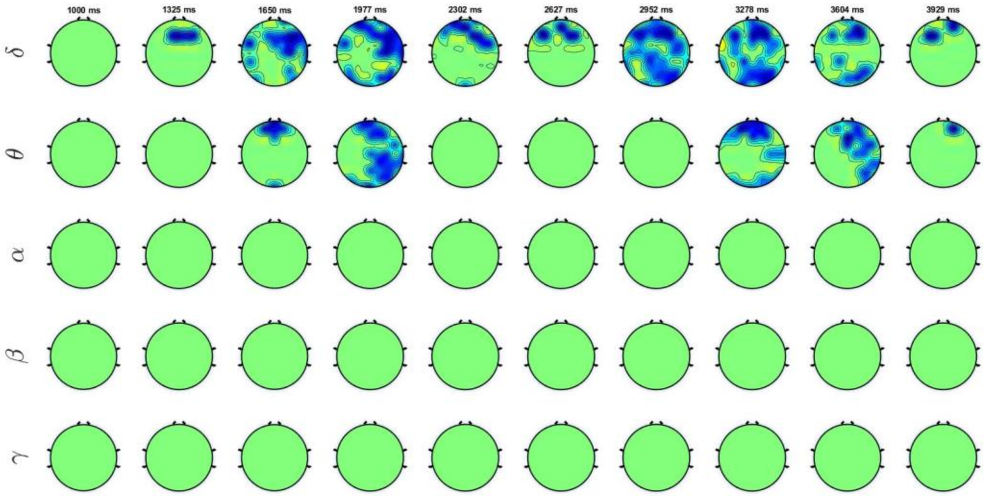

Fig.4.3A Topographic representation of the time-frequency representations of the difference in delta, theta, alpha, beta, gamma bands for Happiness facial expressions. Red areas indicate significant positive clusters (Genuine > Posed). Blue areas indicate significant negative clusters (Posed > Genuine)

With regards to the emotional expressions of Fear, statistical analysis showed a significant positive cluster (t sum =81986 ; size = 259285; p=0.0059). This cluster revealed a large increase in the power of several bands during the processing of genuine expressions of fear. Specifically, we observed a strong increase of the theta power spreading from occipito-parietal sites toward the whole scalp. At the same time we observed an increase in the alpha and beta power over frontal and occipital sites, respectively. With regards to the timing, these modulations were observed more prominently after the first half of the facial display. The topographic representation of the results are presented in Figure 4.3B.

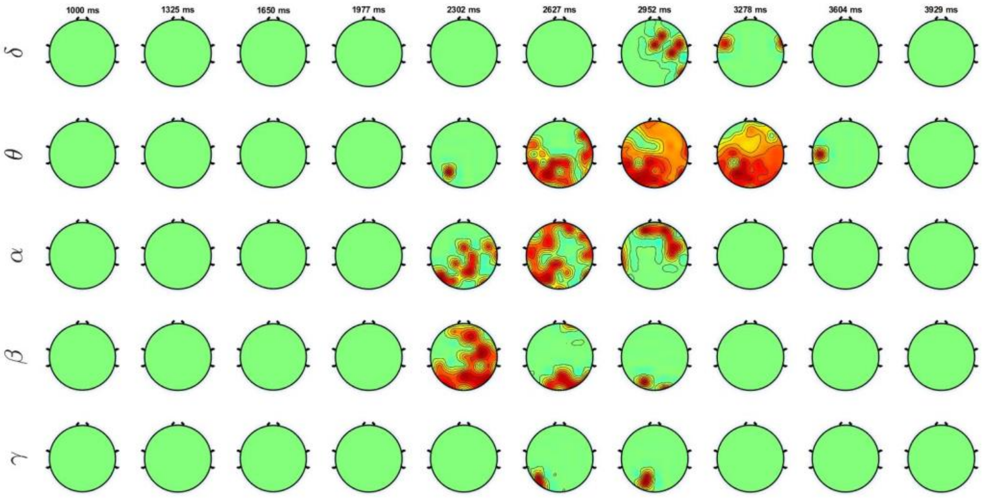

Fig.4.3B Topographic representation of the time-frequency representations of the difference in delta, theta, alpha, beta, gamma bands for Fear facial expressions. Red areas indicate significant positive clusters (Genuine > Posed). Blue areas indicate significant negative clusters (Posed > Genuine)

