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Automatic Assessment of Human Personality Traits: A Step Towards Intelligent Human-Robot Interaction

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***Abstract*— Personality is nothing but individual differences in the way we tend to think, feel and behave. It is ingrained in our basic instincts which tend to answer the question of why people differ in behavioral aspects in our day-to-day life. The assessment of personality traits is highly significant in human-human interaction. However, the topic has not been studied extensively in the context of human-robot interaction. This study focuses on the significance of nonverbal cues with respect to personality traits. A supervised learning approach has been used to recognize 3 personality traits of the *big five* model namely extroversion, agreeableness and neuroticism traits. Nonverbal cues such as head gestures, postures, proxemics, facial expressions and bodily cues are used to construct a feature vector for classification. A humanoid robot, ROBIN, is used for the assessment of personality traits in different scenarios. Sequences are labeled with the help of a psychology expert. The system shows above 90% accuracy in the automatic assessment of personality traits.**

I. INTRODUCTION

Human interactions are highly dominated by the perception of social and behavioral traits. Personality is a significant part of behavioral traits that expresses the characteristics of individuals in different situations. Humans constantly assess personality of their counterparts to interact robustly so as to flourish Human-Human Interaction (HHI). The old but famous saying *First impression is the last impression*, although one of many clichés, is also based on the fact that humans tend to evaluate personality and make assumption of oneself. This can be validated from comprehensive research conducted in social psychology about the perception and evaluation of behavioral traits that involve spontaneous, unintentional and unaware processes [1].

In Human-Robot Interaction (HRI), a direct relationship between personality and behavior has long been recognized [2][3]. There are many implications of assessing personality that can be reached based on the HHI scenarios. Persons engaged in an interaction behave differently based on the personality types they possess and the overall environment in which they act. For example, extroverts seem to have more control and comfort over an interaction, whereas introverts often show less intimacy, control and dominance over a conversation. More to the point, submissiveness - dominance culture in HHI is fairly trivial and can be assessed based on the verbal and nonverbal cues. According to Nass *et al.* [3], generally humans are more likely to interact with others having similar personality type. This fact can be observed from our social circle, e.g., outgoing people tend to make more interactions with people having similar type of personality. Furthermore, sexual orientation, age, social status etc. also play a great role in this regard. This shows the significance and role of human personality in daily life interaction scenarios. Hence, there is a need to assess human personality trait in context of robots for robust and natural HRI.

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The work in this paper is focused on exploiting human personality traits in real-time using vision sensors for robust and successful intelligent HRI. The first goal of this work is to evaluate the significance of nonverbal cues in personality traits. This has been done by using correlation analysis between the traits and the features. The other goal of the paper is to enable a humanoid robot to recognize human personality traits using nonverbal features in real-time. Due to the unavailability of labeled data with respect to personality traits, a psychology expert has been consulted for the generation of ground truth. A supervised learning strategy has been employed. Experiments show that the robot system is able to assess the personality trait of an interaction partner with an accuracy of above 90%. The rest of the paper is organized as follows: Section II discusses state-of-the-art works in context of personality traits and HRI. Section III explains the perception of nonverbal cues. Section IV discusses the approach of assessing personality traits using nonverbal cues. In Section V, a detailed explanation of experimentation and evaluation studies are discussed. We conclude the paper in Section VI.

II. LITERATURE SURVEY

The most dominant theory in the research of personality traits has been presented by McCrae and Costa [4], known as the *Big Five* model. The model consists of five big dimensions namely Extroversion, Openness to new experience, Conscientiousness, Agreeableness and Neuroticism. As far as this model is concerned, each dimension is considered to be

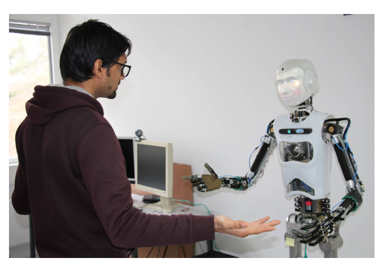

Fig. 1: Humanoid robot, ROBIN, is interacting with a person.

a continuum or spectrum, in which the extremes are quite distinct. In other words, a person is placed somewhere on the continuum of each dimension based on the individual scores. Verbal and nonverbal features are taken into account to recognize possible personality trait. Interestingly enough, a person can be placed in more than one dimension, but there is a dominant personality trait ingrained in each person [5].

