Chapter 17
Emotional Expression as a Means of Communicating Virtual Human Personalities

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Abstract Virtual humans with realistic behaviors have become prominent actors of compelling virtual experiences in domains as diverse as entertainment, education, and healthcare. A significant factor contributing to their behavioral realism is their personality, which characterizes distinctive traits consistent over time. Virtual humans can express personality traits through various channels such as voice, face, or body. In this chapter, we will focus on how emotional expression through facial expressions and body pose affect the communication of virtual human personalities. Throughout the chapter, we refer to the five-factor model of personality, which consists of five orthogonal dimensions of openness, conscientiousness, extroversion, agreeableness, and neuroticism. We will investigate their representation through the expression of the basic emotions of happiness, sadness, fear, anger, and disgust.

17.1 Introduction

Whether for an ant building the colony's nest or a lion hunting for food, communication is essential to an organism's survival. As much more complicated social beings, humans communicate with the purpose of more than just a message transfer between sides. We exchange feelings and desires, expressing our inner selves through intricate verbal and non-verbal signals. Despite the signal complexity and independent of the closeness of the relationship, understanding the feelings

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of another individual is straightforward for an average person. We unconsciously analyze the facial expressions, gestures, and vocal signals of the person we communicate with and make instant deductions about their emotions. Emotional signals have universal associations and can be recognized similarly across cultures or even species [20, 27]. This knowledge allows actors to replicate signals of affect, regardless of whether they have internalized the corresponding feelings or not [81]. Such knowledge also informs the design of virtual characters: although virtual characters do not "feel", their accurate manifestation of emotional signals makes them believable and engaging.

Virtual characters are essential to the digital world, from video games and animated films to virtual assistants and social avatars. We expect these characters to look and act like humans, exhibiting consistent behaviors representative of their characteristics. Consistency and human-like behavior can be established by imbuing personality into virtual characters as personality quintessentially defines an individual's long-term and distinctive traits. Additionally, multiple studies have shown that people can accurately assess the personalities of virtual humans based on verbal and non-verbal cues [25, 42, 45, 70, 85]. In this chapter, we examine how virtual humans' emotional facial expressions and body postures affect the perception of their personalities.

Ample research indicates that personality traits control the intensity and frequency of emotional responses [55, 61, 63, 69]. Even without a causal link, we associate certain emotional responses with specific personality traits [13, 85]. First impressions of personality are often influenced by the perceived emotional content of an individual's neutral facial expression, which is controlled by physical features such as the shape of the face [1]. This influence carries the risk of overgeneralization and stereotyping, as certain features may be attributed to specific emotions and genders. For example, rounder faces are often associated with females and resemble fear and surprise expressions, leading to the perception of submissiveness. Without falling into the trap of stereotyping, this chapter presents our research on the relationship between the usage of facial expressions and body poses, rather than physical features, that indicate emotions and their impact on personality perception.

For personality description, we use the five-factor model [23], which is an established and widely-adopted personality model. The five factors are openness, conscientiousness, extroversion, agreeableness, and neuroticism. For emotions, we refer to the six basic emotions of sadness, happiness, anger, fear, surprise, and disgust [46]. Although there are contradicting theories on which emotions are universal [28, 80], these six are commonly recognized in the Western world.

We describe two user studies to collect judgments on virtual humans' apparent personalities, given images depicting them with emotional facial expressions and body poses. The results indicate statistically significant links between the participants' perception of virtual human personalities and their emotional expressions. For example, we found sadness related to introversion and anger to low agreeableness. We found that facial expression and body pose determine different personality factors. For instance, agreeableness was better represented in facial expressions, whereas emotional poses were more indicative of extroversion.

Body poses that express the same emotion have higher variance than facial expressions, which directly correspond to emotions; consequently, we take a closer look at the subtle pose differences that cause personality shifts. We also discuss how pose descriptors based on Laban Movement Analysis (LMA) can explain these personality shifts.

Controlling the emotional content of a virtual character in line with these findings can help animators and researchers design better personality expressions and more realistic communication. We should note that the interpretation of emotional expression may vary without contextual information [64]. In such cases, different signals such as body pose [9], lighting conditions [100], or the background scene [98] can provide context and improve the accuracy of emotional perception. However, in this chapter, we analyze emotions in isolation from context, for the sake of facilitating controlled experiments by reducing the number of variables involved.

