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Salvatore Maria Anzalone, Giovanna Varni, Serena Ivaldi, Mohamed
Chetouani

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Automated prediction of Extraversion during Human-Humanoid interaction

Anzalone S. M. · Varni G. · Ivaldi S. · Chetouani M.

Abstract - One of the most important challenges in robotics is to achieve natural and engaging interactions between humans and robots. Interpersonal interaction, the process by which two or more people exchange information through verbal and non-verbal messages, could be exploited by robots both to establish interaction and to inform about its quality. The production of social signals being influenced by individual factors, such as personality traits, is critical for robots to have personalized models of interaction. This paper focuses on estimating social traits such as human personality from the dynamics of interpersonal interaction. The work was carried out in the framework of the Project EDHHI (Engagement During Human-Humanoid Interaction) which focuses on understanding individual factors influencing joint human-humanoid actions. In particular, this work addresses the automated prediction of the Extraversion trait during a human-humanoid interaction. We show how it is possible to take into account the specificity of Human-Robot Interaction (HRI) scenarios by contextualizing personality through the attitude that participants show towards the robots. This attitude is influenced by the *a priori* knowledge that people have on social robotics, and their prior anxiety in interacting with them. The proposed model exploits a set of nonverbal features chosen according to literature in Psychology and Personality Computing. These features are adopted to characterize human behaviors and the dynamics of human-robot interaction. Experimental results highlight that it is possible to predict Extraversion of the human partner from *nonverbal* behavior *during human-robot interaction* with an accuracy of 62%. A higher accuracy, 70%, is obtained from the computational model by explicitly combining the dynamics of interpersonal interaction and the attitude of the participants towards the robots. Results show that 120s are needed to obtain such performance.

1 Introduction

Researchers in social robotics strive to build machines able to work, play and help people in their daily life activities as real, effective partners [13, 14]. Such machines should express, through their embodiment and their behaviors, a certain degree of *Social Intelligence* [17]. This feature essentially emerges from the coherent exploitation of cognitive and social skills that endow the

robot with “*the ability of getting along with others*” [67]. The grand challenge of achieving such a level of interaction translates into the analysis and the synthesis of social behaviors. Robots should produce coherent, multimodal, “*readable*” social cues [35]. At the same time, they should capture the details of the mutual interplay of verbal and nonverbal behaviors occurring during social activities with humans [7]. The production of the so called “social signals” (verbal and non-verbal signals, i.e., speech, gaze, gestures) can be influenced by some individual factors, such as age, gender, personality and attitudes [36, 42, 63]. This paper focuses on the analysis of the dynamics of *human-robot interaction* to predict individual differences in personality.

Dealing with personality is one of the key “*socio-cognitive building blocks*” [54] needed for creating socially intelligent robots. Interaction with humans can be improved by endowing social robots with an unique personality as well as with the ability of inferring the partners’ personality and adapting to them. These skills will ensure a more intuitive and natural interaction between humans and machines [31, 12].

From this point of view, personality here refers to the “*individuals’ characteristic patterns of thought, emo-*

S.M. Anzalone
Laboratoire CHArt-THIM (EA4004), Département
Ingénierie - Cognition - Handicap, Université Paris 8,
Saint-Denis, France
E-mail: sanzalone@univ-paris8.fr

G. Varni and M. Chetouani
CNRS & Sorbonne Universités, UPMC Université Paris 06,
Institut des Systèmes Intelligents et de Robotique (ISIR)
UMR7222, Paris, France
E-mail: varni@isir.upmc.fr, E-mail: chetouani@isir.upmc.fr

S. Ivaldi
Inria, Villers-lès-Nancy, F-54600, France
Loria, CNRS & Université de Lorraine, Loria, UMR n. 7503,
Vandœuvre-lès-Nancy, F-54500, France
Intelligent Autonomous Systems, TU Darmstadt, Germany
E-mail: serena.ivaldi@inria.fr

tion, and behavior, together with the psychological mechanisms - hidden or not - behind those patterns.” [28]. Previous studies showed that social robots can benefit from the exhibition of compelling personalities through their behaviors [26]. However, a critical limitation of these previous studies is that they neglected the online adaptation and the recognition of the personality of the people interacting with robot: they relied on scripted, *a priori* knowledge. On the contrary, while displaying a personality, socially intelligent robots should be able to grasp the specific personality of their human partner and accordingly adapt their behavior [21, 14]. Recent works showed how the adaptation to individual factors contributes to enhance the interaction between humans and social robots [34, 61]. However, adapting the robot’s behavior to the personality of each individual is not straightforward. Previous studies found evidence of two contradicting phenomena [68]: the *similarity attraction phenomenon*, where similar personalities will tie together; the *complementary attraction phenomenon*, where opposite personalities will be attracted. It is not clear if robots should adapt to people following one of the two paradigms, showing similar (e.g. [3]) or opposite personalities (e.g. [43]). The choice of the paradigm could depend on the task context and the joint activity [39]. Even if we had more evidence that one of the two paradigms should be preferred, the question remains of how to estimate the user’s personality online from his/her behavior.

Adaptation to individual factors is highlighted to be one of the key design issues for engagement in long-term interaction contexts [45]. In particular, a two-month field trial in an elementary school showed how engagement towards the robot decreases among the weeks of interaction when a continuous adaptation of behaviors to the interacting partners is missing [41, 42].

The adaptation of robots behaviors according to people personality opens several questions. In particular, although the correlation between personality and behaviors in human interaction is a well-studied issue, it is still not fully investigated how personality traits influence people’s behaviors in human-robot interaction. Studies in social signal processing proposed methodologies to recognize individual differences in personality traits during interaction with computers, however this topic in human-robot interaction is still under-investigated. The work presented in this paper is part of the EDHHI Project¹, aimed at advancing the current understanding about the individual factors that influence human-humanoid interactions in joint activities. The focus is on the analysis of personality traits of human partners, on their influence on the exchange of ver-

bal and nonverbal signals, as well as on the mechanisms underlying the dynamics of behavior during interaction with social robots.

1.1 Research questions

This work focuses on the prediction of the Extraversion personality trait of a human partner from nonverbal behaviors during human-robot interaction. The effect of personality and attitudes is observable from the overt actions of the individual [1]. We chose to explore Extraversion as this particular trait is the most detectable from nonverbal behaviors [47]. As discussed in [36], Extraversion “*is the personality trait that notably (i) shows up more clearly during interaction, and (ii) has the greater impact on social behavior with respect to the other traits*”. A number of studies report on the influence of Extraversion on social signals, for example on the frequency and duration of gazes during face-to-face interactions [33], as well as on speech dynamics [62, 23]. The three following research questions will be here addressed:

- RQ1: Is it possible to predict Extraversion of the human partner from *nonverbal* behavior *during human-robot interaction*?
- RQ2: How this prediction is influenced by the human partners’ *a priori* on robotics?
- RQ3: How much *time* a robot needs to build an accurate first impression model of Extraversion of its human partner?

