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Personality Prediction in Human-Robot-Interaction (HRI)

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ABSTRACT

For an efficient and smooth human-robot interaction, communication protocols such as verbal and non-verbal communication, emotions, and personality plays an important role. Human-Robot-Interaction is an emerging field and robots are now a part of daily life where it can grasp both verbal and non-verbal cues. Personality prediction is an important research area in Human-Robot Interaction (HRI). Several important question in personality prediction includes: which personality traits will be important and which specific phycology model and robot do researchers use? Secondly, how emotions, facial expression, paralanguage, and bodily movements are related to personality traits? And finally, how will we acquire data to train a robot and what kind of questionnaires can be used? With the support of prior research studies and experiments, this paper will contribute towards developing the ground basis for personality prediction using a robot.

Keywords: Personality, HRI, Traits, Emotions, Human behavior, Facial expression, Paralanguage, Body movement, Head pose

INTRODUCTION

Personality determines a person's beliefs, likes, dislikes, thoughts, behavior, and how they act in various situations. Social network posts reflect the user's personality. Personality prediction using social media posts has been done a lot, but now robots are also in this field and much work has already been done. Social robots come in a variety of shapes and sizes that are used in human-robot interactions. Science fiction has led us to imagine a future in which robots assist us in the work. In the realm of rehabilitation, these humanoid robots are well-known, although designers are cautious to avoid the Uncanny valley idea (Pandey and Gelin, 2018; Henschel, Laban and Cross, 2021), (Mara, Appel and Gnambs, 2022). However, it is widely assumed that humanoid robots should imitate humans so, researchers are utilizing robots in personality prediction work. Recognizing human-like features is the definition of a social or humanoid robot (Fox and Gambino, 2021). Numerous personality theories are used to predict personality. Allport's' Trait theory, Cattell's 16 Factor personality, Eysenck's three Dimensions of personality, and Myers-Brigg's type Indicator (MBTI) (Matz, Chan and Kosinski, 2016) are among the most well-known. The Big-Five is the most famous and commonly used with five primary traits Extraversion, Openness, Conscientiousness, Agreeableness, Neuroticism. Each of these has several sub-traits. Costa and McCrae developed the NEO-Five factor inventory (NEO-FFI), a 60 items variant of NEO-FFI (1992). International Personality Item Pool Big-Five marker Scales (IPIP 50) contains 100 items presented by Goldberg (1992) after many years briefer version 20 items developed by Donnellan, Oswald, Baird, and Lucas (2006). The Big-Five Inventory (BFI) 44 items were designed by john, Donahue, Kentle (1991) after many years 10 item version was developed in German & English by Rammstedt and John (2007). The rest of the paper is organized as, section II which comprises personality traits from the big-five model with sub-traits, questionnaires with how they aid in data collection, and the role of a psychologist in all of this. Section III delves into how human emotions or facial expression, paralanguage, head pose, and body movement are extracted and linked traits. Section IV digs into the specifics of robots engaged in personality studies.

PERSONALITY TRAITS & QUESTIONNAIRES

Personality theories contend that individual human features may be utilized to predict human emotion, cognition, and behaviors. A trait is described as "a dimension of personality used to classify persons based on the extent to which they display a certain feature" (Anzalone *et al.*, 2017). These characteristics are regarded as the basic pillars of personality.

Traits

The Big-Five model traits are prominent both in social science research study and human-robot interaction. To support these attributes OCEAN acronym is utilized, which stands for Openness, Conscientiousness, extraversion, agreeableness, and neuroticism (Bhin, Lim and Choi, 2019), (Shah and Modi, 2021), (Müller and Richert, 2018). Each trait as well as facets derived from McCrae & Costa (2006) and utilized in many studies, with each trait inverse. Each trait has a severity scale ranging from low to high.

Questionnaire

Questionnaires based on Liker Scales are utilized for personality evaluation (Anzalone *et al.*, 2017), (Shen, Elibol and Chong, 2021). These surveys allow humans to self-judgment of personality (Anzalone *et al.*, 2017), (Salam *et al.*, 2016), (Huang *et al.*, 2021). In most circumstances, the psychologist provides judgment, except questionnaires. Psychologists provide judgment (cue validity & utilization) linked with the Lens model (Breil *et al.*, 2021) and in our opinion features accuracy is dependent on it, Although ranking which cue is more important in which trait is tough. As previously noted, many surveys can be utilized, but NEO-FFI, IPIP, and BFI are linked to the Big-Five paradigm. Everyone is preoccupied with their jobs. Long surveys take time to complete, either a one-person survey (participant self-esteem) or when participants are needed to score other groups. These surveys are used for data gathering (features), and data is labeled by consulting a psychologist.