Finally, statistical analysis performed on the brain activity elicited by Disgust expressions, showed two significant clusters, one positive (*t* sum = 56373 ; size =156458; p=0.0059) and one negative (*t* sum = 38549 ; size = -98974; p=0.0439). This result revealed a complex spectral dynamic as a function of the genuineness of the expression presented. For the delta band, we observed that genuine disgust prompted a strong reduction in the power, especially over centro-parietal sites. On the other hand, for the alpha and beta band we first observed a decrease in the power for the genuine expressions, especially over occipito-parietal and central sites; this dynamic was then reverted by an increase in oscillatory activity in these bands in response to genuine expressions. The topographic representation of the results are presented in Figure 4.3C.

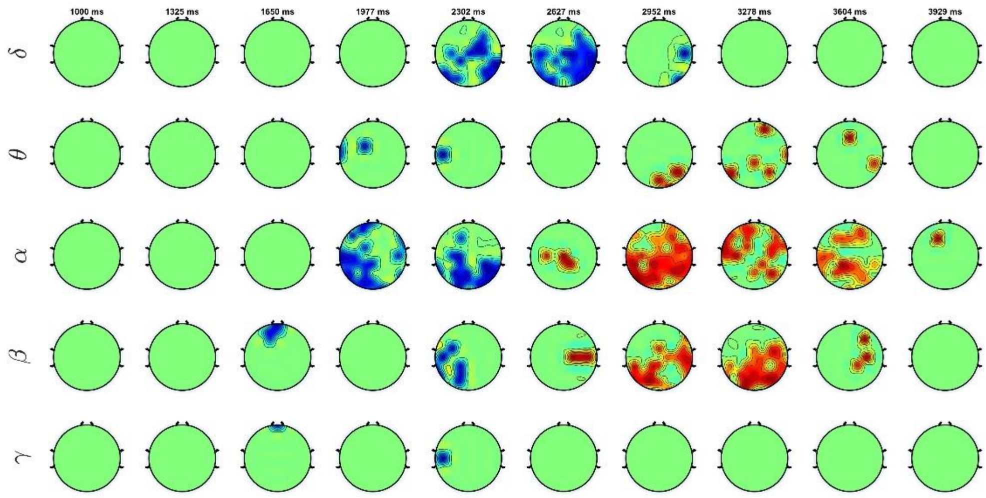

Fig.4.3C Topographic representation of the time-frequency representations of the difference in delta, theta, alpha, beta, gamma bands for Disgust facial expressions. Red areas indicate significant positive clusters (Genuine > Posed). Blue areas indicate significant negative clusters (Posed > Genuine)

4.5. Discussion

In the following study, the perception faces conveying genuine and posed emotions was investigated using Time-Frequency EEG analysis. Genuine happiness, fear, and disgust were compared to their pairwise posed contrast by means of Mass-univariate analysis. We expected to find a difference in the delta and theta bands between genuine and posed happiness at the beginning and after the apex of the emotional display. We also hypothesized a more significant activity of genuine fear and disgust expressions because of their stronger and more ecological valence than the posed counterparts.

Overall, results confirmed a significant difference between the processing of genuine and posed emotion in both the timing and the topography of the canonical EEG bands.

In particular, happiness yielded a negative cluster in delta and theta activity during the processing of genuine expressions, mainly distributed on frontocentral and occipital sites at the beginning and toward the end of the emotional display. In other words, posed happiness expressions are revealed to be more prominent than the genuine ones in these time-frequency representations. In general, the greater frontal activity of the delta and theta bands in happiness perception is in line with the previous literature (Güntekin et al., 2019; Güntekin & Başar, 2016). The boosted activation of posed happiness may be explained, according to our hypotheses, by the higher cognitive load processes involved during the onset and after the apex of the expression. The nature of the explicit task (i.e., categorizing the emotion genuineness) may have led participants to focus on the clues when the difference between genuine and posed happiness is more evident. Different studies, indeed, proved that the relative durations of onset (i.e., more prolonged onset for genuine smiles), apex, and offset phases of a smile would distinguish between spontaneous and deliberate smiles (Guo et al., 2018; Krumhuber et al., 2013; Krumhuber & Manstead, 2009; Schmidt et al., 2006, 2009). The prominent activation of deliberate smiles at the start and after the plateau of the expression may thus reflect the discordant timing facial change appearances of posed happiness compared to the genuine ones.