2 Related Works

In this section, firstly, personality and personality traits are defined according to the state of art on Psychology. Instruments for the evaluation of personality traits are then introduced. Finally, a review of the current research on the interplay between personality and behaviors in Human-Computer Interaction (HCI) and in Human-Robot Interaction (HRI) is presented.

2.1 Human personality traits

Individual differences in personality define ourselves, making each person unique. An accepted definition of personality characterizes it as the “*patterns of relatively permanent traits and unique characteristics that give both consistency and individuality to a person’s behavior*” [25]. This is, therefore, a psychological construct that influences behaviors via the mind-body interplay. However, psychologists are still far from a universally

¹ <http://www.smart-labex.fr/EDHHI.html>

shared definition. For example, Allport identified 4.500 terms in the English vocabulary describing aspects of personality [2]. Our thinking, feelings and behavioral patterns, reflect our personality. Individual differences shape our own identity in a relatively stable way along all our life, guiding behaviors in our social life as well as in the loneliness [48]. At the same time, people observe our behaviors for building mental models of us. In social interactions, these mental models give us the possibility of establishing effective relationships with others, harmonizing our behaviors to them, according to their personality, the social context and our own personality.

The definition of personality provided above grounds on the concept of “*personality traits*”. A trait is defined as “*a dimension of personality used to categorize people according to the degree to which they manifest a particular characteristic*” [15]. These traits are considered as the fundamental building blocks of personality. They are stable across contexts and time and represent people’s disposition to respond in certain ways. From this point of view, a trait is considered as the “*conditional probability of a category of behaviors in a category of contexts*” [51]. It is possible to observe a certain degree of stability in personality traits. Nonetheless, some aspects of our personality may change over time, as a result of specific actions taken to smooth or alter some traits: some people tend to take considerable time and effort to be successful in this process.

Psychologists tried to identify a basic set of traits able to define the uniqueness of each individual. Each person has a different mixture of common traits making his personality unique. In other terms, researchers in psychology tried to find independent factors representing the common traits of personality. The combinations of these traits express all the continuous spectrum of personalities. Being supported by experimental evidence, the “*Big-5 model*” recently gained consensus in the research community [60]. This model defines the basic structure of people’s personality as a set of five “*supertraits*” consisting each one of six subordinated facets. The five supertraits are: *Openness*, *Conscientiousness*, *Extraversion*, *Agreeableness* and *Neuroticism*. The Big-5-model is a data-driven psychological model. The hypothesis on which it grounds, that is that five supertraits are sufficient to cover the complexity of personality, emerges from a Factor Analysis applied to a big amount of data collected through questionnaires.

The instruments proposed in literature for personality assessment are Likert scales-based questionnaires. The most popular questionnaires are: the *NEO Personality Inventory Revised* (NEO-PI-R, 240 items) [19], the *NEO Five Factor Inventory* (NEO-FFI, 60 items) [49],

and the *Big-Five Inventory* (BFI, 44 items) [38]. These instruments were conceived in a “human perspective”: they allow to assess personality through self-judgments and their results were validated via correlation with judgments provided by acquainted persons. These questionnaires were also extensively used to investigate the interplay between personality and the use of technology (see [68] for a survey). However, the relationship between the self-assessment and the behavior of people during Human-Machine Interaction is still under-investigated.

2.2 Personality computing and robotics

People display different facets of their personality through everyday behavior. This implies that the way in which they use technology sometimes also reflects these facets. The interplay between personality and technology is addressed in a growing number of recent studies [11, 57, 37]. In particular, many works in the field of Affective Computing [55] and of Social Signal Processing [69] focused on this issue. Thus, a new and challenging field of research, called “*Personality computing*”, is emerging. For example, Qiu et al. found correlations by the text produced in a month by 142 Twitter users and their Big-5 personality traits [57]. Ivanov et al. successfully recognized personality traits using speech features from a corpus of 119 conversations [37]. In [11], the authors proposed the recognition of “personality states” from the analysis of nonverbal social signals in 442 Youtube video blogs.

During the interaction with social robots, personality plays a relevant role. Each human has a unique identity and wants to be treated accordingly [20]. Robots, then, should personalize their behaviors to the partners they are interacting with, dealing with mental models of people identities, preferences and personality traits [14, 8, 72]. Several studies have been focusing on robots able to express personality [6, 64, 43] and behave accordingly [50, 35].

For example, Lee et al. found that participants enjoyed interacting with a quadruped robot more when its personality was complementary to their own personalities [43]. At the same time, Aly and Tapus [3] synthesized introverted and extroverted behaviors that matched with correspondent interacting partners. They showed how introverted people prefer introverted robots and *viceversa*, confirming the similarity-attraction phenomenon. Notably, in this last work personality is assessed online through the analysis of verbal and non-verbal cues. Behaviors of the robots are then shaped according to this information. Andrist et al. designed and evaluated behaviors for a social assistive robot able

to match its Extraversion/Introversion to that of the human partner during a joint activity [6]. The robot expressed its Extraversion through gaze behaviors synthesized by the gaze behavior of participants involved in a human-human joint activity. As mentioned before, it is not yet clear whether robots, in general, should match the personality of the human partner or behave in a complementary way [68].

In these previous studies the participant’s personality was known *a priori*: robots behaved according to the scores of personality gathered through questionnaires filled before the interaction. Personality computing techniques can be used to fill this gap. However, behaviors in social interactions do not depend only on the personality of the people involved, but also on the specific context in which this interaction takes place. This is especially true in the particular context of Human-Robot Interaction. Robotics has been popularized by media, films, and novels. As a result, people may have developed their own idea on what a robot is, what a robot can do, and so on. As a consequence, they may have developed a positive or negative attitude towards robot. We refer here to “attitude” as a behavior tendency (usually directed towards people, objects or situations, not necessarily to robots) that is determined by the background, knowledge, social context and experiences of the individual. Due to their relation to the prior experience, attitudes are contingent and may change in time. When *naïve end-users*² interact with robots, especially for their first time, a novelty or anxiety effect may appear. As such, people could be excited to interact with a robot, showing a rather positive attitude towards it, or may be afraid to touch it, or feel fearful of the possible actions of a robot, showing a rather negative attitude towards it. The NARS questionnaire, “*Negative Attitude Towards the Robots*” [53], can be useful to detect such kind of projected anxieties prior to an interaction. In [59], it was employed to evaluate the effects of nonverbal gestures of a humanoid during interactions with humans. Further, Kamide et al. adopted the same questionnaire to quantify the perception of human-likeness and anthropomorphism of robots [40].