FEATURES EXTRACTION & TRAITS

According to psychopathology, face expression and body movement have valuable applications in the study of emotions, depression, and personality. These behavior human show in different situations with speech or without it. Research on non-verbal behavior exposed different channels of judgment. Observers sometimes observe a silent film, live user behavior, typescript, or voice. Non-verbal communication that includes bodily motions, posture, gestures, and facial expressions is referred to as kinesics (Saunderson and Nejat, 2019). Humans are quite adept at deciphering body cues particularly when it comes to personality judgments. Some cues are common in personality studies.

Head Pose

In interactions, humans often utilize the head posture to convey their thoughts whether they want to converse or not, and they agree or disagree. Glancing during a talk at the interaction partner indicates attentiveness but gazing elsewhere indicates apathy and anxiousness (Shen, Elibol and Chong, 2021), (Saunderson and Nejat, 2019). The gaze is connected to the head pose because measuring gaze with a robot camera requires high-resolution pictures and increases the computational cost. Head movement and eye contact are both favorably associated with extroverts because social people employ these indicators during the conversation. Head pose is linked to neuroticism as a result of the unstable emotions a person moves his head often to avoid eye contact. Both are favorably associated with openness because the individuals are open to new experiences and want to connect more. To display submissive conduct, an agreeable person avoids eye contact and lowers the head. An organized and disciplined individual is conscientious, eye contact with head motion is used to convey confidence and disapproval. The roll, pitch, and yaw angles were used to predict head posture to determine the gaze score instead of utilizing eyes (Shen, Elibol and Chong, 2021), (Zafar, Paplu and Berns, 2018) and the gap between two adjacent frames was estimated it's referred to as Manhattan distance. Another estimating approach is the direction magnitude pattern (DMP) (Zafar, Paplu and Berns, 2018), which calculates the direction and magnitude of each pixel concerning its neighbor's resultant force. ROI was recognized using the OpenCV version of the Viola and Jones (Viola and Jones, 2004), Haar cascade technique, and then the Intraface library is used to compute head angles (Salam *et al.*, 2016). Hough transformed (Anitta and others, 2021) was also be utilized to extract head posture.

Body Movement

In studies, arm gestures and body movements were assessed and even the tiniest change in the body was measured. Waving, folded arms, pointing, and other hand or arm actions as do postures like thinking posture, erect posture, and crouching posture send messages. Except for head motions, all movements are considered body motions. Neuroticism has a negative relation with some bodily movements due to unstable emotions, but closed arms and thinking posture are positively related. Extroversions demonstrate bodily movements since they are emotionally expressive. Openness includes those individuals that display curiosity in new experiences, as seen by their open stance or self-assured posture. To demonstrate their agreeableness, agree people don't display much body movements, instead they opt for an open stance. Conscientious person is cautious and competent, they display an open posture or closed-arm posture with a change in proximity to express their opinions. Body pose is determined (Salam *et al.*, 2016; Zafar, Paplu and Berns, 2018) by recognizing skeletal joints of the body, if it reaches a certain threshold then movement occurs otherwise nothing happens. The body motion can be extracted using two photographs. Joint angles were calculated after comparing the original and warped images, images suggesting that the skeleton has been rotated in the reference to the initial skeleton (Shen, Elibol and Chong, 2021).

Facial Expression/Emotions

Facial expressions are any facial muscle action, such as smiling and yawning, as well as expressions with the eyes and brows such as winking, scowling, and so on. The study of facial expression focus on emotions (Ekman and Friesen, 1974). People appraise effective estates based on indicators, such as drooping eyebrows indicating anger. A smile is a symbol of happiness, friendliness, and positive emotion for extroverts. Neurotic people experience negative emotions such as fear, rage, and anxiety as a result of their unstable emotions. Agreeableness is associated with laughter and positive social contact since it is connected to friendliness, compassion, and warmth. Conscientious people laugh for some reason, and they have regulated smirk. Negative emotions have a weak association with conscientiousness. Openness to experience is positively associated with the laugh these individuals want to connect and smiling is a form of communication. Basic emotions were distinguished using convolution neural networks (Zafar, Paplu and Berns, 2018). Five techniques for emotion recognition were compared (Kartali *et al.*, 2018), using happiness, sadness, anger, and fear. The deep learning technique AlexNet CNN for prediction, FER-CNN for extraction features, Affdex CNN, and convolution neural network (CNN) compared to differentiate six basic emotions. SVM and MLP ANN classifiers were employed with HOG features extraction, utilizing facial landmarks supplied by OpenFace for detection. The Affdex SDK and convolution neural network (CNN) were then compared to differentiate six basic emotions (Lopez-Rincon, 2019). A review of deep learning for emotion identification is presented in (Abdullah *et al.*, 2021).

