Predicting extraversion from non-verbal features during a face-to-face human-robot interaction

Faezeh Rahbar,[1] Salvatore Anzalone[2], Giovanna Varni[1], Elisabetta Zibetti[3], Serena Ivaldi[4], and Mohamed Chetouani[1]

[1] ISIR, CNRS & Université Pierre et Marie Curie, Paris, France
[2] Psychiatrie de l'Enfant et de l'Adolescent, GH Pitié-Salpêtrière, Paris, France
[3] CHART-Lutin, Université Paris 8, Paris, France
[4] Inria, Villers-lès-Nancy, F-54600, France
{anzalone,varni,chetouani}@isir.upmc.fr, serena.ivaldi@inria.fr

Abstract. In this paper we present a system for automatic prediction of extraversion during the first thin slices of human-robot interaction (HRI). This work is based on the hypothesis that personality traits and attitude towards robot appear in the behavioural response of humans during HRI. We propose a set of four non-verbal movement features that characterize human behavior during interaction. We focus our study on predicting Extraversion using these features, extracted from a dataset consisting of 39 healthy adults interacting with the humanoid iCub. Our analysis shows that it is possible to predict to a good level (64%) the Extraversion of a human from a thin slice of interaction relying only on non-verbal movement features. Our results are comparable to the state-of-the-art obtained in HHI [23].

Keywords: Human-robot interaction, personality, non-verbal behaviour

1 Introduction

Social robots should be able to adapt their behaviour taking into account the unique personality of their interacting partners. To this end, they need to learn a model of their behaviour, that can be built using multimodal features extracted during online interaction, physical features, social context, individual factors etc. [1]. Currently, a crucial challenge for Human-Robot Interaction (HRI) is the automated online estimation of the latter, such as personality traits, and the study of how they influence the exchange of verbal and non-verbal signals, as well the mechanisms underlying the production of behaviors, emotions and thoughts. These issues have been investigated in the project EDHHI[9][1], focused on studying social interactions between humans and the humanoid robot iCub. Within EDHHI, the researchers investigated how the production of social signals during HRI is influenced by individual factors, such as personality traits and attitude towards robots. A number of face-to-face dyadic and tryadic interactions

[1] *http://www.loria.fr/∼sivaldi/edhhi.htm*

were realized in the experiments of this project, between ordinary people without prior experience with robots and the humanoid iCub. Exploiting the dataset collected in EDHHI, the goal of this paper is to investigate whether it is possible to predict the personality trait of extraversion from a set of non-verbal features extracted during a short interaction with the robot. Particularly, we take into account the first thin slices of an interaction (i.e., the first minutes). Personality is generally addressed through the *trait theory* that individuates the factors able to catch stable individual characteristics underlying overt behaviour. Trait theory formalization exploits multi-factorial models, the most well-known being the Big-Five, owing its name to the 5 traits chosen as descriptive of a personality: *Extraversion*, *Neuroticism*, *Agreeableness*,*Conscientiousness*, *Openness to Experience* [11]. In this work we focus on extraversion, the personality trait that notably (i) shows up more clearly during interaction, and (ii) has the greater impact on social behaviour with respect to the other traits [23]. We include in the study also the negative attitude towards robot [15] that could capture a novelty or anxiety effect when the ordinary people interact with the robot for their first time, consistent with the focus of our study on the first thin slice of an interaction.

Background : Studies involving personality assessment, typical of the psychology domain, are now more and more of interest for human-computer interaction (HCI) and human-robot interaction (HRI). In these last years, indeed, a new branch of research in HCI, called *personality computing* is developing. Research on *personality computing* focuses on the following three major issues: (i) *Automatic Personality Recognition (APR)*; (ii)*Automatic Personality Perception (APP)*; and (iii) *Automatic Personality Synthesis (APS)* – see [21] for a review. In particular, APR is aimed at "inferring self-assessed personalities from machine detectable distal cues" [21]. About the modeling, the current exploited models in computing community are the trait based models, that try to isolate a small set of factors, known as Big-Five (BF) [11], able to describe the stable behavioural patterns. The *NEO-Personality-Inventory Revised* [4], the *NEO Five Factor Inventory* [12] and the *Big-Five Inventory* [10] are the most common experimental instruments adopted for this measurement.