3 Materials & Methods

To address our research questions, we designed and performed an experiment where participants freely interacted with a humanoid robot. Information about personality and attitude towards robots were collected using the NEO-PI-R and NARS questionnaires before the

² By *naïve end-users* here we intend people that are not experts in robotics or have no prior significant experience in operating or interacting with robots.

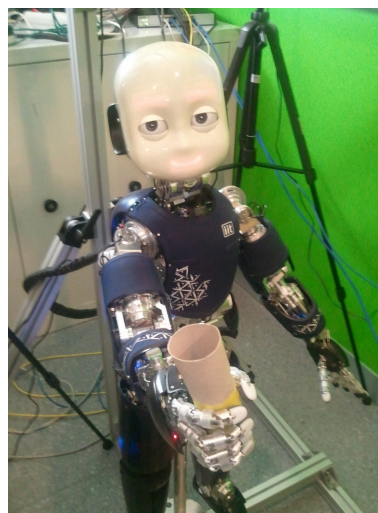


Fig. 1 The humanoid robot iCub holding a paper toy. The robot starts to interact with its human partner few seconds after the encounter with him: it looks at the human and offers him the paper toy. The human partner can decide to take the paper toy or to ignore the robot action.

interaction with the robot. A RGB-D sensor was used to capture the nonverbal behavioral patterns of the participants.

3.1 Setup

The experiments were performed in a laboratory setting, using the child-like robot iCub [52] controlled by an operator. The operator, hidden behind a wall, had a complete third-person view of the robot and of its surroundings using a conveniently placed camera. The robot was controlled through a Wizard-of-Oz (WoZ) GUI. The operator was able to adjust the stiffness of the robot to make it fully compliant [27] when touched. iCub was endowed with multimodal communication, interacting with the human partner by using gestures, speech and facial expressions.

As shown in Figure 2, an RGB-D sensor was conveniently placed over the head of the robot to frontally capture the movements of the upper-body of the human interacting with the robot. At the same time, two HD cameras recorded the scene from the front and from the side, respectively. The experimenter monitored the interaction out from the sensors’ field of views, able in any case to push the safety button and intervene in case of emergencies. Participants were equipped with a wireless Lavalier microphone to have a clear voice recording.

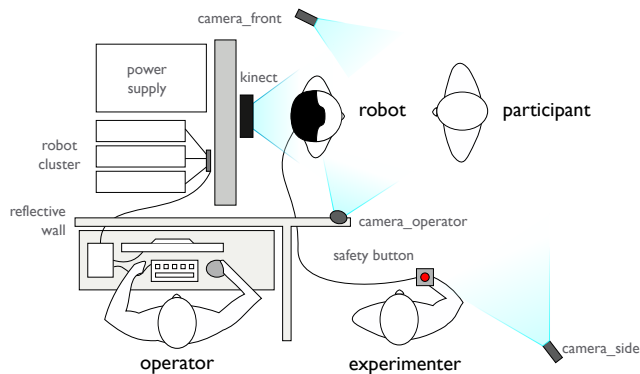


Fig. 2 The experimental setup. The left part of the schema depicts the control area of the experiment: the operator controlling the humanoid partner was hidden behind a wall. The right part of the schema shows the area where the human and humanoid partners interacted. Four cameras captured the interaction: one RGB-D Kinect sensor was set behind the robot to capture the behavior of the human participant, two cameras were used by the operator to follow how the experiment runs, an additional camera was set to record the whole scene. The experimenter followed the interaction and could intervene in case of dangerous situations by pressing a safety button.

3.2 Experimental Protocol

The experiments followed an *ad hoc* protocol³ developed to study the spontaneous behavior of naïve end-users interacting with a robot.

Before the beginning of the experiment, the participants were asked to watch a short video presenting the iCub. The video did not provide any information about the experiments. It was only aimed to guarantee that the participants had a uniform prior knowledge of the robot appearance. Then, each participant was introduced to the robot by the experimenter, who did not provide any specific instruction about how to behave with the robot and what to do. The experimenter would simply say “This is the robot iCub”, then stay on the right side of the robot, to supervise the interaction for safety issues. The participant was not implicitly or explicitly encouraged to interact with the robot: the experimenter did not say anything suggesting the fact that they could interact, speak or touch the robot, nor that they were not allowed to do it. The robot was standing on its fixed pole, gently waving the hands and looking upright, while holding a colored paper toy in its right hand. It was not speaking.

Once the participant was standing and looking in front of the robot, he was free to do whatever they wanted: talking to the robot, touching it, and so on. After few seconds, the robot started to interact with the participant: it would look at him (upward gaze)

and raise the right hand, holding the colored paper toy. The participant could choose whether to interpret the robot’s movement as an intentional and goal-directed action or not, decide to interact with the robot or to ignore it. When a participant had no reaction to the robot action, the robot, controlled by the operator, would lower the hand after 4-5 seconds. Otherwise, the robot would open the hand to give the paper toy to the human (see Fig. 1). As participant did not receive any indication by the experimenter, if he wanted to, he could start interacting more actively with iCub, asking questions, giving back the paper toy, and so on. Due to the absence of guidelines by the experimenter, the behavioral response exhibited by the participants was spontaneous. When a disengagement or inactivity of the participant was detected, the experimenter would invite him to withdraw from the robot and start preparing for performing other experiments with iCub (not related to this work) [36, 29]. The experimenter considered a disengagement event one of the following: *i*) the participant stopping to look at the robot and looking elsewhere, *ii*) the participant addressing a question to the experimenter regarding the upcoming experiments, *iii*) the participant withdrawing from the robot and gazing at the experimenter, *iv*) the participant returning the cylinder to the experimenter.

3.3 Participants

A group of 37 healthy adults, French, without any prior experience with robots was involved in this study. Participants decided voluntarily to participate in the Project. They were recruited via word-of-mouth, mailing list and newspaper announcements. Each participant received an ID number to preserve their anonymity and signed informed consent granting us the use of their recorded data. All the participants received information about the experiment and gave a written consent before attending it. Due to technical problems and data inconsistencies, some recordings were corrupted or incomplete, and were therefore discarded (e.g., ROS/YARP issues, proper detection of the human silhouette). Other sessions were discarded due to the unpredictability of the human behaviors. For example, a participant knelt down in front of the robot for all the interaction; another one sat down on the side of the robot. The final size of the data set included 23 samples (6 men, 17 women, age: 34.95 ± 16.98).

³ Ivaldi et al., IRB n.20135200001072.

