Real-time Recognition of Extroversion-Introversion Trait in Context of Human-Robot Interaction

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Abstract. Human personality has always been an esoteric topic in the field of social science. The five-factor model dealing personality traits plays a critical role in the field of communication studies, psychology and philosophy. Judging or recognizing personality trait is undoubtedly a cognitive aspect which requires intelligence. This judgmental process is extremely fuzzy as there are so many facets ingrained in every human. Interestingly, there is no quantitative standard to judge the severity of each facet. Intuitive and perceptive skills do the trick for the person judging personality of another person. In this work, an approach has been presented that uses only nonverbal cues to recognize extroversion-introversion personality. Major facets, e.g., human posture, facial expression, speech duration, rapid body movements, etc. are considered to recognize extroversion-introversion trait. A job interview scenario has been created in which a robot interacts with a candidate and judges his personality trait. Experimental studies validate the approach which is a promising basis for the development of computing approaches capable of predicting a specific personality trait.

Keywords: human personality, human-robot interaction, nonverbal cues

1 Introduction

Humans use their emotional system to interact intelligently according to the environment. They assess each event based on different emotional categories, e.g., positive or negative, comfortable or uncomfortable, exciting or dull, etc. and change their behavior according to the situation. This is a ground-breaking difference between human and robot. It goes without saying that robots lack intuition and perception. However, computer science has persistently been trying to make robots more intelligent. To some extent, rigorous research activities have paved the way for robots to act and behave more intelligently. Artificial neural networks have shown promising results in this regard. This paper deals with a novel aspect which bridges the gap between cognitive science and robotics. Technological development, now-a-days, has shown that many concrete and fuzzy

ideas can be implemented using artificial intelligence. Although it goes without saying that the recognition of personality has always been a challenging task for humans, our endeavor is a starting point of research in context of Human-Robot Interaction (HRI).

Current humanoid robots have come a long way since their inception. With the advent of high end computer systems and technology, the idea of robots helping in our daily life is not limited to fictional films and novels. As artificial intelligence is growing at a tremendous rate, robotic systems also become much more intelligent every day. A lot of task specific robots have already been presented which are used in assisting patients, visitors, elderly people and so on. These autonomous robots can certainly improve their ability to function in complex environments and to behave appropriately in partnership with people. Using the properties of natural intelligence as a guide, a robot's cognitive system would enable it to figure out what to do, whereas the emotion system would help it to do so more flexibly in complex and uncertain environments. In addition, it helps the robot to behave in a socially acceptable and effective manner with people [1].

The work in this paper is focused on analyzing human behavior over a course of time to extract behavioral cues for recognizing extroversion-introversion traits. The overall goal is to develop emotionally-driven and sociable robot for envisioned applications where the robot interacts with a person or another robot as a partner. In the following sections, we describe the overall approach and experimental results in detail. The rest of the paper is organized as follows: literature survey is discussed in Sect. 2, Sect. 3 discusses approach for recognizing extroversion and introversion in detail. Experimental results and performance evaluation is discussed in Sect. 4. The paper is concluded in Sect. 5.

2 Literature Survey

Judging or recognizing personality trait is undoubtedly a cognitive aspect which requires intelligence. This judgmental process is extremely fuzzy as there are so many facets ingrained in every human. Interestingly, there is no quantitative standard to judge the severity of each facet. Intuitive and perceptive skills do the trick for the person judging personality of another person. The humanoid robot that has been used in the experiments is capable of recognizing a diverse set of nonverbal cues. Although real-time recognition of individual cues is a challenging task, the robot system shows high accuracy in this regard. Integration of all the cues recognized yields an aggregated result, suggesting in which dimension of personality trait an interacting partner lies. Provided that evaluation of personality is always a cryptic and subjective task, this work is a starting point in the direction of research in personality traits using technical systems. Proper implementation of personality traits paves the way for a better perceptive HRI, motivated by human behaviorism and Human-Human Interaction. An improved HRI ensures natural communication process, providing us with more natural reactions and feedback.