Paralanguage

Paralanguage gives speech rate, voice break, frequency, pitch variance, amplitude, and variation in amplitude (Breil *et al.*, 2021). Individuals rely on their voices to make an impression on others and these cues convey emotions. The big-five factors are related to communication (Sims, 2017). Extroverts are good communicators and use language signals to express intentions. A neurotic person has unstable emotions and refuses to communicate. Agreeableness indicates generosity, sympathy, etc. whereas aggressiveness is the converse. Pleasant people don't adopt aggressive speech to defend their point of view. The creativity, and complexity of one's thoughts are measured by openness, these people are expressive, witty, and verbally proficient. Goal-oriented and self-efficient persons are conscientious. These folks attain their objectives through aggressive communication. After classifying features with k-nearest neighbor (KNN) and Support vector machine (SVM), Linear domain frequency and Mel Frequency Cepstral Coefficients were collected (Jothilakshmi, Sangeetha and Brindha, 2017). The speech feature extractor OpenSMILE was used to extract acoustic features from audio data (Mawalim *et al.*, 2019), which were then combined with head motion and communication abilities as well. The classification techniques employed were SVM, random forecast, Naïve Bayes, and decision tree algorithms. Pitch and vitality of the voice, Mel-frequency cepstral coefficient was extracted (Pandey and Gelin, 2018), and auto-correlation function was employed to monitor pitch before calculating the average of short-term energy.

SOCIAL ROBOTS

Human-Robot-Interaction (HRI) is an exceedingly new topic and has gained a lot of interest. Robots are rapidly being created for global applications such as eldercare, rehabilitation, robot-assisted treatment, and many more. The purpose of social robots is to engage with people utilizing both verbal and non-verbal cues. Many social robots feature anthropomorphic (humanoid) or animal-like appearances. Many social robots have been developed over the years such as Geminoid, Pepper, Nao, Roman, KASPAR, Aibo, Paro, kismet, Keepon, and others (Breazeal, Dautenhahn and Kanda, 2016). NAO and Pepper have commonly used robots. Emotions (Lopez-Rincon, 2019), Autism (Ali *et al.*, 2019), tutoring (Kanero *et al.*, 2021), therapies (Jiménez *et al.*, 2019), tourism (Park, 2020), and a variety of other researches have employed NAO. Pepper operates as a teacher at home (Tanaka *et al.*, 2015), in shopping malls for amusement (Aaltonen *et al.*, 2017), exhibiting emotions (Tuyen, Jeong and Chong, 2018), tourism guide (Park, 2020), and many more sectors, just as the NAO. Many robots are utilized in personality research. NAO was employed (Salam *et al.*, 2016), and participants have a cooperative engagement with each other and NAO. Using the iCub robot (Anzalone *et al.*, 2017) single extraversion trait was measured. A ROBIN humanoid robot was used (Zafar, Paplu and Berns, 2018), for the analyze personality traits in various circumstances. Using pepper (Shen, Elibol and Chong, 2021) features extraction was done, and the robot was interacting with a person at the time. RoBoHoN (Huang *et al.*, 2021) was used to measure personality by recognizing verbal features. Aside from that, iCat, PeopleBot, Meka are employed in numerous personality research.

CONCLUSION

Personalities understanding is vital in HRI. The Big-five is the most used model. Extraversion is the most quantifiable trait. Openness and agreeableness were the least examined traits. All interactions were done in a controlled setting. Each study used a survey as a baseline, and psychologists were asked to classify the observed traits. NEO and IPIP was the most used survey. Skeletonization is often used for extracting body motions while deep learning is extensively used for emotion or facial expression identification.

Features pairing can improve the accuracy of traits. People node heads with remarks to show disapproval. When people interact, they show open posture with staring and zero-degree head stance. When people are angry, they turned heads to avoid eye contact, show close arms, facial expressions change, and shout. Face expression is often linked with speech as compared to other cues. Based on cues it is easy to tell if someone is joyful, sad, furious, scared, or thrilled.

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