3.4 Questionnaires

To assess the personality traits of the participants, two questionnaires were administered to all the participants of the EDHHI Project few weeks before the experiment. The two questionnaires were: the Revised Personality Inventory (NEO-PI-R) [18], assessing the personality traits according to the Big Five model [60], and the Negative Attitude towards Robots Scale (NARS) [53].

From the first questionnaire, only the 48 questions related to Extraversion were retained. The official French translation was used. The order of the questions followed the original questionnaire, the answers were from 1 (*Totally disagree*) to 5 (*Totally agree*). Figure 3 shows the distribution of the NEO-PI-R Extraversion scores. According to the authors of NEO-PI-R [18], people with a score between 100 and 120 have a neutral level of Extraversion. People with very low scores (≤ 80) can be considered introverts, whereas people with very high scores (≥ 140) can be considered extroverts. In between the extreme and the average range of scores, there are people exhibiting *tendencies* of introversion (80-100) or extraversion (120-140). It must be noted that the NEO-PI-R scale is normalized, so it is normal to have more participants with a medium/average score of extraversion, because very extrovert people and very introvert people fall in the tails of the distribution.

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 (*Strongly disagree*) to 7 (*Strongly agree*). The total score is computed by adding the scores of the three subscales, with some items reverse coded. The minimum and maximum scores for the three subscales are respectively 6-42 (NARS-S1), 5-35 (NARS-S2) and 3-21 (NARS-S3). Figure 4 shows the distribution of the NARS scores. The range of possible NARS scores is between 18 (very positive attitude) and 98 (very negative attitude). Scores around 58 can be considered as neutral attitude. For the experiments, we used the French adaptation of the NARS questionnaire from [36], which is also already used in other studies [29].

The participants retained for our analysis have similar distribution in terms of individual factors; their average Extraversion score is 104.21 ± 21.74 , whereas their average NARS score is 51.70 ± 13.40 .

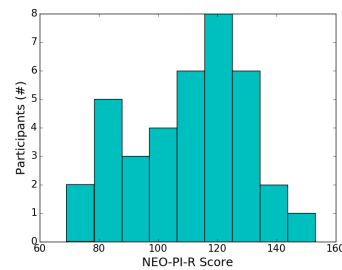


Fig. 3 The distribution of the NEO-PI-R scores of the 37 participants involved in the study.

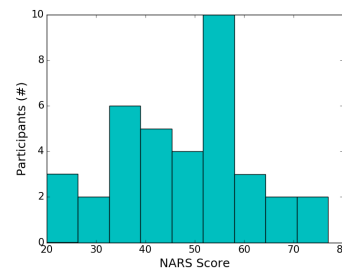


Fig. 4 The distribution of the NARS scores of the 37 participants involved in the study.

3.5 Data Collection

The data stream was captured by a RGB-D sensor (33fps). The RGB-D images kept synchronized with the robot behavior logged by the WoZ GUI. These recordings captured the first minutes of the interaction of each participant with iCub.

To investigate if there is a relationship between the duration of the interaction and the Extraversion or the participants' attitude towards robots, correlations were calculated. No significant correlation emerged from both the analyses (duration-NEO-PI-R: $\rho = 0.19$, $p = 0.40$; duration-NARS: $\rho = -0.19$, $p = 0.39$). According to such results, we conclude that no relationship exists between time and scores.

3.6 Observed behaviors

From the behavioral point of view, 65.22% of the participants changed their standing posture after taking the object from the robot (e.g., bending more towards the robot, reducing the interpersonal distance). Only 1 participant from the 23 did not take the object. About half the participants (12 over 23) asked to the experimenter if they could take the object from the robot, whereas only 5 participants (21.74%) asked if they were allowed to speak to the robot. After taking the object, 17 participants gave the object back to the robot (77.27%) and 5 of them took this exchange as a chance

to “play” with the robot, for example asking to take it with the other hand (4/5). Most participants (73.91%) naturally engaged in an interaction with the robot by talking to it and explaining what they were doing - some sample behaviors are shown in <https://www.youtube.com/watch?v=L9ZIOwAqeug>, where some different non-verbal cues of the participants can be seen (movements, gestures, gaze etc.). Figure 5 shows four typical reactions of the participants interacting with the robot: the pictures on the left capture the participants when the robot starts lifting the hand holding the object, whereas the picture on the right shows the participants after taking the object. Some participants came closer to the robot (first), some kept the distance but tried to continue the interaction (second), some went further and asked the robot to take it back with the other hand (third), whereas other participants did not act particularly but rather stayed put a bit puzzled (fourth).

4 Nonverbal behavioral features

A set of 15 nonverbal behavioral features were automatically extracted from the video corpus for each participant. Table 1 reports the list of the features.

Table 1 The set of nonverbal behavioral features extracted from the video corpus.

	Feature ID	Feature name
Indiv. features	F1	Average of QoM
	F2	Standard deviation of QoM
	F3	Skewness of QoM
	F4	Kurtosis of QoM
Dyadic features	F5	Instantaneous change of the human-robot distance
	F6	Instantaneous amount of synchrony
	F7	Average of F6
	F8	Standard deviation of F6
	F9	Skewness of F6
	F10	Kurtosis of F6
	F11	Instantaneous direction of synchrony
	F12	Average of F11
	F13	Standard deviation of F11
	F14	Skewness of F11
	F15	Kurtosis of F11

The first four features ($F1 - F4$) were computed from the *Quantity of Motion* (QoM) of each participant. QoM is a measure of the amount of motion detected from a video-camera and it is used in computer vision as an approximation of the kinetic energy of the movement. These features, called *Individual features*, are related only to the behavior of the participant during the interaction. The fifth feature ($F5$) was the in-



Fig. 5 Some participants reacting to the robot’s gesture.

stantaneous change of the human-robot distance. The features from $F6$ to $F15$ are related to the human-robot movement synchrony. Synchrony measures the degree to which the human and the robot adapt in time their behaviors. Features $F5 - F15$ are called *Dyadic features* and they take simultaneously into account both the behavior of the participant and the behavior of the robot. A full description of these features is provided in the following of this Section. The features were arranged in a feature vector to obtain a behavioral characterization of the participants during the interaction. These feature vectors were used as inputs to feed the model to predict Extraversion during interpersonal interaction.

Psychology and previous studies on personality computing support the hypothesis that personality can be inferred from nonverbal communication features as argued in the *personality externalization-perception-attribution* chain of the Brunswik Lens model [68]. Further, the use of nonverbal features stemmed also from real world constraints in which a robot could act. Real life scenarios include several sources of noise as environmental sounds, people talking or the sound produced from the robot itself. For this reason, audio features were discarded, although in controlled set up they could be able to provide better classification performances.

