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Authors: Silvia Rossi, Francois Ferland, Adriana Tapus

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To: Gabriella Sanniti di Baja
Editor-in-Chief Special Issues
Pattern Recognition Letters

Dear Editor and Reviewers,

> Thank you for your comments concerning our manuscript entitled "User Profiling and Behavioral Adaptation for HRI: a Survey". We appreciated the constructive criticisms of the Reviewers and provided a general review of the paper trying to address all the suggestions. Two main modifications were addressed. Firstly, the survey is now focused on papers from the last 5 years, so few older references were removed and some newer added. Moreover, we provided a table and the end of the survey article to provide a global view of the presented approaches with respect to the considered classification and to better discuss common problems and issues. In detail, we have addressed each of their concerns as outlined below.

Reviewer #1:
1) Proof read for English

> We made some modifications in the article to improve the English quality.

2) It seems that the paper tried to mainly focus on the past two years 2015 and 2016. It would be good to clarify this to the readers.

> All the reviewed papers are now within the last five year (not considering the references to survey papers and research articles introducing the main concepts). We removed few ones that were not published in such time-frame and added some others (see comments to reviewer #2). Hence, we explicitly clarified our approach in the introduction.

3) While the major issue is an over representation given to the same lab in certain area of expertise even if the work in the named lab is highly relevant. For example, in the social signal processing paragraph, it is recommended to the reader who has a great interest in this area to read a 2012 survey paper while a survey paper was published last year in 2016 in the area (Palaghias, N., Hoseinitabatabaei, S. A., Nati, M., Gluhak, A., and Moessner, K. (2016). A survey on mobile social signal processing. ACM Computing Surveys (CSUR), 48(4), 57.). It would be good to at least mention it. Also the personality paragraph in the social adaptation section also suffers from the same problem. It could have mentioned the two contradicting

theories of similar/opposition attraction towards a robot with the same personality, for example (Joosse, M., Lohse, M., Prez, J. G., and Evers, V. (2013, May). What you do is who you are: The role of task context in perceived social robot personality. In Robotics and automation (ICRA), 2013 IEEE international conference on (pp. 2134-2139). IEEE.)

> We thank the reviewer for this suggestion. We actually added the reference to the newer survey and the suggested paper on personality.

Reviewer #2:
1) Giving more synthesized information on each part. This does not mean reducing the current parts, which I think are good. But nevertheless, providing some summary tables, or other elements that can help easily and quickly extract the main points from each section for which more extensive surveys exist.

Finally, I think that the discussion would greatly benefit from discussing more thoroughly the similarities and differences in the methods for profiling physical, cognitive and social aspects, and similarities and differences in behavioral adaptation based on these three types of profiles. Is one category of profiled information more appropriate for efficient robot behavioral adaptation? Do different categories imply different adaptation mechanisms? Etc.

> Instead of providing a table for each session, we provided a general table at the end of the paper where all the considered works are categorized with respect to the provided classification. The aim of the table is to present relationships among the topics and the considered categories. This also helped in modifying the final discussion in order to provide a global view on the approaches.

2) The literature review on work linking user profile with behavioral adaptation could be extended a little bit, to really identify common methods, common challenges, and possibly highlighting fundamental differences in behavioral adaptation from different types of profiled information. I suggest below a few papers that I know to help in this direction. Nevertheless, it would be useful if the authors could add even more papers on this issue.

> We followed the reviewer suggestion adding more papers on the topic as listed:
>
> - Anzalone, S.M., Boucenna, S., Ivaldi, S., Chetouani, M., 2015. Evaluating the engagement with social robots. International Journal of Social Robotics 7, 465478.
> - Benedictis, R.D., Cesta, A., Coraci, L., Cortellessa, G., Orlandini, A., 2014. A user-adaptive reminding service, in: Workshop Proceedings of the 10th International Conference on Intelligent Environments, Shanghai, China, June 30 - July 1, 2014, IOS Press. pp. 1627.
> - Boucher, J.D., Pattacini, U., Lelong, A., Bailly, G., Elisei, F.E., Fagel, S., Ford Dominey, P., Ventre-Dominey, J., 2012. I reach faster when I see you look: Gaze effects in human-human and

human-robot face-to-face cooperation. Frontiers in Neurorobotics 6, 111.

- Bussy, A., Gergondet, P., Kheddar, A., Keith, F., Crosnier, A., 2012. Proactive behavior of a humanoid robot in a haptic transportation task with a human partner, in: IEEE RO-MAN: The 21st IEEE International Symposium on Robot and Human Interactive Communication, pp. 962967.
- Eyssel, F., Hegel, F., 2012. (s) hes got the look: Gender stereotyping of robots. Journal of Applied Social Psychology 42, 22132230.
- Granata, C., Bidaud, P., 2012. A framework for the design of person following behaviors for social mobile robots, in: IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 46524659.
- Joosse, M., Lohse, M., Prez, J.G., Evers, V., 2013. What you do is who you are: The role of task context in perceived social robot personality, in: IEEE International Conference on Robotics and Automation, pp. 21342139.
- Kennedy, J., Baxter, P., Senft, E., Belpaeme, T., 2016. Social robot tutoring for child second language learning, in: The Eleventh ACM/IEEE International Conference on Human Robot Interaction, IEEE Press, Piscataway, NJ, USA. pp. 231238.
- Khamassi, M., Velentzas, G., Tsitsimis, T., Tzafestas, C., 2017. Active exploration and parameterized reinforcement learning applied to a simulated human-robot interaction task, in: IEEE Robotic Computing Conference.
- Mower, E., Mataric, M.J., Narayanan, S., 2011. A framework for automatic human emotion classification using emotion profiles. IEEE Transactions on Audio, Speech, and Language Processing 19, 10571070.
- Palaghias, N., Hoseinitabatabaei, S.A., Nati, M., Gluhak, A., Moessner, K., 2016. A survey on mobile social signal processing. ACM Comput. Surv. 48, 57:157:52.
- Sung, J., Ponce, C., Selman, B., Saxena, A., 2012. Unstructured human activity detection from rgbd images, in: IEEE International Conference on Robotics and Automation, pp. 842849.
- Vollmer, A.L., Wrede, B., Rohlfing, K.J., Oudeyer, P.Y., 2016. Pragmatic frames for teaching and learning in humanrobot interaction: Review and challenges. Frontiers in Neurorobotics 10, 10.
- Vu, K.P.L., Proctor, R.W., 2011. Handbook of Human Factors in Web Design, Second Edition. 2nd ed., CRC Press, Inc., Boca Raton, FL, USA.

3) In the introduction, page 2, the authors wrote the following sentence: "On the contrary, information obtained by "looking over the user's shoulder" is an acceptable alternative, but it has a level of uncertainty". But some references/justifications are missing to claim that it is "acceptable".

We discussed more this issue and added a reference in the context of user profiling in HCI.

4) Same page, right column: "Interactions are human activities that involve two or more people and/or objects (Coppola et al., 2016). Finally, group activities are the activities performed by groups composed of multiple people and/or objects (e.g., a group having a meeting) (Vazquez et al., 2015).". The way this is presented does not make the difference between interaction and group studies clear, since both involve interaction between multiple people and/or objects. The authors should be more precise here.