These studies are now of high relevance for robotics. Tapus et al. [19] designed an assistive therapist robot matching its Extroversion with the one of its patients, and proved its effectiveness in terms of therapy performance. Meerbeek et al. [13] provided guidelines to design and evaluate personality and expressions in autonomous domestic robots. An important line of research is to probe into the influence of personality and individual traits on the production of verbal and non-verbal signals during HRI, as done in [9] and in our study.

Hypothesis: The literature on personality traits and HRI shows that personality traits influence the production of verbal and non-verbal signals during HRI. Preliminary analysis on the EDHHI dataset reveal that extroversion and NARS influence the production of gaze and speech [9]. Here, we contend that it is possible to predict the human's extraversion from the analysis of non-verbal features.

Overview of the proposed system for automatic prediction of extroversion in HRI: The proposed system is sketched in Figure 1. We extracted a set of relevant non-verbal features from the depth image of a Kinect placed above the head of the iCub interacting face-to-face with adult participants to the EDHHI experiments. As it will be discussed in Section 3, the relevant features include quantity of movement, synchrony and the personal distance between human and robot (frequently studied in proxemics). To predict extraversion from these features, we trained a model in a supervised way thanks to the ground truth provided by the score of the questionnaires filled up by the participants, as reported in Section 2. The classification system and the experimental results are detailed in Section 4.

2 Methods and Materials

This section briefly describes the experiments that provided the dataset used in this work, along with the questionnaires and the participants to the study.

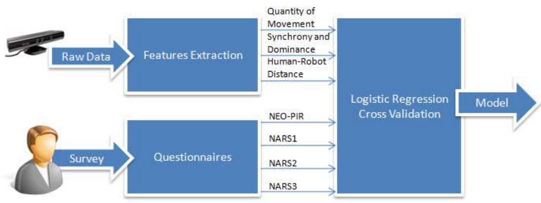

Fig. 1. Overview of the proposed system.

Questionnaires: To assess the personality traits of the participants, two questionnaires were used: the Revised Personality Inventory (NEO-PIR) [4], assessing the personality traits according to the Big Five model [11], and the Negative Attitude towards Robots Scale (NARS) [15]. From the first questionnaire, only the 48 questions related to Extraversion were retained. The order of the questions followed the original questionnaire, while answers were on a Likert-type scale from 1 (Totally disagree) to 5 (Totally agree). The second questionnaire consists of 14 questions divided into three sub-scales: 'Negative attitude toward situation of interaction with robots" (NARS-S1), "Negative attitude toward social influence of robots" (NARS-S2) and "Negative attitude toward emotions in interaction with robots" (NARS-S3). The order of the questions followed the original questionnaire, while answers were on a Likert-type scale, from 1 to 7 (Strongly disagree / agree).

Robotics setup: The experiments were carried out with the humanoid iCub [14], a robot shaped like a 4 years old child. The robot was standing on a fixed pole and it was controlled by an operator hidden behind a wall. The operator was constantly monitoring the status of the robot, and could intervene to send high-level commands and respond to unexpected actions or requests of the participants, using a Wizard-Of-Oz GUI designed to control the robot. For satefy issues, the experimenter monitored the interaction and was able to intervene and stop the robot in case of urgency. The robot was velocity controlled when there was no physical interaction with humans, but its stiffness was adjusted to make it compliant in case people would touch it [6]. Facial expressions and speech were enabled. The robot was able to say few sentences, such as "yes", "no", "thank you".

Experimental Protocol: The experiments of Project EDHHI followed a protocol[2] developed to study the spontaneous behavior of ordinary people interacting with a robot. The personality traits of the participants were retrieved by questionnaires that were filled up through a web form two weeks before doing the experiments, to avoid influences of the questions on their behavior.