Handful of personality theories have been reported in the literature of psychology and communication studies [2][3][4]. Among all these theories, the most dominant theory has been presented by McCrae and Costa [5] also known as the *Big Five* model. The model consists of five big traits namely Open to new experience, Conscientiousness, Extroversion, Agreeableness, and Neuroticism. As far as the Big five model is concerned, each dimension is considered to be a continuum or spectrum in which the extremes are quite distinct. In other words, a person can be placed somewhere on the continuum of each dimension based on the individual scores. Out of these five traits, extroversion trait has been studied extensively because of its greater impact on social behavior with respect to other traits [6]. Hence, this work explores extroversion-introversion trait using nonverbal cues during HRI.

A work in this regard has been done by Degroot and Gooty [7] to deduct human personality attributions using human nonverbal cues in employment interviews. Different nonverbal cues has been considered, e.g., visual information, audio information, range of pitch, speech rate, voice breaks and fluency. Authors explore the correlation between performance of a candidate with his/her nonverbal cues. They find out that nonverbal cues do not necessarily lead to error in interview judgments. However, visual cues are interpreted by an expert throughout the interview.

Another work presented by Ge et al. [8] reports recognition of extroversion and introversion based on web browsing history and consumption records of campus cards of students. They introduce different categories, e.g., traveling, study, personal entertainment, culture and education, etc. Based on web history, features are populated in each relevant category. In addition, using campus card of a student, they collect information about the places visited by a student, i.e., market, canteen, etc. Using Support Vector Machines (SVM) classifier, they classify extroversion and introversion with an accuracy of 72%.

An interesting approach proposed by Ferwerda et al. [9] use instagram photos to predict human personality trait. Authors extract hue, saturation and value related features and use Pleasure-Arousal-Dominance (PAD) model to get values for pleasure, arousal and dominance. They also use content-based features which estimates number of humans present in a photo. Using SVM classifier with radial basis function (RBF) network, they get accuracy of 96% for extroversion-introversion personality trait.

The works mentioned above are able to assess human personality in different scenarios. However, the major shortcoming in these approaches is the lack of real-time recognition of human personality trait based on human appearance in daily life interactive scenarios. In addition, limited research has been conducted to realize human personality traits in context of Human-Robot Interaction (HRI). In order to address these shortcomings, the approach presented in this paper focuses on real-time recognition of extroversion-introversion trait in context of HRI. The approach is described in the following section in detail.

3 Proposed Approach

According to [10], personality traits can be strongly correlated with the nonverbal cues. Out of big five personality traits, only extroversion-introversion dimension has the most correlation towards nonverbal cues [11]. This highlights the significance of nonverbal facets in the assessment of this trait. The system uses different facets namely activity, postures, facial expressions, gaze, proximity and duration of speech. Due to unavailability of ground truth for the assessment of extroversion-introversion trait, this work explores unsupervised learning approach, i.e., clustering to detect extroversion and introversion using the mentioned nonverbal features.

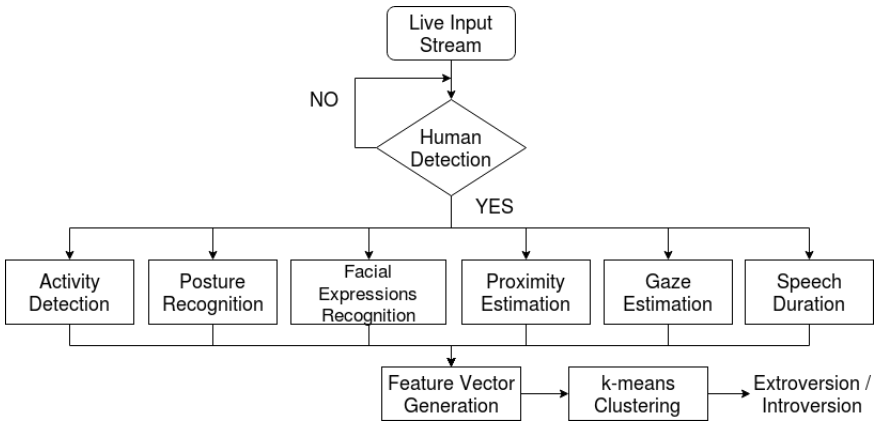

Fig. 1. Working schematics of proposed approach

Figure 1 shows the work flow of our approach which uses human nonverbal cues for recognition of extroversion-introversion trait. The robot uses ASUS Xtion sensor along with OpenNI and NiTE Library to detect humans in the scenario and recognizes major facets relevant to extroversion-introversion dimension. K-means clustering has been used to place each sequence in clusters. These clusters are used to predict extroversion-introversion trait. In the following sub-sections, we describe each module of the approach in detail.