In the recent years, few works with novel ideas have already been published to assess personality traits. Most of the works place nonverbal behavioral cues in the center of attention as far as automatic personality recognition (APR) is concerned. There are some approaches that deal with the nonverbal communication in order to infer human personality [6][7]. The approach applied in [8] uses interpersonal distances and the speed at which persons walk. The most important features have been extracted from the openSMILE [9] to infer if an individual's behavioral pattern is associated with extroversion or conscientiousness.

Aly and Tapus [10] uses verbal cues and speech to extract personality traits and then using PERSONAGE natural language generator, robot adapts its speech and gestures according to the personality trait to change its overall behavior. The authors have found that users preferred interacting more with a robot if it has the same personality type. Although the work is in the context of HRI, the approach uses naïve postures and gestures to assess behavioral traits. Another important work in this regard has been presented by Salam *et al.* [11] in human-human robot interaction scenario. Individual features which include body activity and body appearance along with interpersonal features are extracted. Interpersonal features consist of visual focus of attention, global quantity of movement, relative orientation and distance of participants with respect to the robot. Separate regressors are used for each personality trait. The authors found that the best results are obtained with only individual features.

Srivastava *et al.* [12] assessed big five personality traits by using visual features, i.e., facial expressions, number of faces present in the video etc., audio features, dealing with acoustic analysis and lexical features which deal with the semantic analysis of speech. These features are combined together to construct a feature vector. They used a regression model, Sparse and Low-rank Transformation (SLoT), and showed that the SLoT method helps to improve personality prediction accuracy.

III. PERCEPTION OF NONVERBAL CUES

Generally, there are two established ways in psychology namely self-reporting and personality impressions that serve the task of personality assessment [13]. Self-reporting assessment demands that an individual judges himself based on different aspects of life. In contrast, personality impressions assessment requires a person to observe other person's personality traits. Based on the observational data provided by the observer, the personality trait of a particular person is assessed. Interestingly, studies have shown that the outcomes of both measures are quite similar [13]. However, these methods require human(s) to assess personality information. For a robot to assess personality traits of humans automatically, there is a need to analyze human nonverbal cues. Nonverbal cues can be useful to bridge the gap between technical and non-technical evaluation of personality traits. It is potentially easier to predict the behavioral pattern of a person, even in a zero-acquaintance scenarios, based on the nonverbal cues.

A. Posture Recognition

Posture plays an important role in indicating human behavior and his internal emotional state. According to psychological studies, all the varieties of posture are a direct result of change in emotions and take part in human development over time. Moreover, postures are significant cues in the context of human personality assessment. Researchers indicate several key postures, e.g., crossed arms, hands on the head, shrug, open arms, etc. that describe human behavior and personality type.

This paper uses the work of Zafar *et al.* [14]. Depth data is used to extract human skeletal joints using OpenNI and NiTE libraries. Since each joint has positional data, these joint positions are highly variant to the height of the person, position and physique. A unique method is employed which converts joint position into joint angles, thus making it invariant to height, position or physique of the person. After preprocessing, these joint angles are used to construct feature vector and trained it using Support Vector Machines (SVMs) using linear kernel. The system is able to recognize 12 different postures, i.e., crossed arms, open arms, thinking postures, pointing postures, self-touching posture, casual stance, attentive posture, shrug posture, raised arms, etc.

B. Head Pose Estimation

Head movements convey great deal of information regarding human focus and behavior during the interaction. Humans use head gestures frequently to express agreement or denial. However, some head movements express human internal state, e.g., head falling forward with slumped shoulders indicates dejection and is a sign of neurotic behavior. Detection of human head movements involves estimation of head pose and its orientation. This work uses Direction-Magnitude Pattern (DMP) approach presented by Saleh *et al.* [15].