17.2 Background

The five-factor model of personality is supported by a considerable number of empirical studies [89] that explain its cross-cultural coverage [48], neurobiological correlates [22], temporal stability across the life span [78], and genetic structure [99]. The model investigates the psychological nature of an individual under five orthogonal dimensions [23], each grouping multiple traits on a bipolar and continuous scale. Openness measures curiosity and creativity. People with high openness tend to enjoy trying new experiences; in contrast, individuals with low openness dislike change. Conscientiousness is related to controlling and planning. High conscientiousness relates to being organized; people with low conscientiousness tend to act irresponsibly. Extroversion examines the social aspect of interaction. Extroverted individuals tend to be more outgoing and energetic, while introversion is associated with being reserved. Agreeableness measures empathy. High agreeableness relates to being understanding and kind; low agreeableness involves rude and irresponsible behavior. Neuroticism examines the tendency towards anxiety and negative feelings. High neuroticism is associated with anxious behavior, while low neuroticism corresponds to being calm and secure.

The face is the focal point of interpersonal communication. We are evolutionarily attuned to facial expressions [33] as they have evolved from our needs. For instance, we express pain to request sympathetic attention [96] and fear to alert others [91]. A combination of facial muscles acts together to form an expression. Rather than focusing on individual muscle activities, Facial Action Coding System (FACS) [29] describes facial expressions where each atomic movement on the face is classified with an Action Unit (AU). For example, the facial expression of joy includes AU 6 (Cheek Raiser) and AU 12 (Lip Corner Puller). The omission of an AU influences the genuineness of the corresponding expression—a happy expression without AU 6 is more likely to be perceived as fake. The realism of the facial expressions of the computer-generated characters highly depends on the correct usage of AUs.

Primary emotions are strongly related to facial expressions with well-defined parameter combinations. Body poses also convey emotions, although their link is not defined precisely. For example, rising and spreading joints can signal happiness, but there is no universally accepted single posture to show happiness, unlike the facial parameters of happiness. Introducing context, such as placing a gift box in front of a person to convey happiness, can improve the understanding of emotions. However, in this chapter, our focus is on analyzing the influence of different body poses on personality perception, without the presence of contextual factors. Thus, evaluating a set of poses regarding a specific emotion is more meaningful than using a single pose.

A possible choice to associate individual joints' contribution to the emotional content of a pose is to utilize LMA. LMA [38] offers a formal system to describe, visualize and interpret human movement under four main categories: Body, Effort, Shape, and Space. The Body category describes the structural and physical attributes of the human body during movement. The body parts involved in the movement and their influence on other body parts are examined under this category. Effort defines the dynamic characteristics of movement concerning inner intention. The difference between an angry punch and a friendly tap is identified by four Effort Factors (Space, Weight, Time, and Flow). Shape expresses the way the body changes shape during movement. Shape Qualities, a subcategory of Shape, describe this change relative to a spatial reference point (Rising/Sinking, Spreading/Enclosing, and Advancing/Retreating). Finally, Space examines the motion in connection with the environment.

17.3 Related Work

Research on expressive virtual humans spans various fields with the ultimate goal of creating human-like behavior. Accurate representation of emotions and personality is a part of achieving this goal. Under these two categories of affect, we discuss research focusing on recognition and expression/synthesis. Although our main objective is to establish expressive communication, recognition is essential for uncovering the factors contributing to successful expression.

17.3.1 Emotion and Personality Recognition

Works that study emotion recognition generally focus on the face and body [3, 10, 16, 40, 47]. Wegrzyn et al. [95] investigate the influence of each facial region on emotion recognition by revealing one sub-region until the participant decides that the expression is recognizable. They report that sadness and fear are manifested in the eyes while disgust and happiness in the mouth. They devise and validate a correlation between facial action units and the expressions that they describe. Glowinski et al. [35] analyze the upper body motion to relate actor movements with four emotional categories of anger, joy, relief, and sadness, utilizing geometric descriptors based on the triangle formed by the head and the hands. They employ features inspired by LMA, such as calculating the convex hull volume of the body joints to describe the Shape component [4]. Parameters that describe movement style can be used for identifying emotions [15, 18, 39, 76].

Although face and body play the most critical roles in emotion recognition, speech [56], psychological signals [82], and text [6] also give extensive information. Context can improve the accuracy of emotion recognition by providing additional information to the otherwise ambiguous emotions [9, 98, 100]. The most successful approaches utilize multiple audiovisual features in deep architectures [93].