This work focuses on Extraversion prediction during a human-robot interaction, thus features relying both on the Extraversion facets (*sociability, energy, assertiveness* and *excitement-seeking*) and on the attitude towards robots were chosen. Quantity of movement is known to be a clue of Extraversion: extroverted people frequently gesture, use a large body area and energetic movements (e.g., [46]). More, energy can indicate if a person feels nervous or relaxed when she is face to face with a robot. This feeling is also partially revealed by the spatial distance that a participant maintains while interacts with a robot. Proxemics rules as defined by Hall [30] display their effects also when humans and robots interact. In such scenarios, a low familiarity or confidence with robots (that is, a negative attitude toward robots) results in increasing this spatial distance [63]. Further, proxemics is directly linked to sociability: previous studies showed that extroverted people tends to adopt smaller distances when they interact [71]. Also interpersonal synchrony is able to describe the dynamics of interaction and its quality [22]. It can be broadly defined as “*the degree to which the behaviors in an interaction are non-random, patterned or synchronized in both form and timing*” [10]. People spontaneously tend to dynamically adapt their behavioral rhythms (e.g., walking rhythm, turn taking) when they interact [35]. This synchrony improves communication of content and

sharing of goals. Recently, synchrony started to be investigated in HRI. For example, [32] showed that it can facilitate the natural interaction with robots decreasing the cognitive load of the human partner. Basically, at the present, synchrony was explored in the following three ways: movement synchrony, synchrony of direction (that is opposite direction or same direction), and synchrony towards a specific target (e.g., object, person or location). Lehmann et al. endowed a non-anthropomorphic robot with the skill to perform even minimal positively synchronized movements in an object-oriented task [44]. Their results showed an increase in the engagement of human partners and in a positive feeling with the robot.

Other behavioral features could be added to have a more complete characterization of the participants. The identification and the evaluation of other features is out of the scope of this work.

In the following subsections a description of the features conceived starting from this knowledge is provided. The algorithms for features extraction and computation were implemented in Python. Synchrony was analyzed by using the open source Python library *SyncPy* [66].

4.1 Quantity of Motion

Quantity of motion (QoM) is a Silhouette Motion Image (SMI)-based measure of the amount of motion detected from an optical sensor like a video-camera [16]. In computer vision, it is adopted as indicator of the energy of the movement. SMI at time t is an image carrying information about changes in the silhouette shape and position in the last few frames of a video. The corresponding QoM at time t is evaluated as the area, that is the number of pixels, of the SMI at the time t normalized over the area of the silhouette at t . The following equations show how SMI and QoM are computed:

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

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

where n is the number of frames taken into account, t is the time at which the SMI and the QoM is being computed, and *Silhouette* is an image showing only the silhouette extracted from the background.

In this work, QoM was computed from the depth images provided by the RGB-D sensor. First, the silhouette of the participant was extracted by thresholding the depth image in order to remove the background.

Unlike [16], the resulting silhouette was not binarized: this was 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) which is detectable when depth images are used. The SMI was obtained by subtracting the silhouette of a current frame from that of the n last frames. This image was then normalized by the value of n . Finally, the area of the SMI was calculated and normalized by the area of the silhouette of the current frame in order to define the Quantity of Motion of the current frame.

In this work, QoM was computed over a sliding-window of 500ms (window step=30ms). Then, a statistical description (average, standard deviation, skewness, and kurtosis) is computed and used as first entry of the feature vector.

4.2 Human-robot distance changes

Estimate of human-robot distance was computed from the depth image provided by the RGB-D sensor. The instantaneous distance change was approximated by the mean of the rolling standard deviations (window size=1.5s) of the distance between the iCub head and the centroid of the silhouette of the human partner (see Figure 2).

4.3 Behavioral synchrony

Behavioral synchrony was addressed as movement synchrony between the two partners. To take into account the different nature of the behavioral patterns of the two partners (continuous for the human and discrete for the robot), movement synchrony was faced in terms of synchrony among movement events. The movement events of the human partner were identified as the peaks of the Quantity of Motion, whereas the movement events of the robot were extracted from the log files. These events included gazing behaviors, hand motions and speech events, as these last ones are followed by movements behaviors. Starting from this data, movement synchrony was analyzed through the *Event Synchronization* (ES) method [58] that allows to quantify at which extent two univariate time-series showing events are synchronized and their time delay patterns. The equations in the following show the couple of measures of ES. The amount of synchrony Q^τ is the count of the fraction of event pairs matching in time; it ranges from 0 (no matching at all) to 1 (complete matching). The number of times each time-series leads the other one in these matches is q^τ . It was here used to show how often an action of one of the two partners comes before the corresponding action performed by the other one.

This **value** ranges in $[-1, 1]$ providing the *direction* of synchrony. It allows at discriminating between causal ($q^\tau = 1$ or $q^\tau = -1$ depending on which of the two time-series precedes the other one) or mutual ($q = 0$) interaction. In other words, q^τ shows who, by a chronemic point of view, is leader.

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

where: x_2 and x_1 are the two time-series of the movement events of the participant and the iCub, respectively; m_{x_1} and m_{x_2} are the events occurring at the times $t_i^{x_1}$ and $t_j^{x_2}$ ($i = 1, \dots, m_{x_1}; j = 1, \dots, m_{x_2}$) in the two time-series; τ a time lag for which two events could be considered as synchronous. Let us denote by $c^\tau(x_1|x_2) = \sum_{i=1}^{m_{x_1}} \sum_{j=1}^{m_{x_2}} J_{ij}^\tau$, the the number of times an event appears in x_1 after it appeared in x_2 ; with $J_{ij}^\tau = \{1 \text{ if } 0 < t_i^{x_1} - t_j^{x_2} < \tau; 1/2 \text{ if } t_i^{x_1} = t_j^{x_2}; 0 \text{ otherwise}\}$. In this work, in order to have a better understanding about the dynamics of synchrony during the interaction, also the frame-resolved variants of these measure were extracted. These variants are obtained simply replacing $c^\tau(x_1|x_2)$ with $c_n(x_1|x_2) = \sum_{i=1}^{m_{x_1}} \sum_{j=1}^{m_{x_2}} J_{ij}^\tau \Theta(n - t_i^{x_1})$, where Θ is the Heaviside function (i.e. $\Theta(x) = 0$ for $x \leq 0$ and $\Theta(x) = 1$ for $x \geq 0$) and $n = 1, \dots, N$ is the frame number.