In order to estimate three pose angles of head namely roll, pitch and yaw, depth data has been used. Eight different head gestures have been recognized using this approach, i.e., nodding, shaking, tilting, looking up, looking down, looking right, looking left and looking ahead. The attention of human can be inferred from the orientation of the head. According to Sidner *et al.* [16], looking at the interaction partner is indicative of attentive behavior, while looking elsewhere during conversation for a longer period is a sign of disinterest or nervousness. This cue plays an important role in the assessment of agreeable personality type because of the fact that an agreeable person nods head frequently during interactions.

C. Body Movements and Proximity Detection

Body movements during an interaction is an important nonverbal cue which sheds light on the spirit of a person. These movements are related to person's limbs and body in general. Excessive hand movements along with other body cues is a sign of confidence [17]. Similarly, another nonverbal type known as proxemics, which deals with the amount of interpersonal space, also contributes considerably during interaction. Individuals standing closer show more trust and willingness to interact as compared to individuals standing far.

To detect body movements, we use skeletal joint angles of upper body and analyze it over time. The change in angle values are recorded and if it exceeds threshold, δ, activity is flagged. Proximity information can be extracted by using the depth data of tracked human. A change in stance near or farther from the robot shows comfortability of a person. If a person is extrovert, he is more likely to move closer to an interlocutor and vice versa.

D. Facial Expression Recognition

Facial expressions play an important role in assessing the internal emotional state and intentions of humans. We use expressions to convey our thoughts and feelings during interpersonal communication. Numerous works in literature have already highlighted the significance of facial expressions for personality assessments [18][19]. According to the psychological studies, extrovert or agreeable persons convey more positive facial expressions as compared to neurotics or introverts [5]. In order to recognize this nonverbal feature, we use an approach presented by Al-Darraji *et al.* [20]. The work uses convolution neural network to recognize different action units related to six basic expressions namely happiness, sadness, surprise, disgust, fear and anger. More expressive facial expressions lead to extroversion, whereas anger leads to self-centered personality.

IV. PERSONALITY TRAITS ASSESSMENT

A handful of technical systems have been reported in the literature for personality assessment. Most of them either lack in considering all bodily cues or are not applicable in daily life scenarios for automatic personality analysis. As established in previous sections the significance of nonverbal cues with respect to personality, this section discusses the impact of different personality traits on different nonverbal cues. A supervised learning strategy has been employed for this task in order to evaluate personality traits using nonverbal features. Figure 2 shows the working schematics of our approach.

The moment human is detected based on skeleton and face information, all the mentioned nonverbal features are extracted in real-time. Features playing no or negligible role during the traits assessment are discarded after correlation analysis. Selected features are used to train 3 different classifiers namely extroversion-introversion, agreeableness-self-centered and neuroticism-emotionally stable in classification stage. Recognized nonverbal cues in this work do not show any correlation with conscientiousness trait or openess-to-new-experiences trait. These dimensions require more nonverbal and contextual cues along side verbal for their assessment. SVMs are used for classification task. A binary result from each classifier is generated which shows whether that trait is active or not. The personality assessment methodology is discussed in following sub-sections in detail.

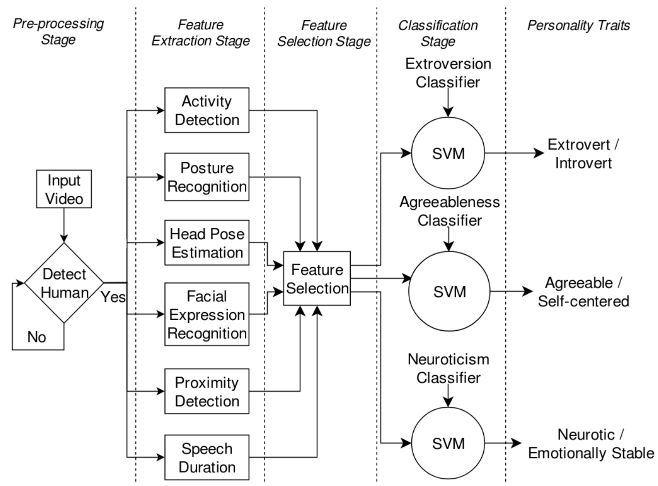

Fig. 2: Working flow of personality traits assessment.