Concerning the emotional expressions of fear, statistical analysis revealed a strong increase in several bands' power during genuine fear processing around the emotional expression's high peak intensity. This effect resulted in being larger in the theta band, from occipito-parietal sites toward the whole scalp, and in alpha and beta power over frontal and occipital sites. We suggested that this result may be due to the endogenous valence of genuine fear expressions, resulting in being more salient than the posed counterpart. According to that, the prominent activation during the processing of genuine fear expressions would indicate a greater impact of authentic emotional expressions on participants' arousal and perception. Likewise, the weaker activation of posed fear could be caused by the lower valence of posed fear expressions. Consequently, participants might have simply mirrored the shown posed expression without directly "feeling" scared. This suggestion would be in line with the mirror neuron system (Adolphs, 2002; Gallese, 2007) and with previous literature that showed enhanced specific brain activation patterns for more ecological and natural stimuli (Trautmann et al., 2009). Additionally, these results also appear coherent from an adaptive point of view. Indeed, fear recognition plays an essential step in our evolution to appropriately identify and respond to potential threats (Sun et al., 2012). The emotional resonance of genuine/real fear processing, in this sense, would be stronger and more relevant to the observers' perception than a "fake alarm" displayed in posed fear because of the adaptive role of (authentic) fear in augmenting human sensory vigilance (Davis & Whalen, 2001; Whalen et al., 1998). The same pattern would have been expected for the processing of disgust since it overlaps with fear for its avoidance and aversion effects to the perceived stimulus (Phillips et al., 1997; Woody & Teachman, 2000). However, in contrast with our hypotheses, a significant cluster of larger cortical response for genuine disgust can be detected only in the second half of the facial display. At the beginning of the facial dynamics, posed disgust processing seems to have a greater effect on the perceiver. We suggested that this result may be due to the fact that the arousal and the more dominant/aversion effect of disgust become prevalent only after that genuine disgust reaches the maximum intensity of its facial display. Another suggestion that could be advanced to interpret this finding regards the discrimination of the facial clues in the genuineness detection of disgust. Even though there are no facial clues able to discriminate genuine from posed disgust, it may be plausible that the delta band activation for posed disgust, like in the posed happiness, reflect a different facial expression kinematics that yields a more cognitive load and more attention (as reflected in alpha bands) at the beginning of the posed disgust display.

Overall, the present study shows how the perception of the genuineness of an emotion is reflected in the cortical activity of the observers. Valence of the emotional expression seems to be extremely relevant. In response to fake positive expression we were able to identify for each emotion a unique pattern of response, in terms of timing, spectrum and topography On the other hand, unpleasant expressions of fear and disgust are associated with a larger cortical recruitment when they are genuine. This is particularly expressed over centro-parietal regions and in the theta, alpha and beta bands.

These results represent the first evidence of neural dissociation of the processing of genuine and simulated emotions. This dissociation is particularly relevant for studies of social cognition investigating individual differences in social interactions. Indeed, an appropriate ability to discriminate genuine from not genuine emotions is critical for successful social interaction. For instance, the perception of genuine smile might promote social interaction, while the perception of a posed smile might promote avoidance. Similarly, the perception of a genuine fear might promote a state of alert, while the perception of a posed fear might not. Thus, the current results on the perception of emotional genuineness are pivotal for a complete understanding of the behaviors emerging in social interactions.

Furthermore, the evidence that simulated facial expressions are processed differently from genuine expressions is relevant for studies that employ the former kind of stimuli (*i.e.* avatar, computer-generated faces, morphed faces). Thus, we feel to recommend future investigation to further characterize this difference and its potential impact for the study of emotional expressions and their neural correlates.

Finally, it is important to highlight that this study is not devoid of drawbacks. The first limitation concerns the nature of the task used in the experimental design. Indeed, the explicit task used in the present study may have affected the processing of the emotional stimuli. In particular, participants were asked to categorize the emotion as well as the genuineness of the emotional display, thus prompting them to orient their attention on the facial clues that could facilitate the discrimination between emotions (i.e., disgust, fear, happiness) and condition (i.e., genuine and posed). However, the choice of an explicit task was a forced-choice since the complex nature of the task. Several studies demonstrated how people tend to perform not far from the chance level when asked to recognize deceit in emotional displays, in particular, if they have to rely on visual cues only (Bartlett et al., 2006). Considering that, the explicit task was an unavoidable choice to delete mistakes due to the wrong categorization of the stimuli or a drop in participants' attention.