The events of the two partners were extracted as follows:

- *Human partner’s events*: the first derivative of the moving standard deviation of QoM computed over a centered window of 60ms was obtained. Then, an amplitude threshold was applied on this signal (the threshold value was empirically estimated from the distribution of the derivative, a small multiple of the 75th percentile is used). This resulted in a dense cloud of candidates events that, finally, were grouped by using a DBSCAN (Density-Based Spatial Clustering of Applications with Noise) clustering [24]. The algorithm uses a brute-force search of neighbors (radius of neighborhood=400ms) to detect the events of the human partner.
- *iCub’s events*: the detection of the events of the iCub started from the analysis of the log files. All the candidates events of the classes mentioned above were parsed from the files. Then, as for the human partner, a DBSCAN clustering was adopted to detect the final events. Also in this case, the parameters of the algorithm were brute-force searching of the neighbors with a radius equal to 3s.

The values of Q^τ , q^τ and their first fourth statistical moments of their frame resolved versions were included in the feature vector.

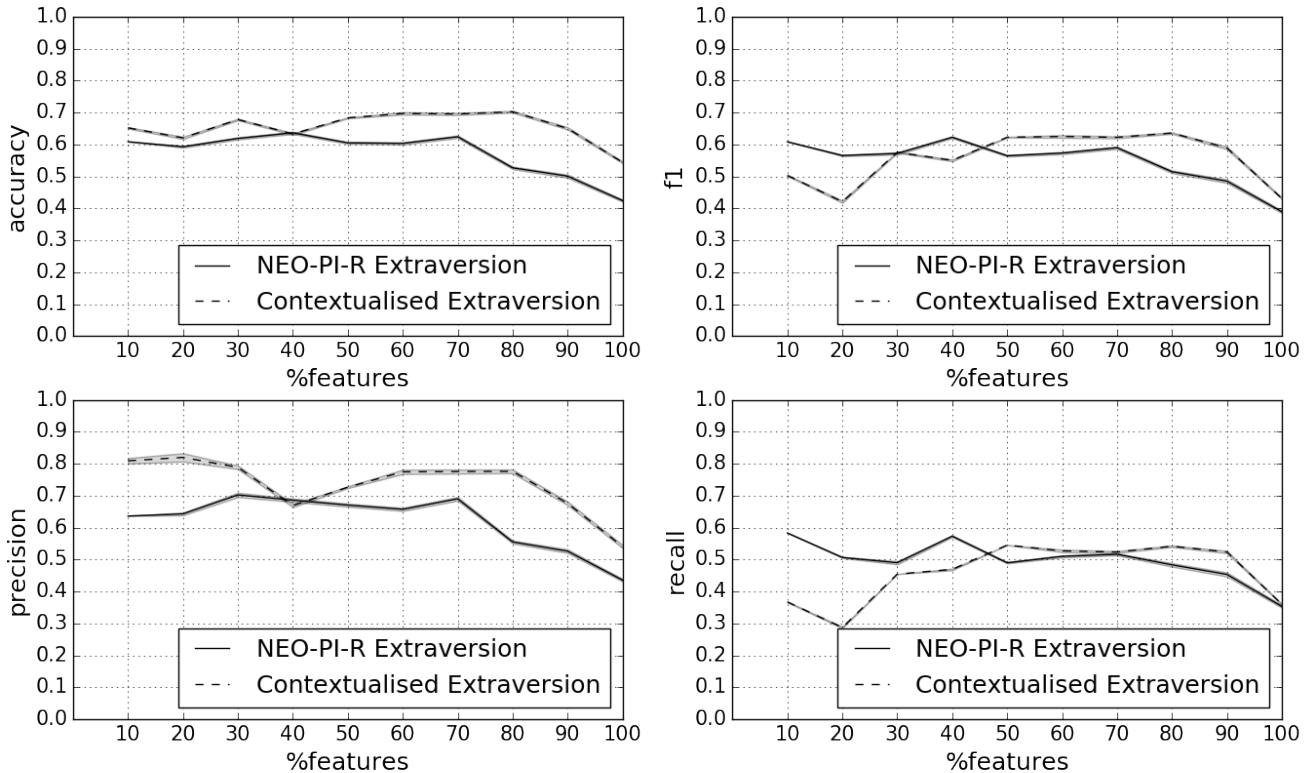


Fig. 6 Performances (accuracy, F1-score, precision and recall) of the classifier vs the percentage of features kept when classes' labels are computed from (i) NEO-PI-R (solid line) and (ii) Contextualised Extraversion scores (dashed line). The confidence intervals of each measure are also provided (shaded area around lines).

5 Data analysis and experimental results

The features extracted from the human-humanoid interaction were analyzed using a two-classes Logistic Regression classifier as prototypical model to predict Extraversion. In this section we will investigate: the feasibility of Extraversion prediction in HRI from nonverbal features (RQ1); the influence on this prediction of *a priori* on robotics (RQ2); and the time the robot needs to infer an accurate Extraversion first impression (RQ3).

5.1 Extraversion prediction over the whole interaction

As already discussed in Section 2.1, people behavior depends on the personality but also on the particular context in which the persons act. In the particular scenario of a joint activity with an humanoid robot, people's behavior can vary accordingly to their attitude towards the robots. This attitude depends on self-beliefs of the participants with robots. The NARS questionnaire is adopted to contextualize the Extraversion scores from the NEO-PI-R questionnaire to this *a*

priori knowledge. The Spearman's correlation between the NEO-PI-R Extraversion scores and the NARS context scores showed how those measures are uncorrelated ($\rho = -0.15$; $p = 0.5$). A combination of the NEO-PI-R Extraversion scores and the three NARS context scores was obtained through their Principal Component Analysis (PCA). The PCA showed that only the first component was meaningful (explained variance by the first component equal to 85%): this can be interpreted as the Extraversion in social interactions with robots. In the following, we will refer to this component as *Contextualised Extraversion score*. The median of the distribution of the Contextualised Extraversion scores of the participants was used to define the labels of the two classes for the classifier: *low-Contextualised-Extraversion* and *high-Contextualised-Extraversion* classes. The same approach was also adopted for building classes from the NEO-PI-R Extraversion scores (*low-Extraversion* and *high-Extraversion*) as well as from NARS Context scores (*low-Negative-Attitude* and *high-Negative-Attitude*), respectively. The choice of median as **criterion** to define class labels was done ac-

ording to the state of the art on automated personality traits detection (e.g., [73]).

In order to investigate which features allow to have a better discrimination between the classes, a feature selection step was performed. The feature selection strategy adopted in this work was the Fisher criterion: features were ranked on their f-score and only a prefixed percentage of them (those ones having the highest f-scores) was retained. This selection was applied to the classes obtained from NEO-PI-R Extraversion, NARS Context and Contextualised Extraversion, respectively.

A leave-one-participant-out cross validation strategy was applied. This approach consists in building partitions on the participants: let's suppose to have N participants, in turn all but one participant are used to train the classifier and the remaining participant is used to test it. The mean performance metric (e.g., accuracy) of the classifier results from averaging the N obtained values of the metric. In this work, the penalty parameter was optimized using a 5 folds grid-search in the range $[10^{-5}, 10^5]$. To account for the differences in the cross-validation and to have a statistical significant sample size useful to compare the results of the classifier, the procedure described above was repeated 25 times.