Apparent personality can be estimated based on motion cues [57], facial videos [26], body shape [43], social network profiles and messages [31, 50], physiological sensor data [86], and portrait images [71]. Even an individual's room can reveal cues about their personality [36]. Multi-modal systems that combine numerous cues yield superior performance in personality recognition [8, 11]. Using LMA-based features improves emotion [7] and personality [30] recognition from the skeletal pose. The success of affect recognition, which relies on data-driven methods, is often dependent on the availability of a large data set. Therefore, many studies use in-the-wild data sets in order to increase the sample size [64]. Such data sets introduce higher variance compared to acted data sets acquired in controlled environments. Because we are interested in discovering the personality connections of different emotional poses, we require each sample to have strong emotional associations. To this end, we utilize the BEAST data set [21] that includes acted poses with clear emotional associations.

17.3.2 Emotion and Personality Synthesis

Existing work mostly focuses on the facial expression of emotions [41, 44, 54, 74, 97] as the lack of facial expressions can cause an uncanny effect, dramatically reducing a virtual human's plausibility [90]. For a facial expression to be recognizable, the virtual character should include sufficient detail signaling the emotion [12]. When the faces of the individuals are not visible [62], such as crowd simulations [24], certain patterns of body motion help portray specific emotions [19]. When the emotions conveyed by the face and body cooperate, they improve communication [87]. However, when body and face express conflicting emotions, body language is more influential than the facial expressions on observers' judgments [68].

LMA is used to control high-level motion parameters that govern the style of human motion. Through automatic adjustments that affect these parameters, generative systems can convey different emotions using the same input motion [14]. To this end, qualitative LMA elements are translated into quantitative motion features utilizing empirical frameworks [17]. Designing the character's motion using such LMA-based quantitative attributes is highly beneficial in gesture animation [5, 25]. These attributes are also used in expressing emotions in robot motion where physical constraints are more restrictive [67].

Gestures can help express different personalities in human-like robots and virtual characters [53, 73, 84]. Motion of the hands [94], the use of facial expressions [85], voice style [75], and dialogue content [66] are all important factors that influence personality expression.

In this work, we focus on static emotional facial expressions and poses and leave the analysis of animations as future work. The perceived intensity of emotional expressions for static images is slightly less than their dynamic counterparts [52], but emotion recognition accuracy in static and dynamic images are mostly similar [51]. Consequently, we investigate the interactions in the static space where fewer variables are involved. We expect a similar but stronger response in dynamic emotional facial expressions and poses. Nevertheless, static emotional faces and poses are heavily used in websites, illustrated books, and visual novels due to their lower cost and the limitations of the media.

Recent work in synthesizing novel poses using human images [34, 60, 83] is promising for generating realistic virtual agent imagery. Combined with methods of facial expression transformation [65, 88], a single image can span many frames expressing a wide range of emotions. Generative Adversarial Network (GAN)-based architectures can be an alternative to the tiresome process of creating realistic 3D humans. Generative networks can also produce novel poses that exhibit the target emotions [2]. We follow such an approach for body pose generation.

17.4 The Effect of Emotions on Personality Perception

Devising a one-to-one mapping between emotions and personality is impractical, as people can feel and express the same emotions regardless of their personalities. On the other hand, a large body of research acknowledges some personalities' increased susceptibility to specific emotions and their control of emotional expressivity [49, 77]. In this chapter, we explore how this knowledge applies to virtual humans and to what extent emotions expressed through the face and body pose impact the perception of the five personality factors.

We describe two user studies designed to find associations of specific image categories with the apparent personality factors they suggest. The first study investigates the effect of emotional facial expressions of 3D human models, and the second study analyzes the impact of emotional poses of synthetic images on apparent personality.

17.4.1 Study 1: Emotional Facial Expressions and Personality Perception

For the first study, we designed the facial expressions of happiness, sadness, anger, fear, and disgust on a 3D model using Adobe Fuse. We tuned the facial blend shapes of the model according to the FACS specification of AU intensities. We captured six images of the model with neutral, happy, sad, angry, scared, and disgusted expressions (cf. Fig. 17.1). We did not include surprise as it was indistinguishable from the scared expression, given the facial blend shapes of our model. Because of the universal recognition and precision of the facial expressions, we prepared one image per category.