Another limitation regards the stimuli used. Genuine and posed emotional facial expressions are known to differ in their kinematics display (Ambadar et al., 2009; Cohn & Schmidt, 2003; Guo et al., 2018; Krumhuber et al., 2013; Namba et al., 2021; Sato et al., 2004; Schmidt et al., 2006; Valstar et al., 2006; Yoshikawa & Sato, 2006). However, time-frequency analyses require stimuli that match in timing in order to be correctly investigated. To overcome the kinematic mismatch of stimuli, we extended the first frame of each clip, thus making the genuine and posed emotional displays of the same duration. In this way, the facial change appearance (i.e., onset, apex, offset) of genuine and posed emotions do not overlap perfectly, thus reducing the possibility of a more fine grained characterization of the cortical dynamics. Future studies need to address the following limitations, reducing the endogenous difference between genuine and posed emotional facial expressions as much as possible in order to provide more accurate insights into the genuineness perception of emotions conveyed by faces.

4.6. Conclusion

In conclusion, this study adds to the literature on emotion genuineness perception a new important step forward, by highlighting that genuine and posed emotions, and in particular happiness, fear and disgust, are processed differently in our brain, as revealed by EEG time frequency analysis. These results suggest that the knowledge we have so far on the perception of emotions conveyed by faces could potentially be partial and biased by the (un)conscious perception of the non-genuineness of perceived emotions. As the first of its kind, we hope that this study will serve as the foundation for future studies that are needed to further explore this interesting topic.

I can feel you now. I know that you're afraid. You're afraid of us. You're afraid of change. I don't know the future.I didn't come here to tell you how this is going to end. I came here to tell you how it's going to begin.

Neo, Matrix

GENERAL DISCUSSION

The human nature to lie makes the genuineness of the emotional facial expressions a topic extremely important in research and daily life.

Surprisingly, to date, this topic has been neglected in the psychological literature, causing a significant limitation in the understanding of emotions, and more specifically, of genuine/spontaneous and posed/fake emotional facial expressions.

The following thesis aimed to explore the emotion genuineness under two different perspectives: detection and perception of spontaneous and posed emotional facial expressions.

A unique dataset of emotions displaying spontaneous and posed facial expressions has been created for this purpose. A total of more than 1450 clips portraying the six basic emotions by 56 subjects are included in the final version of the dataset, called Padova Emotion Dataset of Facial Expressions (PEDFE). PEDFE represents a new opportunity in the study of emotion genuineness, providing to the scientific community a new dataset of emotional facial expressions including both spontaneous (i.e., genuine) and posed emotions from the same actor and validated by independent raters.

In this dissertation, PEDFE was used in chapter 2 as input to train cutting-edge Machine Learning algorithms to detect emotions' genuineness automatically. The results obtained revealed the significant inter-individual variability in the display of emotional facial expressions, making the generalization of the detection of spontaneous and posed emotional facial expressions an unrealistic aim, also raising doubts about the universality of emotional displays as well as the reliability of emotion recognition software adopted so far. However, the infinitive possibility to get access to different sources and data (e.g., Tik Tok, Instagram, and forth on) allows specializing the automatic genuineness detection ad hoc for each subject/user. This approach resulted in being highly effective in the automatic prediction

achieving up to 84% of accuracy.
Additionally, by using highly accurate in vivo 3-D motion analysis, we investigate the muscles kinematics of both the upper and lower face. Promising results about the difference between spontaneous and posed emotional expressions were obtained, providing new insights for future analysis in the classification of emotion genuineness.
In the last chapter, a different perspective was adopted by investigating the perception of spontaneous and posed emotional facial expressions from an observer's point of view. A time-frequency EEG analysis was used for the first time. Significant differences were found in the explicit perception of genuine and posed fear, disgust, and happiness, highlighting the significant differences in the brain mechanisms involved in processing emotional displays. These results may suggest that the knowledge we have so far on the perception of emotions conveyed by faces could potentially be partial and biased by the (un)conscious perception of the non-genuineness of perceived emotions. Additionally, it contributed to the necessity to consider the authenticity of emotional facial expressions as a crucial factor to consider in future studies and in general in psychology and neuropsychology.

Supplemental Material A

1A. Pearson correlation table between "hit rates emotion" (HRE), "hit rates for genuineness" (HRG), and "emotion intensity perceived" (EI).

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