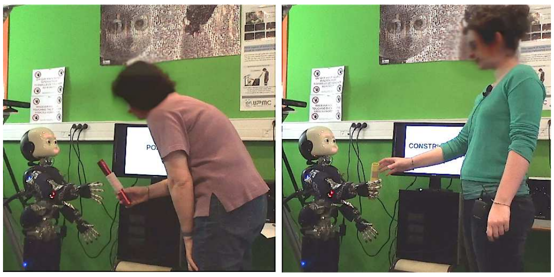

Fig. 2. iCub interacting with two participants.

The day of the experiment, participants were informed about the overall procedure before signing an informed consent form granting use of all the recorded data. Before the experiment, the participants had to watch a short video presenting the iCub. The video did not provide any information about the experiments. It was instrumental to make sure that the participants had a uniform prior knowledge of the robot appearance. After the video, each participant was introduced to the robot by the experimenter, who did not provide any specific instruction to the participants about how to behave with the robot and what to do. The experimenter would simply stay on the right side of the robot, to supervise the interaction for safety issues. The robot was standing on its fixed pole, gently waving the hands and looking upright, while holding a colored toy in its right hand. It was not speaking. Once the participants were standing and looking in front of the robot, they were free to do whatever they wanted: talking to the robot, touching it, and so on. For few seconds, the robot would do nothing, then it would look at the participant (upward gaze) and raise the right hand, holding the colored paper roll. Since no instructions were given about this interaction, the participants could choose whether to interpret the robot's movement as an intentional and goal-directed action or not, therefore interact with the robot, or to ignore the action. If the participant had no reaction to this movement, the robot, controlled by the operator, would lower the hand after 4-5 seconds. Otherwise, the robot would open the hand to give the toy to the human (see Fig. 2). As participants did not receive any indication by the experimenter, if they wanted to, they could start interacting more actively with iCub, asking questions, giving back the toy, and so on. The designed interaction, triggered by a simple movement of the robot, is very simple. However, due to the natural condition and the absence of constraints and indications from the experimenter, the response produced by the participants can be considered spontaneous, which justifies the observed variability of behaviors and non-verbal signals produced during the interaction. When the experimenter would detect a disengagement of the participant, a long pause or inactivity, she would invite

[2] Ivaldi et al., IRB n.20135200001072.

the participant to withdraw from the robot and start preparing for executing the EDHHI experiments with iCub, which are out of the scope of this paper.

Participants : 39 healthy adults without any prior experience with robots volunteered to participate to the experiments (11 male and 28 female, aged 37.8y±15.2y). They received an ID number to preserve the anonymity of the study. They signed an informed consent form to partake in the study and granted us the use of their recorded data and videos.

Data Collection : The dataset from Project EDHHI includes the video stream collected by a Kinect RGB-D sensor (v.1, 30fps) placed above the head of the robot in such a way to retrieve the body and face of the human interacting with the robot. The dataset used in this work includes 39 videos (one for each participants) of the first minutes of their interaction with iCub, synchronized with the robot events logged by the Wizard-Of-Oz application used to control the robot. The average duration of the videos was 110.1s (SD=63.9s).

3 Non-verbal Features Extraction

The use of non-verbal features has been dictated by the real world constraints in which a robot should operate: although audio-based features can produce better performances in laboratory setups, they are unlikely to be reliable in real life scenarios, due to several sources of noise: environment, people talking in background, and robot itself [2]. As stated in psychological literature, Extraversion dimension encompasses specific facets as *sociability*, *energy*, *assertiveness* and *excitement-seeking*. Energy facet can be also an useful hint of the attitude toward a robot revealing, for example, if a person feels nervous or relaxed when she operates in front of a robot or has to share a task with it. Interpersonal distance is mainly linked to sociability and assertiveness and it also describes worry/relax about situations of interaction with robots. Previous studies showed that extraverted people tends to require smaller interpersonal distance [22]. Further, proxemics rules hold true also when one of the interactants is not a human, therefore a low familiarity or confidence with robots (that is, a negative attitude toward robots) results in increasing the interpersonal distance [18]. Interpersonal synchrony is acknowledged as very relevant in early communication between humans [5], and it provides information about the quality of interaction traits of the peers. For example, as referred in [7] *"people tend to synchronise their rhythms and movements ... within a conversation"*. In HRI, it can facilitate the natural interaction with robots with minimal cognitive load [8]. Starting from this knowledge, the features listed below are extracted from the recorded depth videos:

F1) Histogram of Quantity of Motion (h-QoM): Quantity of motion is a Silhouette Motion Image (SMI)-based measure of the amount of motion detected from an optical sensor like, for example, video-camera [3]. SMI (Silhouette Motion Image) is an image carrying information about variations of the silhouette shape and position in the last few frames of a video. Quantity of motion is, basically, an approximation of the energy of the movement and it is computed as the area (i.e. the number of pixel) of a SMI normalised over the area of the silhouette. It is computed using the following formulas:

$$SMI(t,i) = \sum_{i=1}^{n} Silhouette(t-i) - Silhouette(t) \tag{1}$$

$$QoM(t) = \frac{Area(SMI(t,n))}{Area(Silhouette(t))} \tag{2}$$

where n is the number of frames used to compute the SMI, t is the time at which the SMI and the QoM is being computed. In this work, the original algorithm is applied, with some small changes, to the depth images provided by the Kinect RGB-D sensor.

First, the silhouette of the participant is extracted by thresholding the depth image in order to remove the background. Unlike [3], the resulting silhouette is not binarized: this is done in order to keep also the details of internal motions (that is the motion occurring inside the silhouette, e.g., shaking the hands in front of the body) provided by the depth image. The SMI is obtained by subtracting the silhouette of a current frame from that of the n last frames (here $n = 3$). This image is then normalised by the value of n. Finally, the area of the SMI is calculated and normalised by the area of the silhouette of the current frame in order to define the Quantity of Motion of the current frame. H-QoM is computed in 64 bins in order to have a good resolution of the changes occurring in its dynamics. Figure 3 reports two exemplary h-QoM of two participants showing very different NEO-PIR and NARS scores.

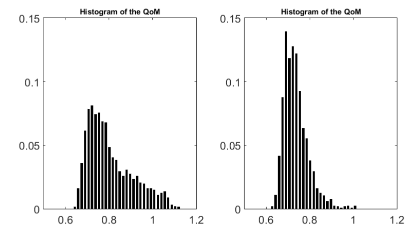

Fig. 3. H-QoM of two participants having very different NEOPIR and NARS scores. Left Panel corresponds to the h-QoM of a participant having the scores:NEOPIR=128 and NARSS1=11, NARSS2=11, NARSS3=3. Right Panel shows the hQoM of the participant having the scores: NEOPIR=69 and NARSS1=27, NARSS2=29,NARSS3=18.

F2-3) Histograms of Synchrony and dominance (h-Sync, h-dom): Event Synchronisation (ES) technique is adopted to analyse synchrony and dominance between the movements of the i-Cub and the participant. This choice is mainly due to the different nature both of the two interactants (that is, a robot and a human being). ES was originally conceived to measure synchrony and time delay patterns between a pair of neurophysiological time-series in which events can be identified [17]. However, it can be extended to measure synchrony between two or more generic monovariate time-series with events [20]. In this work, events are defined as a subset of the iCub actions and the full-body energy peaks of the participant during the interaction, respectively. The analysis concerned only the similar actions performed by the two interactants. ES consists of a couple of measures addressing *"the fraction of event pairs matching in time and how often each time series leads in these matches"*, respectively [17]. The first part of this definition allowed at counting the number of actions occurring quasi-simultaneously with respect to the global number of actions occurred through the overall interaction. This count (Q in Eq. 3) is in the range $[0, 1]$ and expresses the overall synchrony between the two time-series. The number of times each time-series leads the other one in these matches is here used to show how often an action of one of the two interactants comes before the corresponding action performed by the other one. This count (q in Eq. 3) is in the range $[-1, 1]$ and provides the *direction* of synchrony, that is it allow at discriminating between causal ($q = 1$ or $q = -1$ depending on which of the two time-series precedes the other one) or mutual ($q = 0$) interaction. In other words, q shows who, by a chronemic point of view, is dominant.