We modified the text to better clarify the difference between interaction and group activities.

5) In the next sentence, the authors emphasize the need to distinguish ADL from what?

We removed the sentence on ADL since we thought that this specification was not necessary.

6) Page 3, top of left column, a reference presenting human feedback/impression on these types of wearable sensors is needed in support for the claim that they can be found intrusive.

We clarified the meaning of the sentence.

7) Page 4 right column on social profiling. "Moreover, social profiling refers also to the possibility of recognizing social phenomena, such as conflict, empathy, interest, and emotions, that cannot be directly observed, but have to be inferred through the analysis of indirect cues." Another phenomenon which seems to me getting more and more attention in HRI and should be added to the list is engagement. See for instance Anzalone, S. M., Boucenna, S., Ivaldi, S., and Chetouani, M. (2015). Evaluating the engagement with social robots. International Journal of Social Robotics, 7(4), 465-478. Engagement is mentioned later in the manuscript. But I think it is a key phenomenon to highlight from the beginning of the section. Concerning the role of mutual gaze, the study by Boucher et al 2012 is a nice example stuying it both in human-human and human-robot interaction. Boucher, J. D., Pattacini, U., Lelong, A., Bailly, G., Elisei, F., Fagel, S., Dominey, P. F. and Ventre-Dominey, J. (2012). I reach faster when I see you look: gaze effects in human-human and human-robot face-to-face cooperation. Frontiers in neurorobotics, 6, 3.

We followed the suggestion and introduced the engagement topic earlier in the text. We added the suggested references.

8) I think the author should stress more some potential educational applications of profiling for HRI. For instance, profiling can be important to come up with human-specific appropriate teaching methods in a robot educational context. See for instance Vollmer, A. L., Wrede, B., Rohlfing, K. J., and Oudeyer, P. Y. (2016). Pragmatic frames for teaching and learning in human-robot interaction: Review and challenges. Frontiers in neurorobotics, 10. Another reference suggestion here

is relevant concerning behavioral adaptation based on social interaction signals. Complementarily to Mitsunaga et al 2008, Khamassi et al 2017 have proposed to use online measurement of human engagement to dynamically adapt exploration rate in reinforcement learning algorithms for HRI. Khamassi, M., Velentzas, G., Tsitsimis, T. and Tzafestas, C. (2017). Active exploration and parameterized reinforcement learning applied to a simulated human-robot interaction task. IEEE Robotic Computing Conference, Taipei, Taiwan.

We introduced the suggested references and discussed the learning context in the social adaptation category.

9) Page 10, information is missing for the references Ewen et al 2003 and Lara et al 2011.

We corrected the missing info in the references.

Thank you for your time, consideration and again for your comments.
Silvia, Francois and Adriana

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Authorship Confirmation

Please save a copy of this file, complete and upload as the "Confirmation of Authorship" file.

As corresponding author I, Silvia Rossi, hereby confirm on behalf of all authors that:

1. This manuscript, or a large part of it, has not been published, was not, and is not being submitted to any other journal.
2. All text and graphics, except for those marked with sources, are original works of the authors, and all necessary permissions for publication were secured prior to submission of the manuscript.
3. All authors each made a significant contribution to the research reported and have read and approved the submitted manuscript.

Signature____ Date30/04/2017

List any pre-prints:

NONE

Relevant Conference publication(s) (submitted, accepted, or published):

NONE

Justification for re-publication:

Research Highlights

To create your highlights, please type the highlights against each `\item` command.

- A survey of the recent literature on user profiling and behavioral adaptation in human-robot interaction is presented.
- Approaches are categorized with respect to being mainly related to the physical, cognitive or social aspects of the interaction.
- Key themes are highlighted to provide directions for future research.
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User Profiling and Behavioral Adaptation for HRI: A Survey

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ABSTRACT

To effectively collaborate with people, robots are expected to detect and profile the users they are interacting with, but also to modify and adapt their behavior according to the learned models. The goal of this survey is to focus on the perspective of user profiling and behavioral adaptation. On the one hand, human-robot interaction requires a human-oriented perception to model and recognize the human actions and capabilities, the intentions and goals behind such actions, and the parameters characterizing the social interaction. On the other hand, the robot behavior should be adapted in its physical movement within the space, in the actions to be selected to achieve collaboration, and by modulating the parameters characterizing the interaction. In this direction, this survey of the current literature introduces a general classification scheme for both the profiling and the behavioral adaptation research topics in terms of physical, cognitive, and social interaction viewpoints.

1. Introduction

The development of Social Assistive Robotics (SAR) (Feil-Seifer and Mataric, 2005) applications challenges researchers to build and design socially intelligent robots that can collaborate with people. In such domains, Human-Robot Interaction (HRI) effectiveness has not only to rely on the skills of trained users but also on the ability of the robot to adapt to the users' behavior and needs as well (Mitsunaga et al., 2008).

According to Fong et al. (2003), one of the required characteristics of a socially interactive robot should be to perceive, learn, and recognize models of the other agents it is interacting with. Hence, while the correct perception of the human being and of his/her movements is a requirement to achieve the proper collaboration and interaction, such perception should lead the robot to profile the user's preferences during a physical interaction with the robot, or, more generally, regarding the user's physical capabilities. However, a complete model of the user should include also his/her cognitive state, in terms, for example, of the intentions behind the interaction or his/her internal state, and, more generally, his/her preferences regarding social interaction characteristics.

Moreover, to be effective, a robot should also be able to modify and adapt its behavior accordingly. Indeed, for improved and natural human-robot cooperation, human users will learn how to interact with the robot but, at the same time, the robotic systems should adapt to the users (Mitsunaga et al., 2008). This adaptation requires learning a model of human behavior and integrating it into the robot physical movements, the robot decision-making algorithm (Nikolaidis et al., 2015), and the social interaction strategies. Furthermore, Castellano et al. (2008) mention personalization, which they define as the ability to adapt to a specific user over time, as a key requirement for long-term socially interactive companions. Nahum-Shani et al. (2015) also discuss the term customization and individualization and the need to adapt to the user based on static parameters (i.e., gender, personality) and on dynamic parameters (i.e., changes in psychological distress, response to an intervention or task) to better make decisions during the course of the interaction and the task.