A. Data Collection

For any classification task, having a diverse database is quite important. There are some datasets publicly available [21][22][23]. Most of these databases are focused towards audio and video channels and don't consider depth data. Only few uses depth information along with color data to record human behavior during HRI. However, these databases containing depth data are not publicly available and are not labeled according to personality traits. Due to the limitation of these existing datasets, a nonverbal feature-based database is generated. A total of 15 participants appeared during the learning process. Each subject is asked to role-play with the robot in different personality traits. The database is focused only for 6 personality traits namely, extroversion, introversion, agreeableness, self-centered, neuroticism and emotionally-stable personality types. The subjects have been asked to perform on different scenarios so as to interact spontaneously with the robot. For example, the robot, role-playing as a student, has not done the home work with the subject, role-playing as an instructor, scolding him. Each subject takes around 12 minutes to role-play for all the dimensions (half a minute session performed 4 times for each of the six mentioned personality traits). Each session is video recorded for later analysis. All the mentioned nonverbal cues are recorded in a separate file along with the duration of speech at the end of the interaction. These nonverbal cues, extracted every frame, are normalized and averaged over a whole sequence. The features are then used to construct a 25 dimensional feature vector. In order to label the sequences, psychology expert is consulted. Each sequence is labeled with 3 personality traits after careful analysis of video sequences, i.e., either extrovert or introvert, agreeable or self-centered and neurotic or emotionally-stable. After preprocessing, a total of around 200 sequences are generated during this process.

B. Personality Traits and Nonverbal Cues

To statistically analyze the data, correlations are used before the *learning* task. Each nonverbal cue is correlated with the traits to analyze their relationship between them. Table I shows correlations between different human body postures and personality traits. Table II, Table III and Table IV represent correlation scores for head gestures, bodily cues and proxemics, and facial expressions with 3 personality traits respectively. Negative values show that the trait is negatively correlated with that nonverbal cue. We analyze the correlation score trait-wise in the next sub-sections.

TABLE I: Correlation between Personality Traits and Human Postures. (O.P. = open posture, C.P. = crossed-arm posture, C.S.= casual stance, T.P. = thinking posture, S.P. = shrug posture, P.P. = pointing posture, S.U. = stand upright posture)

Trait	O.P.	C.P.	C.S.	T.P.	S.P.	P.P.	S.U.
Ex.	**0.80**	**-0.57**	-0.017	**-0.46**	**0.24**	0.19	0.06
Ag.	**-0.45**	**0.30**	0.03	**0.23**	0	**-0.33**	-0.14
Ne.	**-0.43**	**0.41**	-0.009	**0.41**	-0.15	-0.02	**-0.28**

TABLE II: Correlation between Personality Traits and Head Gestures. (L.U. = looking up, L.D. = looking down, L.L.= looking left, L.R. = looking right, L.A. = looking ahead, Nod. = nodding, Shake = shaking)

Trait	L.U.	L.D.	L.L.	L.R.	L.A.	Nod.	Shake
Ex.	0.10	**-0.38**	-0.15	0	0.4	0.16	-0.13
Ag.	-0.11	0.10	-0.13	0	0.1	**0.31**	**-0.27**
Ne.	-0.15	**0.64**	0.001	-0.04	**-0.30**	**-0.22**	0.07

TABLE III: Correlation between Personality Traits and Bodily cues and proxemics. (B.M. = body movements, F.S. = forward stance, B.S.= backward stance, C.P. = close proximity)

Trait	B.M.	F.S.	B.S.	C.P.
Ex.	**0.63**	0.14	**-0.28**	**0.21**
Ag.	**-0.52**	0.09	**-0.28**	0.15
Ne.	**-0.23**	**0.30**	0.10	**0.20**

C. Extroversion-Introversion Trait

Extroversion is associated with expressiveness. Extroverts are more likely to show physical activities during an interaction, e.g., rapid body movement, head movement etc., which represent confidence [17]. Correlation analysis in Table III shows that body movements play huge role in the assessment of extroversion. They also have an open body stance which shows openness to interaction and sociability. The fact can also be seen in the interactions of celebrities in which they interact with audience as shown in the Figure 3. In contrast, introverts show more self-touching postures, e.g., crossed arms etc. in order to block others for interaction or self-comfort themselves [5]. Table I illustrates that extroversion is positively correlated with *open body* and *pointing* postures, showing the high contribution of these features towards extroversion. However, this trait is negatively correlated with *crossed-arm* and *thinking* postures, showing high contribution of these features towards introversion.