We conducted an Amazon Mechanical Turk study to collect judgments on the perceived personality factors in each image. The virtual human's physical appearance was the same; only the facial expressions changed across each image. We asked participants to rate the personality of the character on the image 7-point Likert scale [58] using Ten Item Personality Inventory (TIPI) [37], which is a validated, brief personality inventory. At the beginning of the study, we showed a set of facial expressions to prepare the participant. The participant was allowed to view each sample without any time limitation. Samples were shown on the screen one at a time in random order. Each image was evaluated by 100 individuals (64 male and 36 female, with a mean age of 29.4).

We grouped the results based on their emotion labels to analyze the relationship between the emotion category and the perceived personality. Following the standard usage of TIPI, we averaged the participants' choices to the related questions to calculate the per-factor personality score. The Likert-scale OCEAN score distributions of each emotional category per personality factor are shown in Fig. 17.2.

Fig. 17.1 Samples with different facial expressions used in the first study

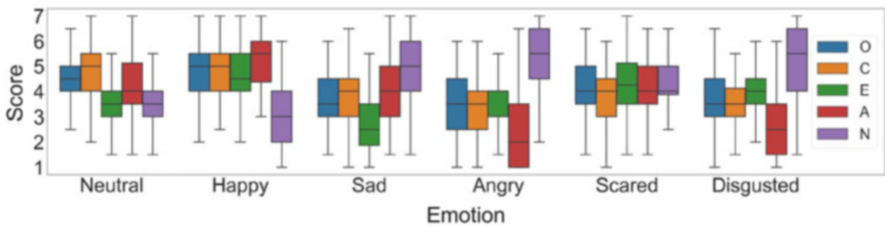

Fig. 17.2 Likert scale OCEAN score distribution of each facial expression in the first study

We observe that the neutral expression portrays subtle traits and does not correspond to a neutral personality (Fig. 17.2). The lack of a facial expression may have led the participants to focus on the character's physical appearance, which can also convey signals about personality [43]. Various traits can influence the perception of a general personality dimension, called the Big One [72, 79]. This is a phenomenon where all personality factors collapse into a single dimension, and are observed as either positive or negative (neuroticism being reversed, as high neuroticism has negative connotations). We observe a general positiveness in happy facial expressions. For the negative pole, we find that high neuroticism is common in sad, angry, and disgusted emotions, while introversion is linked to sadness, and disagreeableness is related to anger and disgust.

The happy expression scores highest in openness, conscientiousness, extroversion, and agreeableness. The angry expression has the lowest openness, conscientiousness, and agreeableness scores, whereas the sad expression has the lowest extroversion score. The highest neuroticism score is achieved by anger, and the lowest score by happiness. Images or animations of virtual humans portraying these emotional facial expressions can communicate the corresponding personalities. Because the personality scores of neutral and scared facial expressions are weak, they can depict neutral traits.

For the emotions highly influential on the perception of a specific factor, we expect more divergence from neutral personality, which corresponds to a score of 4 on a 7-point Likert scale. For example, angry and sad expressions both indicate neuroticism; however, the mean neuroticism score of anger is closer to 7, making it a better candidate for expressing neuroticism.

The highest variance is for agreeableness and neuroticism, while the lowest is for openness and conscientiousness. Low variance in openness and conscientiousness is also observed in similar research [85], possibly because these traits are hard to observe in a short time.

For further analysis, we calculated each image's average scores per personality factor and grouped them based on their emotion category. Then, we performed an ANalysis Of VAriance (ANOVA) per personality factor to evaluate the statistical significance of the differences between the mean scores of emotion categories. The null hypothesis assumes no statistically significant difference. Since ANOVA only reports the existence of statistical significance, we also performed Tukey's HSD [92] to find significantly different means.

The mean differences on a 7-point scale are shown in Table 17.1. The colored cells highlight the statistically significant differences. For each emotion pair and factor of interest, the mean difference was calculated by subtracting the mean score of the emotion on the right-hand side from the one on the left. If the mean score difference is positive, the emotion on the left-hand side has a higher score than the emotion on the right.