3.1 Human Detection

As discussed earlier, NiTE middleware library enables us to detect humans by utilizing depth and IR sensor of ASUS Xtion. Algorithm detects not only humans but also tracks them efficiently. NiTE library also provides human joint positions which are then later used for recognizing different features, e.g., proximity, human posture, activity, etc.

3.2 Nonverbal Features

The system uses low-level perception features to understand high-level perception behaviors, e.g., extroversion-introversion trait. These nonverbal features lie in low-level perception and can be used to recognize high-level perception behavior, when analyzed over time. Therefor, selecting relevant features for extroversion-introversion becomes an important step in recognizing this trait accurately.

Posture Recognition (P) Human posture shows extroversion-introversion behavior, e.g., open arms depicts extrovert behavior and crossed arms shows introvert trait. Our approach uses the work of Zafar et al. [12]. They extract human skeleton joints using NiTE library and convert them into angles. Feature vectors are generated using angles between each joint and classify them using SVM.

Activity Detection (A) Movements performed by the limbs of a human play an important role in the recognition of extroversion-introversion trait. Rapid body movements are recognized by using skeleton joint angles of upper body. Each joint angle is analyzed every 1.5 seconds to detect body movements. Activity is considered only when there is rapid movements of shoulder and arms.

Proximity Estimation (D) The distance between the robot and the person is a very crucial parameter to recognize personality trait. The robot is capable of measuring the distance between its camera and the position of the person. When there is a positive difference between the two positions, the person comes nearer; otherwise the person goes further. However, if there is no difference, this feature has no impact on personality recognition.

Facial Expressions Recognition (E) Facial expressions are vital in the recognition of extroversion-introversion trait. The robot can recognize the 6 basic facial expressions namely happiness, anger, disgust, fear, surprise and sadness using the convolutional neural network approach presented by Aldarraji et al. [13]. Positive expressions, e.g., smile, happiness, etc. lead to extrovert trait.

Speech Duration (S) As mentioned in [10], extroverts are more talkative. This feature can easily be correlated with the duration of speech. We categorize the speech duration by analyzing the time taken by the human in two classes, i.e., long duration and short duration based on a fixed threshold.

Gaze Detection (G) Another nonverbal aspect which this paper considers is human head movement or head gestures. Humans use head direction as a cue to estimate gaze direction. The current work utilizes head pose estimation used in [14][15]. Eight head gestures are recognized in this work. These gestures are nodding, shaking, tilting, looking ahead, looking left, looking up and looking down.

3.3 Unsupervised Learning

Integration of these nonverbal cues in a meaningful way is highly critical for overall outcome. Simplest approach is to add all the outcomes of each facets to generate a score. However, the problem lies in the situation when one or more nonverbal feature(s) would either be detected wrongly or not detected at all. This would cause misleading outcome. As mentioned earlier, unsupervised learning approach in this context is more meaningful as it can perform well even without the availability of the ground truth. The initial goal of the system is to detect stereotypical extroversion-introversion trait.