The development of robotic systems capable of correctly modeling and recognizing the human behavior and of adapting their own behavior with respect to the user is a very critical task, especially in the domain of assistive robotics when working with vulnerable user populations (Tapus et al., 2008). Adaptability plays an important role in the Almere model of the acceptance of assistive social agent by older adults (Heerink et al., 2010). As observed by Heerink (2011), while elderly

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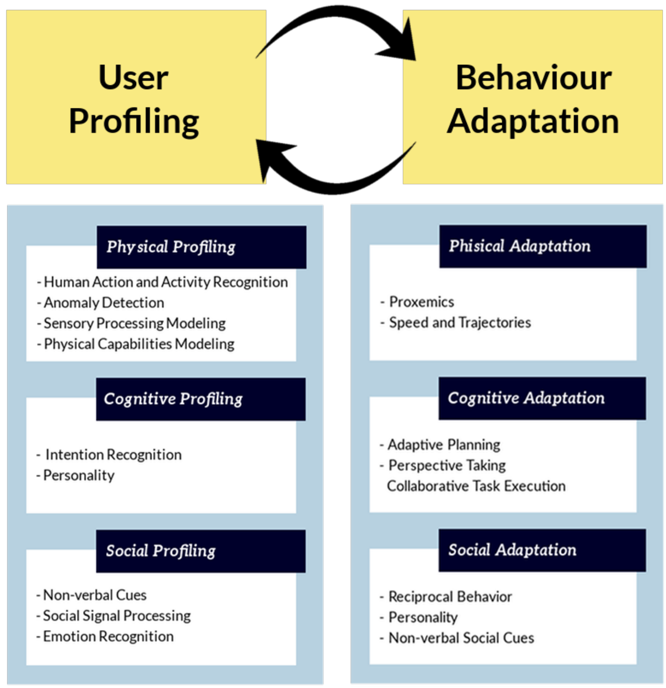

Fig. 1. Profiling/Behavioral Adaptation cycle from the physical, cognitive and social interaction viewpoints

users want to retain control over assistive devices, they prefer adaptive systems over fully user-configured ones.

In this survey, we introduce research topics addressed in this context by providing some pointers to the current literature on user profiling and behavioral adaptation. These two aspects open a complex search space that covers different research areas beyond HRI. To structure the search space and to cover a diversity of works, we introduce a classification scheme based on the concepts of physical, cognitive, and social interaction for both the profiling and behavioral adaptation aspects. Based on this scheme, we selected over 60 articles from the HRI literature published within the last five years. Our survey does not aim to be exhaustive, but, more importantly, to highlight that these two aspects are both fundamental in the development of effective and well accepted social robot. There is a closed loop relationship between profiling and adaptation, as the typical action-perception cycle, that should be addressed both from the robot point of view as well as from the interacting user's one (see Figure 1).

2. User Profiling

Understanding more about users enables a robot to adapt its behavior with respect to their characteristics and preferences, hence to enhance the user satisfaction and robot acceptance. User preferences and defining profiles can be explicitly determined, by getting users' response/feedback to information/questionnaire. Stereotyping is an example of user classification, based on the measurement of pre-defined features (Wagner, 2015). However, while explicit information is accurate, users refrain from providing it for various reasons. On the contrary, information obtained by "looking over the user's shoulder" could be a viable alternative that does not rely on the user filling questionnaires, but it has a level of uncertainty due to errors in the recognition and classification process (Vu and Proctor, 2011). Here, we introduce both the approaches since it is proven that the ability to provide a service to the users, when it is needed, without the user intervention, is crucial for the success of every human-robot natural interaction. Moreover, while some user characteristic may be considered statistical with respect to a long-term interaction, many others are not.

In this section, we introduce the topics related to the recognition and profiling of a user by providing a classification with respect to three different interaction viewpoints, namely from the physical (Section 2.1), the cognitive (Section 2.2), and the social aspects (Section 2.3) of the interaction.

2.1. Physical Profiling

With the physical profiling term, we mean modeling and learning user characteristics that are related to the human body, such as sensing the motion capabilities that may shape the interaction process, but also its intended movements in the space.

Human Action and Activity Recognition. The ability to recognize and model physical human activities constitutes an enabling technology for developing effective HRI applications. Depending on the activity complexity, Aggarwal and Ryoo (2011) provided a classification of the physical recognition process into four different levels: gestures, actions, interactions, and group activities. Gestures are elementary movements of a person's body part (e.g., a waving hand) that could be interpreted also as elementary commands to be provided to the robot (Rossi et al., 2013). Actions are single-person activities that may be composed of multiple elementary patterns temporally organized, such as "walking" (Bruno et al., 2015). Interactions, here, are intended as activities that involve the physical contact between two or more people and/or objects (Coppola et al., 2016), for example, two persons fighting or a person passing an object toward another one. Finally, group activities are the physical activities performed by groups composed of multiple people that do not necessary require a physical contact (e.g., a group having a meeting or a group visiting a museum) (Vazquez et al., 2015).

Existing studies on human activity recognition typically follow a pattern recognition approach to the users' movements in the space. Such approaches extract different information/features from the sensor data and use machine learning algorithms, typically classification methods, to identify activity patterns. Recently, Lara and Labrador (2013) provided a very detailed description of the state of the art in human activity recognition (HAR) and the challenges related to it, such as the difficulty to accurately detect the activities under realistic conditions by using portable, unobtrusive, and inexpensive data acquisition systems. At the same time, the paper also shows the variety of types of activities recognized by the state-of-the-art HAR systems.

With respect to the considered sensors, the recognition process has been approached, in literature, in two different ways, namely using external (e.g., switches and cameras) and wearable sensors. In the former, computer vision-based techniques have widely been used for human activity tracking and gesture recognition from RGD-B data (Sung et al., 2012; Faria et al., 2014). In the latter, the devices are attached to the user (e.g., wristbands, wristwatches, armbands), hence, the approach is to process the data from inertial measurement unit sensors worn on a user's body or built in a user's smartphone to track his/her motion (Li et al., 2012; Bruno et al., 2015). Such motion sensors are compact, power-aware, and can provide a fast sampling of human motion including acceleration, angular rate, and magnetic field. Furthermore, physiological signals can also be used. Several works used either the physiological signals alone (e.g., heart rate, respiration rate, skin temperature, ECG) or a combination of accelerometers and physiological data (e.g., heart rate) to perform activity recognition. It was also shown in (Lara et al., 2012) that vital signs used in a multimodality system can improve recognition accuracy. However, the use of many wearable sensors, while producing a richer information that can be extracted from the measured attributes, may lead to an uncomfortable and invasive configuration that is not accepted by the user (Lara et al., 2012).

Anomaly Detection. One application of human activity recognition is the detection of anomalies in the behavior. For instance, fall detection is a common anomaly that can be detected. Mubashir et al. (2013) published a survey on approaches based on wearable, ambient, and vision sensors. In contrast to activity recognition, classification methods cannot generally be used for anomaly detection because such anomalies are usually rare and unexpected, hence resulting in having an insufficient training data (Meng et al., 2016). However, some approaches showed the feasibility of identifying abnormal behavior by finding behavior patterns that are dissimilar to the learned normal patterns (Ordóñez et al., 2015).

Sensory Processing Modeling. Another manner of performing physical user profiling is by modeling human's movement, visual, touch, and auditory sensory processing preferences described in terms of the quadrants in Dunn's model of sensory processing (Dunn, 1999): low registration, sensation seeking, sensory sensitivity, and sensation avoiding. These quadrants are formed by the junctions between individual differences in neurological thresholds for stimulation (high-low) and self-regulation strategies (active-passive). Chevalier et al. (2016a) used this methodology in a more precise context, for the therapy of individuals suffering from Autistic Spectrum Disorder. The authors used proprioceptive and kinetic profiling to predict the success of future interactions with a robot. Along with questionnaires based on Adolescents/Adults Sensory Profile (AASP) (Brown and Dunn, 2002), an experiment using a force-sensing platform in front of a screen presenting a virtual scene was designed to measure user's posture stability in respect with various moving visual stimuli and assess his/her proprioceptive cues integration and visual dependency.