Figure 6 shows the average performances (accuracy, F1-score, precision, and recall) of the classifier vs the percentage of features kept in the analysis. The classifier highlights the best performance of Contextualised Extraversion when the 70% of the features are employed. Table 2 summarizes the results.

Results highlight that we can infer the Extraversion according to the NEO-PI-R scores with an accuracy of 62%, providing an affirmative answer to the research question RQ1. By combining NEO-PI-R with NARS scores through PCA, the Contextualised Extraversion model shows an accuracy of 70%. This confirms the importance of the contextualization of Extraversion proposed in RQ2.

A paired Wilcoxon signed-rank test was run to evaluate the differences between the performances showed by the classifier when labels from NEO-PI-R Extraversion and Contextualised Extraversion were used, respectively. The reference significance level for the test was $\alpha = 0.05$. Statistical significant differences were found for accuracy ($V=20.5$, $p < 0.01$), F1-score ($V=61.0$, $p < 0.01$) and precision ($V=27.5$, $p < .01$), whereas the difference was not significant for recall ($V=141$, $p > 0.05$).

5.2 Extraversion first impression prediction

Previous study on psychology in human-human interactions showed that people need at least 30s to perform valid inferences about personality [4, 5]. Similarly, we tried to evaluate how much time the robot required to predict Extraversion in a reliable way.

As designed by the experimental protocol, interaction patterns with the robot were not totally fixed, they depended on the spontaneous behavior of each participant. Thus, due to the unstructured nature of interaction, its segmentation in common phases was impossible. Consequently, we chose to use fixed, cumulative time slices of 10s. As reported in the state-of-the-art, the use of fixed size slices for the analysis of unstructured interaction does not seriously affect the results. Figure 7 shows the accuracy on prediction over time of NEO-PI-R Extraversion and Contextualised Extraversion scores. According to the results illustrated in the previous subsection, the 70% of the most relevant features were used to feed the classifier. Results show that 120s are needed to recognize the contextualised Extraversion with 70% of accuracy. Moreover, results confirm that the recognition of Contextualised Extraversion outperforms the performance of NEO-PI-R Extraversion score across the time.

6 Discussion

In this paper we addressed the automated prediction of personality traits from the dynamics of interpersonal interaction with social robots. In particular, we proposed a set of nonverbal features able to model such dynamics and we showed the results of the Extraversion prediction obtained by training a classifier with these features. We also studied how such results are improved by contextualizing the personality with the specificity of the explored scenario, a social interaction with an humanoid robot. Finally, we investigated how much time a robot needs to find an accurate prediction of the Extraversion of the human partner, without having prior information.

The performances obtained in this study are comparable with the state-of-the-art on automated personality recognition in human-human interaction. In particular, Zen et colleagues [73], using visual and nonverbal features, obtained an accuracy of 66% to classify Extraversion. The adoption of multimodal features, in particular acoustic features, has the potentiality to improve the performances of prediction, as shown in [56]. However, in their work acoustic features were retrieved from audio recordings in a controlled environment, where a good quality of the captured signals cap-

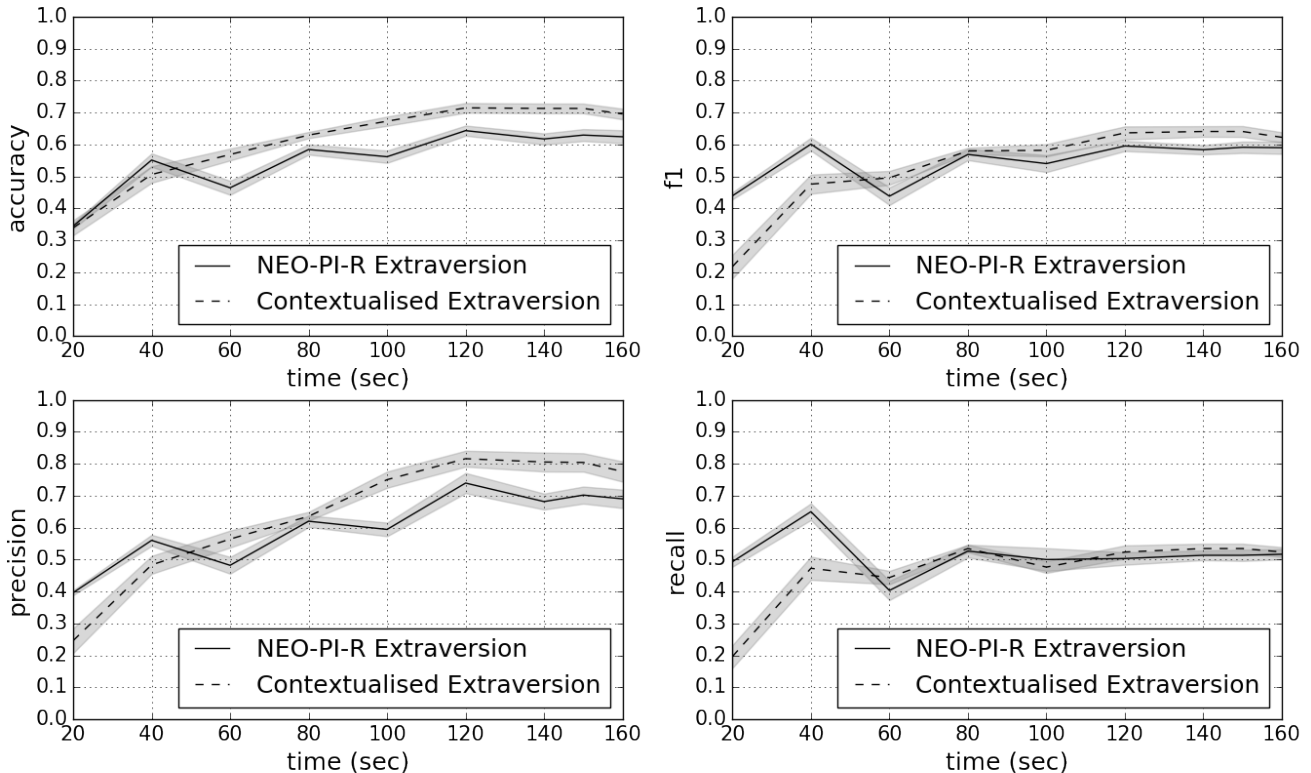


Fig. 7 Performances (accuracy, F1-score, precision and recall) of the classifier according to the cumulative thin slices when classes' labels are computed from NEO-PI-R Extraversion (solid line) and Contextualised Extraversion scores (dashed line). The confidence intervals of each measure are also depicted (shaded area around the lines.)