$$Q^\tau = \frac{c^\tau(x_2|x_1) + c^\tau(x_1|x_2)}{\sqrt{m_{x_1} m_{x_2}}} \qquad q^\tau = \frac{c^\tau(x_2|x_1) - c^\tau(x_1|x_2)}{\sqrt{m_{x_1} m_{x_2}}} \tag{3}$$

where: x_2 and x_1 are the two time-series of events describing the participant and the iCub, respectively; m_{x_1} and m_{x_2} are the suitable events occurring at the times ${t_i}^{x_1}$ and ${t_j}^{x_2}$ $(i = 1, ..., m_{x_1}; j = 1, ..., m_{x_2})$ in the two time-series; $c^\tau(x_1|x_2) = \sum_{i=1}^{m_{x_1}} \sum_{j=1}^{m_{x_2}} J_{ij}^\tau$ is the the number of times an event appears in x_1 after it appeared in x_2; τ a time lag for which two events could be considered as synchronous; with and $J_{ij}^\tau = \{1 \text{ if} 0 < {t_i}^{x_1} - {t_j}^{x_2} < \tau; 1/2 \text{ if} {t_i}^{x_1} = {t_j}^{x_2}; 0 \text{ otherwise}\}$.

Two different approaches are adopted to extract the events for the iCub and the participant. For the iCub, a log-file is used to store its head/arms/hands movements, the timestamps corresponding to the beginning of an action/command as well as the type of actions/commands, that together define the main events. As regards the participant, the events are defined from her QoM. First, it is filtered by using a fifth-order Savitzky-Golay filter and a FFT is applied. Then, the energy of the QoM is computed from its spectrum.

The first derivative of the energy is computed over a sliding window having a size of 1s frames and a step of 33ms. Further, this derivative is weighted frame-by-frame by the amplitude of the energy so as to amplify the fast and the largest movements and reduce the impact of movements which can be considered as noise. The events are extracted by applying a threshold on the amplitude of this resulting signal. Finally, the up edges are retained as events (see Figure 4).

The frames resolved variants of Q and q are computed through each video. To have these variants, the previous equation is modified as follows [17]: $c_n(x_1|x_2) = \sum_{i=1}^{m_{x_1}} \sum_{j=1}^{m_{x_2}} J_{ij} \Theta(n - {t_i}^{x_1})$, where Θ is the Heaviside function (i.e. $\Theta(x) = 0$ for $x \leq 0$ ans $\Theta(x) = 1$ for $x \geq 0$) and $n = 1, ..., N$. Then, a sliding window is applied to both Q and q (window size of 3s, step=1.5s), and the count of how many times Q and q step up is done. Finally, the histograms of these countings are built according the obtained values in the ranges of $[0, max\_no\_steps\_up]$ and $[-1, 1]$, respectively.

F4) Standard deviation of human-robot distance (STD-d): it is computed as the average of the pixels' values of the silhouette extracted from the

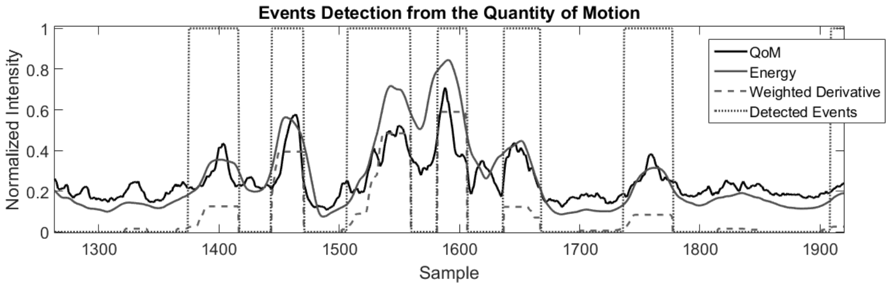

Fig. 4. The different steps of the events detection from the QoM. The solid black line stands for the QoM signal. The solid gray line corresponds to the Energy of QoM. The dashed line is the Weighted Derivative of the Energy of QoM. The dotted line stands for the intervals in which events have been detected.

depth image of the Kinect. Considering its position in the set-up, it is a good approximation of the distance between the two interactants.
→ The features F1-F4 are merged into a 72-dimensional vector. The resulting dataset included 39 instances, that is a feature vector for each participant.