Sensor processing modeling can be used to classify the user with respect to his/her ability in the interaction. For example, in experiments involving interaction with a Nao robot, it has been shown that individuals showing low proprioceptive integration but high visual dependency had more successful interaction with the robot by focusing for longer periods of time and using more speech and social gestures (Chevalier et al., 2016b).

Physical Capabilities Modeling. When dealing with modeling and learning of preferences of movements in the space (e.g., trajectories), the typical approaches rely on the so-called learning by demonstration methods, where the user shows the preferred trajectories to a robot by providing examples (Argall et al., 2009), via also kinesthetic teaching (Lee and Ott, 2011). Indirect teaching can also be achieved, as in the approach of (Jain et al., 2015), where the robot learns by relying only on user feedback. At each iteration, the robot computes a trajectory with respect to a task and evaluate the user feedback in terms of an evaluation for the computed trajectory to improve it.

Nikolaidis et al. (2015) present a framework for automatically learning human user models from joint-action demonstrations that enables a robot to compute a robust policy for a collaborative task with a human. The demonstrated action sequences are clustered into different human types using an unsupervised learning algorithm. The learned model is then incorporated into a mixed-observability Markov decision process (MOMDP) formulation, wherein the human type is a partially observable variable with the goal to compute a policy for the robot that will be aligned to the user's preference.

In the domain of assistive robotics for people with physical disabilities, machine learning techniques, as reinforcement learning that requires multiple trials and errors, might put the user at risk (Gao et al., 2015). In this context, dynamic profiling mechanisms can provide a solution to this problem by creating a user model the robot can use. For example, Gao et al. (2015) presented an approach providing personalized dressing assistance that models the movement space of human upper-body joints. The human upper-body pose is recognized with a random forest on a depth data and an unsupervised expectation-minimization algorithm is used to learn Gaussian mixture models to define the movement space.

2.2. *Cognitive Profiling*

Beyond the recognition of observable behavior due to the physical subject interaction with the external world, there is the necessity of recognizing the intents of the observed agent (Demiris, 2007). The capability of inferring and of recognizing the individuals' intentions, desires, and beliefs, as well as their internal states, personality, and emotions, is often referred to as Theory of Mind (ToM) (Scassellati, 2002). Humans have a natural ability to communicate and recognize their internal state through non-verbal means such as body language, gesture, and facial expression, but also to adapt their behaviors in response to their interpretation and prediction of the intentions of others starting from the observable actions.

Intention Recognition. As we already discussed, for interacting with an individual, a robot should be able to form a representation/recognition of his/her actions. During an interaction, the meaning of a single physical action is often related to other actions as well as to the user's possible goal motivating the interaction itself.

Intention and goal/plan recognition is an enabling capability in order to have a proactive collaboration between humans and machines relying on implicit user commands (Hofmann and Williams, 2007). Most of the research on intention recognition focused on retrieving the intent behind a verbal communication. For example, the authors in (Wahlster and Kobsa, 1989) and (Zukerman and Litman, 2001) focused on the field of user modeling (i.e., understanding the user's beliefs, goals, and plans) in artificial intelligence dialog systems, and illustrated the importance of such modeling on the interaction. Recently, the ability to allow robots tracking and updating the beliefs of their interlocutors was explored in (Briggs and Scheutz, 2011) by developing a belief revision and expression algorithm that models and updates task-relevant beliefs and intentions of all the participants in a verbal interaction.

Intention recognition from the indirect observation of physical actions was also explored. This ability is important also to forecast what will be his/her next operations (Magnanimo et al., 2014). In this context, a robot is required to recognize the already known possible human intentions from the observation of the HRI workspace, the human actions (e.g., either commands and gestures, or the interaction with the objects of the environments (Krauthausen, 2013)), and the physical interactions with the robot (e.g., force/torque signals in case of a cooperative object transportation (Bussy et al., 2012)). Several researchers have proposed probabilistic approaches to predict future events and intentions, mainly by using Hidden Markov Models (McGhan et al., 2015), Finite State Machines (Awais and Henrich, 2012; Liu et al., 2015), Bayesian Networks (Kwon and Suh, 2012; Magnanimo et al., 2014). For example, Magnanimo et al. (2014) focused on analyzing the pattern of common daily-life activities in terms of a sequence of manipulated objects and performed actions. By modeling these patterns and by using a dynamic Bayesian network, or, as in the case of (Kwon and Suh, 2012), temporal Bayesian networks, a system could be able to predict future user actions. Finally, since on large domains the inference process can be costly, Krauthausen (2013) dealt with the problem of reducing the action/intention modeling space by operating in a reduced system to restrict inference to the most important features.

Finally, in the case of intentions learning, robots are required to learn complex causal and temporal relationships existing between multiple events and actions (Kwon and Suh, 2012). The approaches differ from each other with respect to the available information: objects in the scene, human actions, environmental context, and human intentions. The given information is used as input for the learning system. For example, Liu et al. (2015) developed an Evolving Hidden Markov Model approach to learn and infer human intentions according to the observation of objects manipulation actions for an assembly task.

Personality. Among the fundamental aspects to characterize the cognitive state of a user, there is the personality. Personality is a key determinant in human social interactions. Several research works from psychology have shown a direct relationship between personality and behavior (Ewen, 2003; Morris, 1979). Morris (1979) indicated that personality: (1) shows behaviors that are relatively pervasive in the person's lifestyle in that they show some consistency across situations; (2) shows behaviors that are relatively stable in the person's lifestyle across time, and (3) is indicative of the uniqueness of the person. While there is no generic definition of personality, a common definition of it is the pattern of collective character, behavioral, temperamental, emotional and mental traits of an individual that have consistency over time and situations (Morris, 1979). Several common models to describe the personality of an individual are the Big-Five personality traits (Goldberg, 1990), the Eysenck Personality Model (Eysenck, 1991), and the Myers-Briggs model (Murray, 1990) with associated specific questionnaires to classify the personality.

Related to the recognition of the user personality dimension, many psycholinguistic studies focused on personality markers in language and so to classify personality traits from indirect observations (e.g., it was found that extraverts are more loud-voiced and talk more iteratively with less faltering and pauses than introverts). In the work of (Mohammadi and Vinciarelli, 2012), prosodic features (vocal pitch, energy, and speaking rate) are used to automatically perceive these personality traits from voice samples with more than 70% accuracy, while the work of (Al Moubayed et al., 2014) represents one of the first attempt to classify personality from face recognition.

2.3. Social Profiling

For robots to successfully take part in social interactions with people, they must be capable of recognizing, interpreting the social cues displayed by a human (McColl et al., 2016). According to Vinciarelli and Pentland (2015), social signals are observable behaviors that produce, or should produce in the case of robots, behavioral changes during the interaction. Hence, while in the previous section we discussed the recognition of a user's cognitive (or inner) state, which can either be represented by his/her own mental state in terms of beliefs and goals, but also includes the personality of the user, here, we concentrate on the model and recognition of social signals and preferences that are specifically related to the human-robot interaction process. Moreover, social profiling refers also to the possibility of recognizing social phenomena, such as engagement, conflict, empathy, interest, and emotions, that cannot be directly observed but must be inferred through the analysis of indirect cues.