In this work, k-means clustering approach is used to detect extroversion-introversion trait. K-means clustering clusters anonymous data in k clusters in which each instance belongs to the cluster with the nearest mean using euclidean distance metric. The clusters are represented by the centroid of the whole cluster. In order to build a clustering model, 50 sequences are generated. Each participant has been asked to interact with the robot in extrovert and introvert manner. Five subjects participated in the experiments and each one performs extroversion trait 5 times and introversion trait 5 times. All mentioned nonverbal features are recognized to construct feature vectors for clustering task. However, k-means clustering algorithm requires *apriori* specification of the number of clusters, k. In our approach, different values of k has been tried to observe the effects of clustering on the data. Using empirical studies, the value of k is set to 2 in which each cluster represents extroversion and introversion instances respectively. Results show that the 22 instances are grouped in first cluster and the remaining 28 in second cluster. Upon analysis, it has been found out that the 20 instances of first cluster represents introversion while 23 instances of second cluster represents extroversion. In our experiments, it has been shown that the approach is able to identify stereotypical extroversion-introversion trait accurately. However, the system reports mixed results when some of the nonverbal features are not active.

4 Experimentation and Evaluation

In order to validate our approach, an experimental interview scenario is created. A humanoid robot, ROBIN [16], has been used as an interviewer. It asks a series of job related questions, e.g., *Can you please introduce yourself?* or *Why do you think you are good-fit for this position?*, etc. The candidate answers each of the questions showing natural and appropriate nonverbal cues. The system recognizes all nonverbal features mentioned earlier. Four new subjects are used to validate the clustering results. Each subject has been asked to act twice extrovert and twice introvert in the given interview scenario. Table 1 shows the confusion matrix of the extroversion-introversion trait.

It can be observed from Table 1 that the system in general is able to detect extroversion-introversion trait with an accuracy of 75%. It can be seen that extroversion trait is falsely detected as introversion trait three times. The reason lies in the nonverbal features especially activity feature. Extroversion trait

Table 1. Confusion Matrix for Extroversion-Introversion Trait

	Predicted: Extrovert	**Predicted Introvert**	Total
Actual: Extrovert	**5**	3	8
Actual: Introvert	1	**7**	8
Total	6	10	

highly depends on activity feature. If activity appears less during interaction, the person is grouped in introvert cluster. Moreover, subjects participated in the experiments are not professional actors and sometimes, therefore, are not able to produce extrovert or introvert behavior on demand. Nonetheless, robot is able to detect traits accurately when the candidate shows stereotypical extroversion-introversion behavior. Figure 2 shows the graphical interface where ROBIN recognizes different nonverbal features.

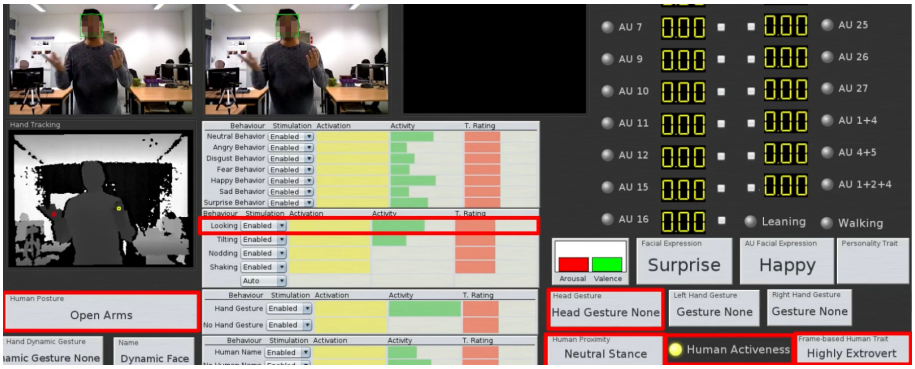

Fig. 2. Graphical Interface of ROBIN. The candidate is detected as an extrovert.

5 Conclusion

In this paper, we have presented an approach that can recognize human personality traits in real-time. The approach uses only nonverbal cues for this task. Different nonverbal cues have been considered, i.e., human posture, facial expressions, rapid body movements, gaze direction, speech duration, etc. An unsupervised learning algorithm, k-means clustering, is used to construct feature vectors in order to detect extroversion-introversion trait. A humanoid robot, ROBIN, has been used to recognize extroversion-introversion trait in an interview scenario. Experimental results show that the system is able to recognize this trait accurately most of the times. The approach can be extended in the

recognition of other personality traits by considering verbal content as well as contextual knowledge.

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