The highest mean differences are achieved for agreeableness and neuroticism between happy-angry and happy-disgusted pairs. Compared to the neutral expression, the highest difference is achieved by the angry expression, while the lowest is for the happy expression. The happy and sad emotions have opposite signs for each

Table 17.1 Facial expression ANOVA study results. For each emotion pair, the mean difference was found by subtracting the mean score of the emotion on the right-hand side from the mean score of the emotion on the left, where per factor mean scores were calculated in terms of the 7-point Likert scale. Colored cells show statistically significant differences. Gray shows differences up to 1; blue shows differences between 1 and 2, and yellow shows differences higher than 2

Emotion pair	Δ_O	ρ_O	Δ_C	ρ_C	Δ_E	ρ_E	Δ_A	ρ_A	Δ_N	ρ_N
Neutral − happy	−0.345	0.243	−0.205	0.765	−0.945	0.001	−0.935	0.001	0.445	0.094
Neutral − sad	0.725	0.001	0.770	0.001	0.785	0.001	0.200	0.843	−1.420	0.001
Neutral − angry	1.06	0.001	1.22	0.001	−0.220	0.741	1.870	0.001	−1.985	0.001
Neutral − scared	0.190	0.812	0.880	0.001	−0.820	0.001	−0.020	0.900	−0.885	0.001
Neutral − disgusted	0.765	0.001	1.050	0.001	−0.375	0.209	1.675	0.001	−1.740	0.001
Happy − sad	1.070	0.001	0.975	0.001	1.730	0.001	1.135	0.001	−1.865	0.001
Happy − angry	1.405	0.001	1.425	0.001	0.725	0.001	2.805	0.001	−2.430	0.001
Happy − scared	0.535	0.009	1.085	0.001	0.125	0.900	0.915	0.001	−1.330	0.001
Happy − disgusted	1.11	0.001	1.255	0.001	0.570	0.008	2.610	0.001	−2.185	0.001
Sad − angry	0.335	0.275	0.450	0.055	−1.005	0.001	1.670	0.001	−0.565	0.012
Sad − scared	−0.535	0.009	0.110	0.900	−1.605	0.001	−0.220	0.777	0.535	0.021
Sad − disgusted	0.040	0.900	0.280	0.494	−1.160	0.001	1.475	0.001	−0.320	0.415
Angry − scared	−0.870	0.001	−0.340	0.271	−0.600	0.004	−1.890	0.001	1.100	0.001
Angry − disgusted	−0.295	0.422	−0.170	0.892	−0.155	0.900	−0.195	0.860	0.245	0.676
Scared − disgusted	0.575	0.004	0.170	0.892	0.445	0.079	1.695	0.001	−0.855	0.001

factor. Anger and disgust are perceived very similarly, but negative associations with disgust are slightly less than with anger. The highest mean difference total is between happy and angry expressions. Sadness differs from other emotions of negative connotation (anger, fear, and disgust) in terms of extroversion, as sadness is more associated with introversion while others are with extroversion. This aspect of sadness can help isolate extroversion to control the apparent personality better.

17.4.2 Study 2: Emotional Body Poses and Personality Perception

The second study investigates the relationship between emotional poses and apparent personality. In contrast to facial expressions, the emotional content of different body poses is not universally recognized. Therefore, we represented each category with multiple images in this study. We generated 40 full-body images from four emotional categories (angry, happy, sad, and scared) using Liquid Warping GAN [60], a pre-trained pose transfer network. Liquid Warping GAN is a multi-task model that can be used for *human motion imitation*, *novel view synthesis*, and *appearance transfer*. We used human motion imitation that takes a source image and a target pose to generate a novel image of the source expressing the target pose. Each emotional category included ten pose variants to compensate for the variance in poses representing emotions.

We generated full-body images from the emotional poses in BEAST database [21], which includes 254 poses produced by 46 individuals expressing four emotions. Images in the BEAST database lack the faces of the actors, which occasionally causes pose estimation failure in specific images. To overcome this issue, we imitated a subset of 40 poses in the database. For the input source images that represent the body appearance, we utilized the DeepFashion [59] data set. Figure 17.3 shows three images generated from each emotion category. Unlike the first study, the categories of neutral and disgusted were not included since they were not available in the reference database, possibly because they lacked clear representations of body poses.

We conducted an online user study where 35 participants (25 male and 10 female, mean age of 21.6) rated the apparent personality in each image using TIPI [37]. Due to the increased sample size in this study, we used a 5-point Likert scale [58].

Like the first study, we showed a set of sample poses for warm-up at the beginning. The participant was allowed to view each sample without any time limitation. Samples were shown on the screen one at a time in random order. Participants of the two studies were non-overlapping.

We grouped the results based on their emotion labels to analyze the relationship between the emotion category and the perceived personality. The Likert-scale OCEAN score distributions of each emotional category per personality factor are shown in Fig. 17.4.