Non-verbal Cues. In a face-to-face interaction between humans, several modalities are normally used for coordination or to smooth the interaction. For example, body posture, gestures, gaze, vocalization, and facial expressions are commonly used to convey not content-related information. Hence, the effective recognition of such cues can be used to improve the interaction between the human and a robot.

For example, non-verbal social cues with a bartender robot are interpreted in (Gaschler et al., 2012) to decide when to initiate or terminate an interaction with possible clients. Body posture, head pose estimation, and the mutual arrangement of the people in a group are used to train a Hidden Markov Model. Static body poses were also analyzed in (McColl and Nejat, 2012) to perceive and interpret a person's affective state during an interaction. An automated affect recognition and classification system are developed using 2D and 3D visual information to measure the degree of accessibility (i.e., openness and rapport) of a person towards the robot.

In addition to head pose, recognition of eye movements and of gaze may provide useful non-communicative information about the interaction (Das et al., 2015). Examples are mutual gaze (e.g., eye gaze that is directed from one agent to another eyes or face, and vice versa), referential gaze (e.g., when the gaze is directed towards an object of interest with verbal references or pointing gestures (Staudte and Crocker, 2011)), joint attention (e.g., the gazes of different agents are directed towards the same object), or gaze aversions (e.g., intentionally not looking towards a specific object or face (Andrist et al., 2014)). For example, Boucher et al. (2012) showed that the correct recognition and use of referential gaze can influence the speed and accuracy of the human/robot actions.

Non-verbal cues such as gaze, posture, and back-channels can be used for evaluating the user engagement during an interaction. The evaluation of the user engagement can be also considered as a coordination signal and as an index of the effectiveness of the interaction. In particular, the recognition of back-channeling is an enabling characteristic to achieve coordination, to evaluate the engagement in the interaction or to monitor the development of the teamwork (Jung et al., 2013). As an example, Sanghvi et al. (2011) developed an engage recognition process based on the automatic analysis of the features characterizing affective body postures from videos capturing children's behavior from a lateral view. Anzalone et al. (2015) propose a methodology relying on the analysis of static and dynamical properties of gaze to evaluate the engagement aroused during interactions between social robots and human partners, based on metrics that can be easily retrieved from off-the-shelves sensors such as depth cameras and microphones.

Social Signal Processing. The main target of Social Signal Processing (SSP) is the automatic analysis of verbal and non-verbal cues to recognize social phenomena such as empathy, conflict, interest, attitudes, dominance, flirting, attention, politeness, or agreement (Vinciarelli and Pentland, 2015) with limited user intervention. Hence, social profiling relates to the possibility of profiling the user with respect also to his/her social interaction role (e.g., dominance) or modifying the robot beliefs about the social setting (e.g., making them aware of a conflict or a disagreement). Such kinds of signals recognition have not been the mainstream in the current robotic literature, while there is a growing interest in the wider human-machine interaction (HCI) community. For a review on social signal processing please refer to the work of Palaghias et al. (2016).

Lately, some related attempts, dealing with human multi-party interaction, are starting to consider the dynamic recognition of interaction social roles in the context of robot mediation of groups. For example, in an educational environment, Strohkorb et al. (2015) explored the recognition of children social dominance from non-verbal features for a robot to mediate the interaction and improve the learning process.

Emotion Recognition. Differently from the personality that is a stable characteristic over time, emotions are variable and need to be recognized during the interaction. The recognition of the user's emotions can be used, of course, to characterize his/her cognitive state, but their variations may also depend on the interaction. In this sense, emotional reactions could be used to characterize the course and the evolution of the interaction process. Emotion recognition, or more generally affect detection, is the capability of automatically recognizing which emotional state a human is expressing among a finite domain of possibilities; this can be done using a single input (Cid et al., 2013) or multi-modal inputs (Prado et al., 2012). Typical modalities used to infer human emotions are the visual input (i.e., facial expression recognition (Cid et al., 2013), body language and touch (Cooney et al., 2012)), audio input (i.e., tone analysis), or physiological signals. For example, Cid et al. (2013) developed a real-time emotion recognition system based only on facial expression analysis that extracts relevant emotional features and uses a Bayesian Network as a classifier. Mower et al. (2011) investigated the implementation of emotion classification from vocal and motion-capture cues describing emotion profiles in term of the presence/absence of a set of four basic emotion labels, instead of a single label, implemented by SVMs. For a recent literature review on existing automated affect recognition and classification systems for social robots please refer to the work of McColl et al. (2016).

3. Behavioral Adaptation

During an interaction, the ability to adapt its own behavior with respect to the behavior of the others is a fundamental characteristic that affects the effectiveness and the naturalness of the interaction itself (Mitsunaga et al., 2008). If the flow of the interaction is not smooth, for example, people might even be irritated (Lorenz et al., 2016).

Profiling capabilities are of no use if the robot is not able to modify its own behavior accordingly. As in the previous section, here, we discuss the current literature dealing with behavioral adaptation from the physical (Section 3.1), cognitive (Section 3.2), and social (Section 3.3) interaction points of view. Indeed, from the physical level, the robot behavior should be adapted in its movements in the space, from the cognitive, the robot decision-making algorithm should include a model of the other agents to make better decisions during the interaction and to select the proper actions to achieve collaboration. Finally, from the social level, the strategies and the parameters characterizing the interaction can be adapted. There are several verbal and non-verbal behavior mechanisms that could be personalized and adapted to aid social human-robot interaction, such as dialog strategies, gaze or proxemics.

3.1. Physical Adaptation

In scenarios where a robot must navigate through a space that is occupied by humans, whether to reach a specific location or interact with them, multiple approaches have been proposed. For a general overview, Kruse et al. (2013) proposed a survey on human-aware navigation. More recently, Rios-Martinez et al. (2015) published a survey on socially-aware navigation and defined it as "the strategy exhibited by a social robot which identifies and follows social conventions (in terms of management of space) in order to preserve a comfortable interaction with humans. The resulting behavior is predictable, adaptable and easily understood by humans".

Proxemics. Proxemics is the study of spatial distances used in interaction by human and/or robot agents. The term was introduced by Hall (1966), who also classified interpersonal distances into four categories: 1) Intimate space (less than 46 cm); 2) Personal space (46 to 122 cm); 3) Social space (1.2 to 3.7 m); 4) Public distance (more than 3.7 m). People react and behave differently depending on how their space is occupied when being interacting. Hence, studies on proxemics may help in developing adaptive and polite approach behaviors for service robots.

Based on data on service staff members collected in a shopping mall, Kato et al. (2015) propose a robot behavior that can adapt its approach depending on a visitor's intention. The goal is to not disturb visitors until it is clear they intend to interact with the robot. Two main strategies are used: *proactively-waiting*, which involves the orientation of the robot toward visitors when their intentions are not certain, and *collaboratively-initiating*, where the robot closes the gap separating it from the visitors and initiates the conversation when their intentions are perceived as willing to interact.