In addition, extroverts show a varied number of facial expressions and tend to make direct eye contact with their communicating partner. On the other hand, introverts avoid mutual eye gaze and have problems in expressing emotions [5] as can also be seen from Table II. Extroverts tend to stand near the interaction partner, whereas introverts feel comfortable keeping a marginal distance. This fact can be validated from Table III which shows backward stance is negatively correlated with this trait while forward stance and proximity close to the interaction partner has a positive correlation.

Fig. 3: Examples of extroversion-introversion trait.

Facial expressions are equally important as any other nonverbal facet. As mentioned earlier about the role of facial expressions in context of extroversion-introversion trait, this feature is used to analyze expressive emotions from face. During speaking in an interaction, however, this module performs poorly. The main reason is the dynamic nature of facial action units during speech which leads to false recognition of expressions. Nonetheless, this feature has a trifling contribution towards extroversion-introversion trait. Table IV shows happiness is positively correlated with extroversion while fear and anger are correlated with introversion.

D. Agreeableness - Self-centered Trait Assessment

Agreeableness trait is mainly associated with submissiveness which implies self-touching behavior. Agreeable persons are more likely to be soft-hearted and generous. They tend to nod quite often during an interaction which

TABLE IV: Correlation between Personality Traits and Facial Expressions. (Ha. = Happy, Sa.= Sad, Su. = Surprise, Fe.= Fear, Di. = Disgust, An. = Angry)

Trait	Ha.	Sa.	Su.	Fe.	Di.	An.
Ex.	0.16	-0.11	0.03	-0.30	0	-0.006
Ag.	0.12	0	0	0.17	0	**-0.20**
Ne.	**0.26**	0.18	0	**0.27**	-0.01	0.007

shows their agreeable nature [17] which can also be verified from Table II that head nodding is positively correlated with agreeable trait. Moreover, they show positive and sympathetic facial expressions along with head tilt to show empathy. These people like to have mutual eye gaze [24]. Self-centered persons, on the other hand, tend to look with their chin up [25]. As can be seen from Table II, looking up is negatively correlated with agreeableness trait. They point towards the co-speakers and express anger to show authority and shake head to show denial during communication [25]. These facts can also be validated from Table I and Table II in which *pointing* posture and *shaking* head are highly and negatively correlated with agreeableness trait. Furthermore, self-centered persons also appear to stand far from the interaction partner to show superiority as compared to their counterparts [25]. Table III shows positive correlation between agreeableness trait and *close proximity* which, in other words, means negative correlation between self-centered trait and *close proximity*. Figure 5 shows agreeable and self-centered persons.

Fig. 4: Examples of agreeableness-self-centered trait.

E. Neuroticism - Emotionally Stable Trait

Neuroticism is mainly associated with depression and self-pitying. Persons having this trait are more likely to be vulnerable and emotional. They show self-touching behavior in order to comfort themselves [26]. This can also be observed from Table I in which neuroticism trait is highly correlated with *crossed arms* and *thinking* postures. In addition, they avoid mutual eye gaze and display dejected posture [25]. They feel comfortable looking downwards when they speak and they mostly express anger, contempt and fear facial expressions [25]. Table II shows high correlation between neuroticism and *looking down* gesture. In contrast, emotionally stable persons are calm and even-tempered [5]. They mostly interact with an open upright postures. They tend to have a mutual eye gaze with the interaction partner. Moreover, they show positive facial expressions. In addition, neurotic persons tend to stand close to the interaction partner. Table II shows negative correlation between neuroticism trait and *looking ahead* gesture.

Fig. 5: Examples of neurotic behavior.