4 Automated prediction of extraversion during HRI

Features extracted from interactions with the iCub built the dataset for the prediction of Extraversion. The NEO-PIR scores were used as reference for labeling the personality trait of each subject. However, in the particular context of a first interaction with social robots, people's behavioural response can be not only determined by their personality, but also by their attitude towards robots and the context of the interaction. In particular, due to prior experiences with robotics, the attitude towards the robots plays a relevant role and can dramatically affect people's behaviour towards social robots.

To catch this phenomenon, we seek a linear combination between the scores able to contextualise the personality information in the specific scenario of interaction with social robots. This work addressed this point by relabeling the instances of the dataset using the NEO-PIR extraversion score toghether with NARS questionnaires results. More in the detail, a Principal Component Analysis (PCA) was carried out on a *scores vector* including: NEO-PIR, NARS-S1, NARS-S2, and NARS-S3 scores, respectively. NARS-S3 is an inverse scale, so its scores were reversed. For NEO-PIR, NARS-S1, NARS-S2, and $\overline{NARS-S3}$ scores, the PCA's eigenvalues were respectively 2.17, 0.85, 0.56 and 0.32, while the PCA's component load were 0.32, -0.56, -0.57 and 0.51. Only the first principal component was meaningful (eigenvalue greater than 1). The loadings reflected how the personality scores are captured by the first principal component. The values of the first component were quantized (High-Low) along their median and the final labels were obtained.

The dataset resulted in a 39 (instances) x 72 (features) matrix, that is there are more features than instances. For this reason, we decided to adopt for the

Features	Precision	Recall	F-score
std-d, h-QoM	33%	27%	46%
std-d, h-QoM, h-dom	59%	62%	61%
std-d, h-QoM, h-sync	60%	64%	63%
std-d, h-QoM, h-sync, h-dom	64%	69%	66%

Table 1. Average Percentage of Precision, Recall and F-score

classification a Logistic Regression Classifier (LRC) [16] with penalty parameter $C = 1$ and $L2$ norm $L2$. The averaged performance of the trained classifier was assessed via a multiple-run k-fold stratified cross-validation. In this study, 10 run and 10 folds have been adopted. Table 1 summarises the performances of the LRC, according to the different subsets of used features. The table shows that the classification result relying on the Quantity of Movement alone on the standard deviation of the distance, is not able to overcome the chance level. However, classification results using also dominance and synchrony information overtake this level. Using the whole set of features the classifier reaches the top of the performances. Classification based exclusively on the extroversion does not yield significant results. These results are consistent with previous studies on prediction of Extraversion in human-human interaction only from non-verbal movement features (e.g., [23]).

5 Conclusion and Future Works

This paper presented an automatic prediction of Extraversion personality trait during *thin slices* of interaction with social robots, using non-verbal movement features. A Logistic Regression classifier was fed with the following features: the histogram of Quantity of Motion, the distance between human and robot, and the histograms of synchrony and dominance. To our knowledge, this is the first work dedicated to study thin slices of interaction with social robots, using such kind of predictive features of personality trait. The main limitation presented by this work can be found in the limited space of the room used for the experiments, in the laboratory environment and in the quite simple actions of the robot, that could not lead to the variability of the human behaviour as desired. Also, a random bias towards the specific spatial configurations of human partecipants could limit the effectiveness of the results presented. Thought preliminary, despite their limitations, these encouraging results indicate the good direction of research and good premises to improve personality prediction during HRI. Future works will involve a wider set of features, such as people's posture and gaze, examining in depth their role during complex interactions as signatures of personality traits. Moreover, the space of the parameters of the features extraction will be explored, as well as how the performances of the system will change in time, according to the amount of data collected. The final goal is to build an online, real-time personality recognition system that can be used by social robots to learn a complex model of their human partners.