Mead and Matarić (2016) used proxemics data and robot predictions on the user state for deciding to move to a better position to maximize the potential for its performance in the interaction. The robot detects the inter-agent pose that could be used to predict how loudly the user will likely speak and so the performance of the speech recognition process. The controller uses a sampling-based approach, wherein each sample represents inter-agent distance and orientation, as well as estimates of human speech and gesture output levels (production) and subsequent robot speech and gesture input levels (recognition).

Speed and Trajectories. While studies on proxemics mainly consider the robot approaching behavior, the case of an interaction with both the person and the robot moving in the space needs special considerations. For instance, a key finding of Kruse et al. (2012), in situations where a robot and a person might be crossing each other, is to adapt the velocity of the robot and to use its path to indicate its intention. In the case that the task is to follow a person (Granata and Bidaud, 2012) or to walk side-by-side, the robot thus needs not only to adapt its velocity to maintain an acceptable distance from the person but also it should plan the proper trajectory to move in a legible and comfortable manner. For example, Granata and Bidaud (2012) integrate an estimator of the person state (position and velocity) with a decision layer that uses the fuzzy logic mechanisms to select a strategy for a given context. In a similar situation, where both the robot and a person navigate toward a common goal, similar precautions can be taken regarding distance and velocity. In (Feil-Seifer and Matarić, 2011), a trajectory planner was modified to include the distance to a person as a criterion when evaluating possible trajectories, slowing or even stopping the robot if the person leaves a specific range. In the modified planner, trajectory fitness was evaluated according to a Gaussian Mixture Model (GMM) trained on a small set of a person following a robot demonstrations. Results have shown that the modified trajectory planner maintained lower average person-goal and person-robot distances that the original planner, suggesting a better following performance.

Finally, in human-robot cooperation, robots will inevitably face tasks that require handing over objects to humans. A natural hand-over behavior should consider different factors such as the robot's trajectory or the person's posture and gaze direction (Cakmak et al., 2011). For example, a left-handed user (with respect to the right-handed), e.g., would rather prefer the interactions to happen from his/her left side (right side). In (Broquere et al., 2014), the robot end-effector velocity is reactively adapted with respect to the human pose, distance from the robot and hand velocity in the hand-over task, while in (Cakmak et al., 2011), the robot behavior is dynamically adapted with respect to the user learned preferences, such as the orientation. Learned preferences are considered by comparing them to configurations that are planned by using a kinematic model of a human showing a user preference with respect to different evaluation criteria but not with respect to a better reachability of the object. Moreover, different velocity profiles with respect to the learned user interaction preferences were evaluated to increase the robot acceptance by the user and well as their feeling of safety.

3.2. Cognitive Adaptation

Personalized robot-user interaction requires adaptation in planning capabilities (Dragone et al., 2015) as well as to consider the user preferences into the robot decision making process. Here, we introduce some approaches that explicitly take into account adaptability and a user model for deciding actions, plans and goals from the robot point of view (adaptive planning and dialogue strategies), that take into account the users' perspective and states of mind in the planning process (perspective taking), and to adapt the coordinated execution of the planned actions (collaborative task execution).

Adaptive Planning. To provide a task adaptation process, in the aliz-e project (Belpaeme et al., 2012) a user model is stored in the robot memory system containing general data (e.g., name, gender, age, and whether the child has interacted with the robot before), and specific data related to a particular activity (e.g., a record of performance in an activity or previously asked questions). This information is used by the decision-making system for reasoning about the goals of the activity and the behavior of the child. As part of the same project, Coninx et al. (2016) present an activity-switching framework to avoid repetitive interaction scenarios and adapt the proposed task to the preferences of the child, where the robot and the child meet in an open setting and jointly decide which activity to perform. Adaptation occurs within each individual component, for instance by modifying the robot speech, based on previous performance of the child in a game, and on the structure of an interaction episode. The developed framework, through an *activity manager* module, makes sure that the behavior of the robot transitions smoothly between activities from the point of view of the child. It has been shown to provide a high-level of engagement with the child.

In the planning domain, recent approaches to context-aware planning managed to exploit implicit user feedback to adapt to the characteristics of the personal preferences of the user. In (Bacciu et al., 2014), through the collaboration with a learning layer that encodes contextual knowledge, a control layer yields to a personalized planning where the courses of actions and the device configuration depend on the current environmental context or on the explicitly expressed user preferences (for example, turning on/off the robot camera). Since the control layer reasons on numerical weights encoding the preferences over certain actions, plans or configurations, such weights can be updated by exploiting the incremental learning mechanisms offered by a learning layer. Moreover, Khamassi et al. (2017) proposed to use the online measurement of human engagement (representing the attention that the human pays to the robot) to dynamically adapt exploration rate in reinforcement learning algorithms for HRI.

The development of *dialogues systems* can be framed as a planning problem and deeply relies on the possibility of providing online adaptation. For a review on verbal human-robot communication please refer to (Mavridis, 2015). Here, we introduce the approach of (Perera et al., 2016), where the dialog strategies have been adapted with respect to user preferences as well. An automated verbalization algorithm generates different explanations as a function of the desired user preferences, in the case of a robot providing the explanations with respect to its direction choices along with a route. The authors introduced verbalization spaces to capture the fact that descriptions of the robot experience are not unique and can greatly vary in a space of different dimensions (e.g., abstraction, specificity, and locality).

Perspective Taking. Adaptive planning approaches that explicitly consider ToM applied to robotics focused on perspective taking (Trafton et al., 2005) and belief management. In the context of perspective taking approaches (Milliez et al., 2014), robots reasoning process focused on recognizing what the human partner is able to perceive or not, and consequently, to construct a world model for the planning process from the point of view of the user, in order to reason and decide the current actions, also by considering his/her domain representation. The recognition of user mental states, goals, and intentions allows a robot performing adaptation in collaborative task achievement. In the work of Devin and Alami (2016), starting from the capability of the robot to permanently compute the spatial perspective of its partners and to track their activity, the robot adaptively manages the execution of shared plans in a context of humans and robots performing collaborative objects manipulation. As a result, the robot is able to adapt to human's decisions and actions and to inform them when needed without being intrusive by giving (unnecessary) information that the human can observe or infer by himself.

Moreover, the integration within the planning process of the recognition and of the forecast of human action and plans could help in providing adaptation. Cirillo et al. (2012) integrated into the planning mechanism a human plan recognition process and an action monitor in order not to interfere with the human activities. On the contrary, Dragan et al. (2015) forecast the possibility of considering the human inferences (e.g., possible goals and actions) in the robot planning to provide legible and predictable motions.

Collaborative Task Execution. Coordination in collaborative task execution is, probably, the best-known example of activity requiring online adaptation to the teammate's actions. The dynamical change of mutual task-related roles is one of the approaches to deal with flexibility in task execution (Clair and Mataric, 2013). For example, in the work of (Clair and Mataric, 2013), the collaborative task is formulated as a planning problem compatible with a class of pairwise, loosely-coupled tasks and supporting the notion of role assignment. Roles allocation is achieved by using social communication (speech and embodied gesture) during a collaboration. In the case of physical interaction, dynamic role allocation, with a game theoretical approach, was used in (Li et al., 2015) to adjust the robot role according to the human's intention to lead or follow, which is inferred through the measured interaction force.