The results of the pose study indicate less divergence from the neutral personality (cf. Fig. 17.4). This divergence could be caused by the multiple images representing each emotional category. Subtle changes in the pose could result in different personalities, and grouping such poses together could have diminishing effects. In this case, a closer look at each pose can reveal exciting results, which we leave

Fig. 17.3 Pose samples from each emotional category used in the second study

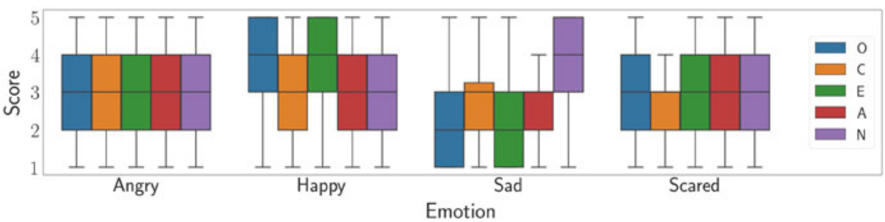

Fig. 17.4 Likert scale OCEAN score distribution of each emotional category of the pose study

Table 17.2 Pose transfer ANOVA study results. For each emotion pair, the mean difference was found by subtracting the mean score of the emotion on the right-hand side from the mean score of the one on the left. Per-factor mean scores were calculated in terms of the 5-point Likert scale. Colored cells indicate statistically significant differences. Gray indicates differences up to 1, and blue indicates differences higher than 1

Emotion pair	Δ_O	ρ_O	Δ_C	ρ_C	Δ_E	ρ_E	Δ_A	ρ_A	Δ_N	ρ_N
Happy − angry	0.301	0.459	−0.071	0.900	0.547	0.187	0.322	0.151	−0.094	0.900
Sad − angry	−0.828	0.001	−0.292	0.130	−1.198	0.001	−0.162	0.676	0.626	0.007
Scared − angry	−0.147	0.880	−0.314	0.092	−0.122	0.900	−0.053	0.900	0.205	0.649
Sad − happy	−1.129	0.001	−0.221	0.338	−1.745	0.001	−0.489	0.012	0.720	0.002
Scared − happy	−0.448	0.141	−0.243	0.258	−0.669	0.075	−0.376	0.072	0.299	0.355
Scared − sad	0.681	0.010	−0.022	0.900	1.076	0.002	0.109	0.875	−0.421	0.107

for future studies. When we group the samples based on emotion, we observe that angry and scared poses are perceived as more neutral. We find that happy poses indicate high openness and extroversion. Sad poses, on the other hand, convey the opposite traits in addition to high neuroticism. Similar to the first study, a tendency to perceive the general positiveness [72] is prominent.

The results are shown in Table 17.2 on a 5-point scale. The colored cells highlight the statistically significant differences. The mean differences were calculated similar to the study of facial expressions.

The highest mean differences are achieved for extroversion, while different emotional poses do not significantly differ in conscientiousness. We observe the highest mean difference between sad and happy poses, while the most similar personalities are found in scared and angry poses. Similar to the first study, sadness is highly related to introversion. Sad poses are also low in openness compared to the other emotions.

We also compare the personality scores of various individual poses because subtle variations in pose can result in significant personality differences. We only look at a few examples of pose couples due to limited space, but the complete results of our user study are available at https://github.com/khasmamad99/personalityTransfer for further research.

In Fig. 17.5, we compare two angry poses. The figure on the left has his hands on his hips. In contrast, the figure on the right keeps his hands together with a slightly turned posture and tilted head. When the figure's body is not directed toward the camera, we observe an increase in agreeableness.

In Fig. 17.6, we compare two happy poses. The figures primarily differ in terms of hand positions. The figure on the left has a spreading pose, while the figure on the right keeps his hands closer to his body. The figure on the right has a slightly wider foot positioning. We observe an increase in the general positiveness dimension when the pose spreads more. The most influenced factors are extroversion and openness.