References

1. Anzalone, S.M., et al.: Towards partners profiling in human robot interaction contexts. In: SIMPAR, pp. 4–15. Springer (2012)
2. Anzalone, S.M., et al.: A topic recognition system for real world human-robot conversations. In: Intelligent Autonomous Systems 12, pp. 383–391. Springer (2013)
3. Camurri, A., et al.: Interactive systems design: A kansei-based approach. In: Proc. Conf. New interf. musical expression. pp. 1–8 (2002)
4. Costa, P., McCrae, R., Rolland, J.: NEO-PI–R. Inventaire de Personnalité révisé. Editions du Centre de Psychologie Appliquée, Paris. (1998)
5. Delaherche, E., et al.: Interpersonal synchrony: A survey of evaluation methods across disciplines. T. Affective Computing 3(3), 349–365 (2012)
6. Fumagalli, M., Ivaldi, S., et al.: Force feedback exploiting tactile and proximal force/torque sensing. theory and implementation on the humanoid robot icub. Autonomous Robots (4), 381–398 (2012)
7. Hall, J., Knapp, M.: Nonverbal Communication. Handbooks of Communication Science, De Gruyter (2013)
8. Hasnain, S.K., et al.: Intuitive human robot interaction based on unintentional synchrony: a psycho-experimental study. In: ICDL. pp. 1–7 (2013)
9. Ivaldi, S., et al.: Towards engagement models that consider individual factors in hri: on the relation of extroversion and negative attitude towards robots to gaze and speech during a human-robot assembly task. arXiv:1508.04603 [cs.RO] pp. 1–24 (2015)
10. John, O.P., Donahue, E., Kentle, R.: The big five inventory-versions 4a and 54. Tech. rep., Univ. of Cal., Berkeley, Inst. of Personality and Social Res. (1991)
11. McCrae, R.: The five-factor model of personality. In: P.Corr, Mathhews, G. (eds.) Handbook of Personality Psychology, pp. 148–161 (2009)
12. Mccrae, R.R., T.Costa, P.: A contemplated revision of the neo five-factor inventory. Personality and Individual Differences (3), 587–596 (2004)
13. Meerbeek, B., Saerbeck, M., Bartneck, C.: Iterative design process for robots with personality. Kerstin Dautenhahn, editeur, AISB2009 Symposium on New Frontiers in Human-Robot Interaction pp. 94–101 (2009)
14. Natale, L., et al.: The icub platform: a tool for studying intrinsically motivated learning. In: B., G.and M., M. (ed.) Intr. Motiv. Learning etc. Springer (2013)
15. Nomura, T., et al.: Experimental investigation into influence of negative attitudes toward robots on human-robot interaction. AI & SOCIETY 20(2), 138–150 (2006)
16. Pampel, F.: Logistic Regression: a primer. Sage Publications (2000)
17. Quiroga, R.Q., et al.: Event synchronization: a simple and fast method to measure synchronicity and time delay patterns. Phys Rev E 66(4)
18. Takayama, L., Pantofaru, C.: Influences on proxemic behaviors in human-robot interaction. In: IROS (2009)
19. Tapus, A., et al.: User-robot personality matching and assistive robot behavior adaptation for post-stroke rehabilitation therapy. Int. Serv. Rob. 1(2) (2008)
20. Varni, G., et al.: A system for real-time multimodal analysis of nonverbal affective social interaction in user-centric media. Tr. on Multimedia 12(6)
21. Vinciarelli, A., Mohammadi, G.: A survey of personality computing. IEEE Transactions on Affective Computing 5(3), 273–291 (2014)
22. Williams, J.L.: Personal space and its relation to extraversion-introversion. Canadian Journal of Behavioural Science 3(2), 156 –160 (1971)
23. Zen, G., et al.: Space speaks: towards socially and personality aware visual surveillance. In: 1st ACM Int. Worksh. on Multimodal Perv. Video Anal. pp. 37–42 (2010)