Relying on intention recognition techniques allows a robot to adaptively and proactively execute action while interacting with a human. For example, Awais and Henrich (2012) by using a probability-based final state machine for intention recognition, developed a robot control mechanism able to adapt to the human behavior and to act proactively in the ambiguous human intentions scenarios. The robot can either wait for disambiguation of the intention, requiring extra human actions or it can proactively act depending on his previous knowledge about the human behavior. Kwon and Suh (2013) proposed a decision-theoretic approach, relying on probabilistic temporal prediction, to infer the best actions and their timing and to minimize delays in human-robot interactions. Temporal utility functions are used to predict the delay between the expected time of a human intention and the provision time of a robotic service. Recently, Baraglia et al. (2016) showed that, in the case of an assembly task, people collaborate best with a proactive robot, yielding better team fluency and high subjective ratings. *Proactive behavior* can be used also for providing alerts and warning. For example, Benedictis et al. (2014) developed a proactive behavior of the robot relying on activity monitoring and temporal constraints to provide personalized reminders.

3.3. Social Adaptation

Social interaction is typically governed by some specific norms that are culturally dependent. Hence, in principle, as in the case of the user profiling mechanisms, some general structure could be hard-wired into the robot control system. An example is represented by implementing turn-taking mechanisms to regulate the conversation flow (Sacks et al., 1974). However, according to Chao and Thomaz (2012), since it requires the multimodal perception of the human's cues, such as gaze, gesture, and speech cues, that can be noisy or unreliable, turn-taking between humans and robots remains an awkward and confusing experience for human users. Moreover, according to Dautenhahn (1997), the dynamics of social interaction could not be totally hard-wired, but it should emerge from adaptation once learned and profiled the user we are interacting with.

Reciprocal Behavior. Recently, Lorenz et al. (2016) analyzed the role of synchrony and reciprocity as key mechanisms of human interaction which affects both the behavioral level (movements) and the social level (relationships). This type of adaptation also counts for common turn-taking in verbal and non-verbal communication as well as for other forms of social interaction such as mimicry and imitation (Clark, 2012). In this context, the mere repetitiveness and biological inspired motions are not the crucial cues underlying emerging synchronization. Instead, the crucial capability could be the online adaptation to the human behavior, and the provision of behavioral feedback to produce an emergent synchronization (Mrtl et al., 2014).

More generally, empathetic mechanisms, as shown in (Dautenhahn, 1997), can create a dynamic coupling between a human and a robot, and so eliciting the interaction, whereas an empathetic reaction is intended to modify the own state toward the one perceived in the other person. In HRI, artificial emotions are typically used to express empathy (Leite et al., 2014) or induce it in the user (Kühnlenz et al., 2013). For example, Leite et al. (2014) explored the positive role of empathy in a long-term interaction between children and social robots. On the contrary, in the work of (Kühnlenz et al., 2013), a robot proactively generates task specific emotions and adapt itself to the user mood, using both facial and verbal expressions, in order to trigger human reactions in terms of increased helpfulness towards the robot.

The past decade has seen a great deal of progress in developing computational theories of emotion that can be applied to building robots and avatars that interact emotionally with humans (Cañamero, 1997). One of the pioneer works on emotion adaptation is the Kismet robot (Breazeal, 2002). In this work, the emotion states of the robot are changed by following the interaction flow with the human being, and such change affects its motivational system, its action and so the interaction with the human. In the same direction, many other works tried to rely on emotions as a control mechanics to drive the behavioral adaptation of a robot, to trigger learning, and make the interaction more natural. For example, Ficocelli et al. (2016) presented an emotional behavior module for task-driven socially assistive robots. The module is used to determine the appropriate emotions that are consistent with its contextual assistive interaction. Moreover, empathetic responses can also foster actions that are taken to reduce the others' distress, such as social supportive behaviors (Leite et al., 2014).

Personality. In the same direction of empathetic adaptation, some HRI approaches focused on the role of the robot personality and on analyzing the way it can affect the robot behavior or the user's perception to improve the interaction. As observed in (Tay et al., 2014; Eyssel and Hegel, 2012), the gender and the personality of a social robot have an impact on its acceptability. Tay et al. (2014) showed that an individual accepted more easily a robot if it conformed to its occupational role stereotype. In this study, the personality was manipulated with non-verbal cues such as faster speech for extroverted robots, and gender by changing names and vocal characteristics. For instance, participants perceived a greater trust and acceptance in introverted security robots than extroverted ones. Furthermore, results showed that in-role personality has a greater impact than in-role gender in term of initial user response. Joosse et al. (2013) evaluated the role of similarity or complementary attraction in the people preferences showing that what is considered an appropriate personality for a robot depends on the task context and on the stereotype perceptions people hold for certain jobs. On the contrary, Eyssel and Hegel (2012) concentrate more on the role of gender, showing that the gender of social robots helps build a common ground between the users and the robots, thereby facilitating intuitive human-robot interaction and positive attitudes toward the social robot.

In the health-care domain, it was demonstrated that robots with adaptive personality can improve the children hospitalized health status. Belpaeme et al. (2012) presented the results of different experiments where each of the children has various game sessions with a robot that choose its personality: extrovert or introvert. In these experiments, an extrovert robot challenges players and moves faster, while introvert robot moves slower, encourages and comforts with many positive comments the player. Moreover, acting as 'friends' and 'mentors' robots could improve the children experience of a hospital stay, support their well-being and aid in their learning about the management of their health condition. Recently, in the work of Karami et al. (2016), a companion robot that adapts its personality, based on the user profile and environment variables using a Markov Decision Process (MDP)-based approach, is presented. In order to adapt the behavior of the robot over time, the MDP reward function is updated after analyzing interaction traces, which are sequences of observed interaction events with the robot, along with user feedback. Furthermore, in the work of Aly and Tapus (2016), human's verbal behavior is matched to a corresponding verbal and non-verbal behavior for the robot in real-time, based on the extroverted-introverted personality trait to improve the pleasantness of the interaction.

Non-verbal Social Cues. In addition to emotions and personality, as in the case of social profiling, the adaptation of verbal and non-verbal cues can be used by a robot to show relevant social characteristics that could influence the interaction flow. For example, in (Fiore et al., 2013), a robot was programmed to traverse a hallway populated with people, where robot gaze and proxemics behavior are adapted to influence human attributions of the robot's social presence and emotional states. When programmed to behave more assertively, the robot was perceived as having emotional states that were indicative of higher states of arousal. Conversely, when programmed to behave in a way that was more passive, more positive valence emotional attributions were made compared to when the robot acted as more assertive.