In Fig. 17.7, we compare two sad poses. While the two figures are mostly similar, the figure on the left is looking down. In contrast, the figure on the right looks directly at the camera and is slightly more rising. We observe a significant

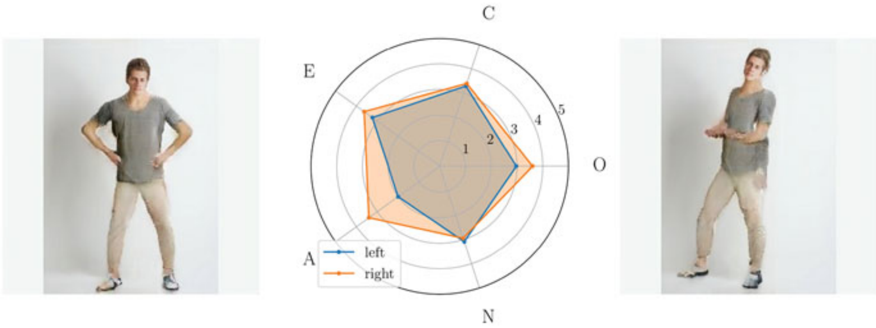

Fig. 17.5 Comparison of two angry poses

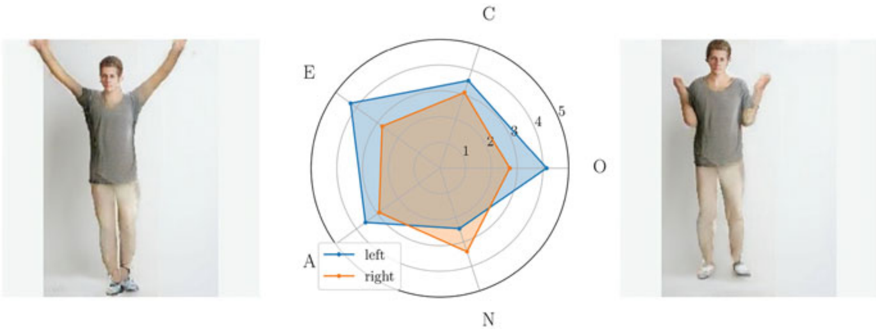

Fig. 17.6 Comparison of two happy poses

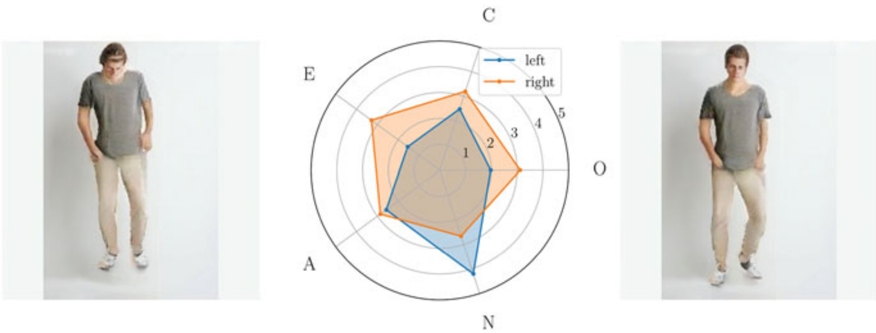

Fig. 17.7 Comparison of two sad poses

extroversion increase when the character faces the camera. The figure on the left has higher neuroticism and lower openness.

In Fig. 17.8, we compare two scared poses. Both figures keep their hands towards their heads, expressing scared gestures. The figure on the right is facing forward, while the one on the left is facing away from the camera. The knees of the right

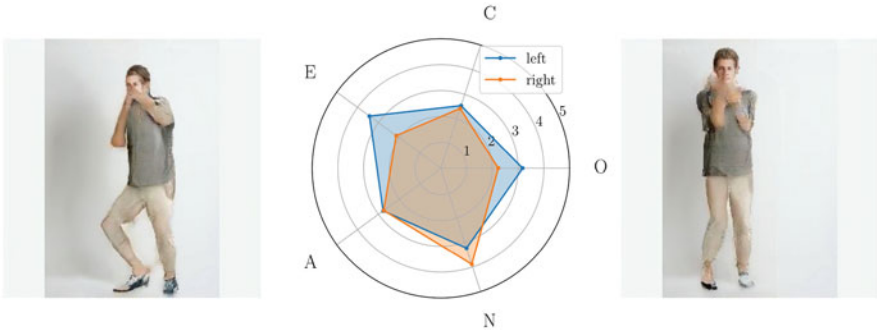

Fig. 17.8 Comparison of two scared poses

figure are spreading. In contrast, the figure on the right keeps his knees closer. We observe higher extroversion and openness in the left figure, probably due to the more relaxed posture. We believe such differences within the groups are the main reason for the mean scores being close to neutral. When the intensity of an expression is low, it can be mistaken for the opposite emotion. Grouping the poses based on emotional intensity can solve this issue.