F. Classification

Classification plays an important role in any recognition task. As mentioned in the section IV-A, nonverbal cues are used to construct a feature vector. At any given time, a person possesses multiple personality traits. However, there is always a dominant trait in every human [27]. Therefore, multiple binary classifiers are trained using SVMs for each trait. 5-fold cross validation approach is used to optimize SVMs parameters. Gaussian kernel has been used with 5 kernel scales. Each binary classifier uses the same 25 dimensional feature vector during training, though the classes are distinct and assigned by psychology expert according to the dimension of personality traits. A total of 205 sequences are used during training stage.

V. EXPERIMENTATION AND EVALUATION

We have used the humanoid robot, ROBIN, for experimentation. It has intelligent hands, which are able to perform almost any gesture with an overall 14 degrees of freedom (DoF) in each hand. It has 3 DoF in torso and 3 DoF in the head. Additionally, it has backlit projected face which enables it to express different emotions. ROBIN uses RGB-D sensor, installed on its chest, to perform the perception tasks. Figure 1 shows a person interacting with ROBIN.

20 subjects have participated during the experimentation. In order to exploit the personalities of the subjects appeared in the experiments, they are provided with 3 different hypothetical scenarios to perform. First scenario concerns with two friends, one is ROBIN and other is a student, discussing the final grade of an oral exam in which the student gets a poor grade. ROBIN acts as an observer and monitors the person's behavioral traits over time. The second scenario is similar to the first one, with the student getting a good grade in an exam. Last scenario deals with an interaction between a boss and a worker in which the boss is not happy with the progress of the worker. In this setting, ROBIN acts as a worker and the person acts as a boss. A total of 37 sequences are generated during the validation stage. Each subject performs any of the two scenarios out of the scenarios mentioned. After preprocessing, three samples are removed due to failure in video recording.

Table V shows confusion matrix for all the recognized personality traits. It can be observed from these tables that the traits, in general, are recognized correctly. In extroversion-introversion trait, 2 sequences are wrongly predicted to be extrovert. After analysis, it has been found out that the subject in the first sequence is initially quite passive, however, after few seconds he becomes active and dynamic. Due to the subjective nature of this labeling process, the person could also be labeled as extrovert. Nonetheless, the human expert consulted in this work has labeled this subject as an introvert. In the second sequence, posture recognizer reports erroneous results due to inaccuracy of human skeleton tracker.

According to Table V for agreeableness personality type, 3 sequences are found out to be false positive for self-centered trait. This trait is dependent on activity facet.

Generally, self-centered persons are quite dynamic and aggressive. In contrast, agreeable persons are softhearted and avoid impulsive actions/movements. Upon analysis, it has been found that the system associates activity with self-centered trait which does not hold true in all situations, e.g., an agreeable person explaining a concept by stretching its arms and body. Nonetheless, the system shows high accuracy for all three trait dimensions with extroversion-introversion, agreeableness-self-centered and neuroticism-emotionally-stable resulting an accuracy of 94.6%, 91.9% and 97.3%, respectively.

TABLE V: Confusion Matrix for 3 recognized personality types (Extroversion, Agreeableness, Neuroticism).

	Pred. Extrovert	Pred. Introvert	
Actual Extrovert	16	0	16
Actual Introvert	2	19	21
	18	19	37
	Pred. Agreeable	Pred. Self-cent.	
Actual Agreeable	20	3	23
Actual Self-centered	0	14	14
	20	17	37
	Pred. Neurotic	Pred. Emo. Stable	
Actual Neurotic	11	1	12
Actual Emo. Stable	0	25	25
	11	26	37

VI. Conclusion and Future Works

Technological advancement has paved the way for an intensive research on many psychological problems which were deemed to be impossible earlier. Automatic inference of human personality traits is highly important to make emotionally intelligent robotic systems for HRI. This work employs supervised learning approach to assess personality traits using different nonverbal cues. Due to the lack of available ground truth, a psychology expert has been consulted. Initial results show that the system is able to assess traits in most of the cases. Sometimes, the results obtained from our system does not comply with the ground truth due to the labeling process often being influenced by the expert's personality trait and his perspectives. This highlights the subjectivity in the assessment process. The system can be made more robust by using verbal cues and the contextual information along with existing features in the future work.

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