Table 2 Average performances of the classifier when 70% of the features is used.

	Accuracy	F1-score	Prec.	Recall
NEO-PI-R Extraversion	62%($SD = 0.05$)	59%($SD = 0.05$)	69%($SD = 0.07$)	52%($SD = 0.04$)
Contextualised Extraversion	70%($SD = 0.04$)	62%($SD = 0.04$)	77%($SD = 0.08$)	52%($SD = 0.04$)

tured was ensured. In real context involving robots, as previously mentioned, it is not always possible to rely on such clean acoustic features. Moreover, both these works addresses interaction among humans. One of the assumptions of our work is that the robot presence can alter the dynamics of interpersonal interaction. In the study of [9], where interaction between people is mediated by a computer, the Extraversion classification accuracy reaches 70%. This result confirms our findings and highlights how the presence of different kind of media can influence the interaction itself.

Our work should be considered as a pioneering study towards the development of social robots able to shape and adapt their behaviors to the personality of the interacting partners. Interestingly, the investigation of the dynamic interplay of social interactions revealed

key elements for designing natural and effective social robots. The coherent exchange of social behaviors with people would be crucial for the emerging of social intelligence. Social robots endowed with such capability would bridge the gap between social animals and un-social machines [70], inducing on humans the illusion of life [65].

The obtained results are encouraging but they should be interpreted in the context of several limitations. First of all, the number of participants to the experiment does not allow us a complete generalization of the results. As mentioned above, the setup complexity was such that many recordings were not retained in this study. Further data were discarded due to the unpredictability of people behavior. Future works should try

to design new scenarios in between the extremes of structured and spontaneous interaction.

In this paper we focused on social interaction with a humanoid robot. Humanoid robots are a strong conveyors of anthropomorphism: their shape could induce a bias in the way people behave in front of the robot, meaning that our result cannot be generalized to any kind of robot at this stage of investigation. Further research focusing on non human-like robots as well as on more realistic, android-like robots, should explore how the anthropomorphism influences the dynamics of the interaction, and consequently the prediction of personality traits like in this study.

In this work we studied a dyadic interaction. While personality traits are stable across situations, group dynamics would alter the behaviors of people and their robot perception. Humans and robots could also cooperate in more sophisticated joint activities. Future works should investigate such complex interpersonal interactions, identifying methodologies and behavioral features able to model such kind of scenarios.

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Compliance with ethical standards

The experimental protocol used in this work (Ivaldi et al., “Engagement during human-humanoid interaction”, IRB n.20135200001072) received approbation by the local Ethics Committee (CERES) in Paris, France. The authors declare that they have no conflict of interest.

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Salvatore Maria Anzalone received his Ph.D. degree in Computer Engineering from the University of Palermo (2010). He cooperated with the Intelligent Robotics Laboratory at the Osaka University during one year of his Ph.D. (2009) and during his post-doc year at the Department of Information Engineering of University

of Padova (2010). He received a grant from the Japan Society for the Promotion of Science and from April 2011 to April 2012 was a research fellow at the Intelligent Robotics Laboratory at Osaka University (2011–2012). From May 2012 to February 2015 joined as Post-Doc researcher the University Pierre et Marie Curie in Paris, France, at the Institute for Intelligent Systems and Robotics (ISIR-UPMC). In 2013 he received a grant from the Japanese National Institute of Information and Communications Technology that he spent as visiting researcher again the Intelligent Robotics Laboratory at Osaka University from November to December 2013. From February 2015 to May 2016 he was associate to ISIR and research engineer at the Child and Adolescent Psychiatry Service of Pitié-Salpêtrière Medical Hospital. He is now Associate Professor at the Department of Engineering, Cognition and Handicap, UFR erITES of Paris 8 University and member of the CHArt laboratory (EA4004). His main research interests are on multimodal interaction in social robotics and on the use of robots in socio-cognitive disorders.

Giovanna Varni received the M.Sc. Degree in biomedical engineering and the Ph.D. in electronic, computer, and telecommunications engineering from University of Genoa, Italy, in 2005 and 2009, respectively. Since 2009, she has been a postdoctoral research assistant at DIBRIS-InfoMus Lab, University of Genoa. At the present, she is a postdoctoral research assistant at the IMI2S (Interaction, Multimodal Integration and Social Signal) research group at the Institute for Intelligent Systems and Robotics (CNRS UMR 7222), University Pierre and Marie Curie-Paris 6. Her research interests are in the area of human-computer interaction, especially focusing on social signals analysis, expressive gesture. She was involved in several FP7 EU-ICT STREP and FET projects.

Serena Ivaldi is a researcher in INRIA. She received the B.S. and M.S. degree in Computer Engineering, both with highest honors, at the University of Genoa (Italy) and her PhD in Humanoid Technologies in 2011, jointly at the University of Genoa and the Italian Institute of Technology. There she also held a research fellowship in the Robotics, Brain and Cognitive Sciences Department. She was a postdoctoral researcher in the Institute of Intelligent Systems and Robotics (ISIR) in University Pierre et Marie Curie, Paris, then in the Intelligent Autonomous Systems Laboratory in the Technical University of Darmstadt, Germany. Since November 2014, she is a permanent researcher in INRIA Nancy Grand-Est. She has been PI in the European Projects FP7 CoDyCo and H2020 AnDy, leading

research in human-robot interaction and collaboration, blending learning, perception and control.

Mohamed Chetouani is the head of the IMI2S (Interaction, Multimodal Integration and Social Signal) research group at the Institute for Intelligent Systems and Robotics (CNRS UMR 7222), University Pierre and Marie Curie-Paris 6. He received the M.Sc. degree in Robotics and Intelligent Systems from the UPMC, Paris, 2001. He received the PhD degree in Speech Signal Processing from the same university in 2004. In 2005, he was an invited Visiting Research Fellow at the Department of Computer Science and Mathematics of the University of Stirling (UK). Prof. Chetouani was also an invited researcher at the Signal Processing Group of Escola Universitaria Politecnica de Mataro, Barcelona (Spain). He is currently a Full Professor in Signal Processing, Pattern Recognition and Machine Learning at the UPMC. His research activities, carried out at the Institute for Intelligent Systems and Robotics, cover the areas of social signal processing and personal robotics through non-linear signal processing, feature extraction, pattern classification and machine learning. He is also the co-chairman of the French Working Group on Human-Robots/Systems Interaction (GDR Robotique CNRS) and a Deputy Coordinator of the Topic Group on Natural Interaction with Social Robots (euRobotics). He is the Deputy Director of the Laboratory of Excellence SMART Human/Machine/Human Interactions In The Digital Society.