17.5 Discussion

Facial expressions and full-body poses portray different personality traits based on the emotional categories they represent. Our experiments suggest that facial expressions can describe more diverse personality traits than body poses when presented in isolation. The broad recognition of emotions in basic facial expressions helps achieve stronger personality associations. In contrast, emotions in different body poses are culturally and contextually more varied, without universal connotations. Thus, subtle changes in pose can be misinterpreted by observers, resulting in mixed reactions with diminishing effects in terms of personality expression. These two modalities can be combined to complement each other for better recognition [68] and thus more precise personality expression [85]. In this respect, body poses can provide a context to facial expressions. A natural extension to this work would be to analyze the combination of emotional body poses and facial expressions. Aviezer et al. [9] have studied this by presenting juxtaposed photographs of extreme facial expressions onto bodies in various poses and contexts, such as a tennis player winning a match or a patient in pain. They found that the observers interpreted the same intense emotional facial expression either as joy or pain depending on the body pose. However, the semantics of the scene might have influenced the results, as they depicted different objects and environments such as a tennis racket or a hospital bed. Therefore, further research is needed to fully understand the influence of combining emotional body poses with facial expressions. Regarding the influence of context on emotion recognition, we refer the readers to the chapter by Filntisis et al. [32] in this volume, where the authors explore the effect of different information streams on the automatic recognition of emotions.

The results of our two studies suggest that agreeableness is the best-represented personality factor in facial expressions, while extroversion is the best-represented factor in body poses. For facial expressions, emotions influence the perception of the personality factors in the same direction, suggesting a Big One [72]-like effect. For instance, happiness, a positive emotion, is associated with high openness, conscientiousness, extroversion, agreeableness, and emotional stability, all considered positive traits. In contrast, anger, a negative emotion, has low scores for all these traits. The Big One disposition is not observed in body poses, where emotions have varying effects on the perception of individual factors.

In general, we observe that emotional facial expressions can convey all the personality traits while emotional poses mostly control the perception of extroversion and openness. However, facial expressions also indicate a higher correlation between different personality factors. This is especially prominent in happiness; i.e., by employing a happy facial expression, we can express higher conscientiousness at the cost of a general personality shift in the positive direction. A conscientious yet disagreeable face needs more subtle control of AUs than the simple employment of a smile.

Following the quantitative LMA-based features used in skeletal animation [4, 7], we can form high-level descriptors for static 2D poses. For example, the area of the convex hull of a set of joints can be a metric related to LMA Space Effort, which measures the attention towards the surrounding space. The horizontal distance between the hands can also be a different metric for the same LMA parameter. One can devise many such features and construct a descriptive weighted linear combination, where the weight, or the importance, of each partial feature would be task-dependent. For example, Aristidou et al. [7] use Pearson correlation analysis to calculate the correlation between their interpretation of LMA features and the recognized emotion in short video clips. Partial weights of the linear combination can be adjusted to maximize the Pearson correlation with the subject of interest, similar to how a neural network trains. Our preliminary experiments show that a linear combination of horizontal distances between all joint pairs can achieve a Pearson correlation coefficient as high as 0.9 for extroversion in our emotional pose set. We leave forming a comprehensive LMA feature toolkit for static 2D poses as future work, which can be helpful in both recognition and synthesis tasks in affective computing.

17.6 Conclusion

We present our findings as a general guide in virtual human design for personality expression. Certainly, our test cases are highly broad and more research on the subtle details of facial expressions and body poses is needed to establish precise connections between emotion expression and personality judgments. However, even by controlling the general aspects of emotional behavior, animators can customize the personality of virtual agents to enhance believability or improve communication. Emotional facial expressions and poses can be used together [85] or interchangeably based on scenario constraints. For example, emotional poses can be utilized in setups where the face is not prominent, and facial expressions can be preferred in close-up views.

Subtle pose elements are essential when the pose's emotional content is unclear. For instance, the distance of the hands to the body can influence the apparent extroversion. In this case, more precise control of the pose, for example, using LMA-based features [25, 85], can result in better personality expression. We publish our pose study data for further analysis. A closer look at the differences between the poses of the same emotional category can reveal exciting results. One possible future research direction is to evaluate whether compound emotions enhance or diminish certain effects, and if they have cultural associations that influence the perception of personality traits. Another research direction is to analyze the effect of adding contextual information to isolated facial expressions and poses.

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