Jung et al. (2013) found that, in addition to team performance, robots can have an impact on stress levels and cognitive load with subtle changes in the robot gaze behavior. Improvement in performances is shown also in the learning context

Table 1. Summary of the considered works pertaining user profiling and behavioral adaptation

			User Profiling			Behavioral Adaptation		
			Physical	Cognitive	Social	Physical	Cognitive	Social
User Profiling	Physical	Rossi et al. (2013); Bruno et al. (2015); Coppola et al. (2016); Vazquez et al. (2015); Sung et al. (2012); Faria et al. (2014); Chevalier et al. (2016a,b); Lee and Ott (2011)	√					
		Nikolaidis et al. (2015); Gao et al. (2015)	√			√		
	Cognitive	McGhan et al. (2015); Liu et al. (2015); Mohammadi and Vinciarelli (2012); Al Moubayed et al. (2014)		√				
		Briggs and Scheutz (2011)		√			√	
		Magnanimo et al. (2014); Krauthausen (2013)	√	√				
		Kwon and Suh (2012); Bussy et al. (2012); Awais and Henrich (2012)	√	√			√	
	Social	Gaschler et al. (2012); McColl and Nejat (2012); Sanghvi et al. (2011); Strohkorb et al. (2015); Cid et al. (2013); Prado et al. (2012); Cooney et al. (2012); Mower et al. (2011)			√			
		Das et al. (2015); Anzalone et al. (2015); Boucher et al. (2012)			√			√
Behavioral Adaptation	Physical	Kato et al. (2015); Mead and Matarić (2016); Cakmak et al. (2011)	√			√		
		Kruse et al. (2012); Granata and Bidaud (2012); Feil-Seifer and Matarić (2011); Broquere et al. (2014)				√		
	Cognitive	Belpaeme et al. (2012); Coninx et al. (2016)		√	√		√	√
		Bacciu et al. (2014)					√	
		Devin and Alami (2016); Cirillo et al. (2012)	√	√			√	
		Dragan et al. (2015)		√		√	√	
		Benedictis et al. (2014); Baraglia et al. (2016)	√				√	
		Clair and Mataric (2013)		√			√	√
		Li et al. (2015); Kwon and Suh (2013); Perera et al. (2016)		√			√	
	Social	Lorenz et al. (2016); Mrtl et al. (2014); Tay et al. (2014); Eyssel and Hegel (2012); Joosse et al. (2013); Fiore et al. (2013); Jung et al. (2013, 2015); Kennedy et al. (2016)						√
		Leite et al. (2014); Kühnlenz et al. (2013); Ficocelli et al. (2016); Karami et al. (2016); Aly and Tapus (2016); Admoni et al. (2016)			√			√

where some studies on human development recognized the social interaction role in facilitating the learning processes. Such facilitation is obtained by providing a stable structure in terms of recurrent patterns of interaction constituted by a set of sequentially organized actions (including verbal, non-verbal, and multimodal behavior which can also occur in parallel) (Vollmer et al., 2016). For example, Kennedy et al. (2016) presented an approach for second language teaching where the robot behavior is modified to be more or less socially available through the verbal interaction it has with the child. In the context of using robots for group moderation, Jung et al. (2015) studied the effect of a robot intervention on perceptions of conflict, perceptions of team members' contributions, and team performance during a problem-solving task. The robot was programmed to intervene in task conflicting situation to regulate negative emotions. The adaptation of non-verbal social cues, such as gaze, shifts in posture or shifts in orientation, in the context of teamwork, improves people's perceptions of the robot and the team performance (Breazeal et al., 2005). Moreover, the robot exhibition of such non-verbal cues helps humans in finding a robot natural and easy to understand.

Finally, Admoni et al. (2016) developed a heuristic method that instead of selecting every relevant nonverbal behavior available to it, adapts such selection to maximize communication while maintaining interaction seamlessness. The approach combines bottom-up saliency cues and top-down context cues to simulate how different elements of a visual scene might capture a user's attention, then selects behaviors that most efficiently direct that attention to a target object. Nonverbal behaviors such as pointing and gaze are top-down communicative factors that influence where people will attend.

4. Conclusions

In this paper, we presented a survey of the recent literature dealing with the possibility of profiling a user during a human-robot interaction and of approaches that proposed a behavioral adaptation with respect to such profiles. The aim of this survey is, of course, not to be a comprehensive one but to try to cover a variety of approaches to highlight some of the key themes in the context of user profiling mechanism and behavioral adaptation.

We tried to classify such approaches with respect to being mainly related to the physical, cognitive, or social aspects of the interaction. A clear categorization of the considered approaches within a single category is not always possible since, in principle, each of these aspects could be necessary when dealing with a physical robot interacting with human beings. In Table 1, we summarized the considered approaches in a single table where the relationships among different categories are showed.

When dealing with physical profiling, especially in the case of recognition of physical activities, a lot of different pattern recognition approaches have been developed in the literature reaching a good classification performance. The effective recognition of the human movements and intended physical interaction with a robot is a fundamental capability to achieve collaboration, and so, such topic is in-depth addressed within the current literature. Their performance is typically evaluated with respect to sample datasets specifically recorded to evaluate the proposed techniques. However, sometimes the human activity models learned on these datasets are too generic to be applied in real application scenarios. Consequently, as shown in Table 1, this activity in not yet linked to the possibility of using such knowledge to provide an adaptive robot behavior. Moreover, the correct perception and identification of the user activity do not directly imply the modeling of the preferences of the users in his/her physical movements and in the interaction. Regarding the physical profiling, the only considered approaches that combine profiling and adaptation are the ones related to *physical capabilities models* since, in this case, the goal is to produce the robot behavior that respects the user preferences. Moreover, it is worth notice that in some cases the same framework (e.g., Markov decision process with hidden/latent variables) is used both for the modeling and the adaptation process. However, such formulation typically confines the user preferences within the partially observable variables, and so they do not rely on an explicit user model.

Recently, some researchers started also to focus on the opportunity of recognizing cues modeling the social aspects of the interaction, in line with a mainstream in the general HCI field. However, the modeling of the social aspects is still in an early stage. Contrary to the analysis of the physical properties of the interaction, the social profiling is a highly interdisciplinary discipline and it requires a deep analysis in different, but HRI correlated research areas. Moreover, it requires the capabilities of recognition of complex and multi-modal perceptions of the interaction. Hence, the only approaches that closed the loop with a behavioral adaptation are typically the ones relying on the recognition of simpler or single cues.

On the contrary, on the behavioral adaptation side, there is not a dominant category that reached a high-level of maturity with respect to the physical, cognitive, and social adaptation of the interaction, but we found a growing interest in all these aspects. Since the processes of profiling and adaptation act necessarily in a closed loop, one cannot be without the other, hence adaptation depends on profiling and the maturity of these approaches is inherently affected by the previous ones.

When dealing with behavioral adaptation, many research articles focused on the effect of the modification of a behavioral characteristic, such as the robot speed or personality, on the user perception of the interaction. This is particularly evident in the case of physical and social adaptation, where many of these studies do not rely on on-line profiling capabilities but on the simulation of the perception capabilities or the consequent behavioral adaptation of the interaction through a Wizard-of-Oz methodology. In particular, in the case of physical adaptation, many approaches rely on the recognition of simple motion-related input for providing a reactive or a learned policy adaptation process.

Of course, approaches that consider both profiling and adaptation exists, but are typically the result of wider projects involving different research groups. Cognitive profiling approaches, with the help of a consistent research activity in AI and dialogue systems, focused on explicitly modeling and recognition of interacting agents' mental models to produce the proper sentences in a dialogue or the relevant robotic actions in reaction to the recognition of the user intention. Hence, cognitive adaptation is the class whose approaches spans over different categories. Almost all the considered approaches involve also the cognitive profiles, even simpler ones, of the user and may also provide adaptation in the physical and social aspect of the interaction.

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