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SERVICE AND INTERACTIVE ROBOTICS (A TAPUS, SECTION EDITOR)

From Humans and Back: a Survey on Using Machine Learning to both Socially Perceive Humans and Explain to Them Robot Behaviours

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Abstract

Purpose of Review As intelligent robots enter our daily routine, it is important to be equipped with proper adaptable social perception and explainable behaviours. To do so, machine learning (ML) is often employed. This paper intends to find a trend in the way ML methods are used and applied to model human social perception and produce explainable robot behaviours.

Recent Findings The literature has shown a substantial advancement in ML methods with application to social perception and explainable behaviours. There are papers which report models for robots to imitate humans and also for humans to imitate robots. Others use classical methods and propose new and/or improved ones which led to better human-robot interaction performances.

Summary This paper reports a review on social perception and explainable behaviours based on ML methods. First, we present literature background on these three research areas and finish with a discussion on limitations and future research venues.

Keywords Social perception · Explainable behaviours · Machine learning methods · HRI

Introduction

Since 1495, when Leonardo da Vinci designed what may be the first humanoid robot thought to sit up, wave its arms, and move its head via a flexible neck while opening and closing its jaw, a lot of progress, evolving from design to actual produced and/or commercialized humanoid robots, has been done in the study of human-robot interaction (HRI) [1].

Nowadays, benefiting from being an eminently multidisciplinary field, studies in HRI gather a large amount of contributions in fields such as socially assistive robots [2] and collaborative robots [3], which result in robots integrating human-like behaviours in order to help improve people's comfort and daily task performance in both their homes and working places.

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In this study, it is considered that successful HRI of social robotic systems can be achieved by applying *machine learning (ML) methods* to have robots with human *social perception (SP)* and *explainable behaviours (EB)*. We believe that human *SP* is an important aspect to be transposed to both socially assistive robots and collaborative ones in industrial settings, as it is important for robots to perceive the environment shared with human beings and how they interact with it; *EB* refer to verbal and non-verbal responses a robot make to communicate the why and how behind the motor-control signals it produces, while the *ML methods* can play the role of a core algorithm in both SP and EB, and also connect both to produce natural interactions between humans and robots.

For these reasons, the contributions of this study respond the following research questions by reviewing the latest studies on HRI involving SB, EB based on ML methods:

1. *Is there a trend in how the ML methods are applied in HRI studies since 2014, and how close are we in having robots with human social and/or explainable behaviours?*
2. *How does SP and EB through ML can help in making robots capable to imitate humans and humans willing to imitate and learn from robotic systems?*

Methods

A thorough search of studies published in (i) ACM/IEEE International Conference on Human-Robot Interaction, (ii) ACM Transactions on Human-Robot Interaction, and (iii) *International Journal of Social Robotics* between 2014 and March 2020 was conducted. We included all studies which contain social human perception and explainable robot behaviours using ML with applications in every aspect of human life. We also used Google Scholar to include relevant papers citing these studies in other publication venues. When feasible, we also included experimental, quasi-experimental, and survey/questionnaire studies with a scope to see how people understand robotic system behaviours or if provides some capacities and/or abilities of recognizing and identifying emotions in others, in addition to biological and physiological processes involved.

In total, we found 127 papers and, after eliminating most of the 2/4-page abstract papers, obtained 79. Another selection process was performed to eliminate all papers which did not investigate ML-based SP and EB methods, ML methods applied to situations involving socially assistive or collaborative robots, or new ML methods in HRI. Finally, we reviewed 70 articles which included 6 survey papers.

Social Perception

Because being able to interact is at the core of social robots, SP is very important in HRI to provide a connection between a social robot and its surrounding environment. A thorough survey [4] was presented in 2014 on widely used perception models, which brings them down to three steps: feature extraction (to convert the raw signals from sensors to feature descriptors for subsequent understanding tasks), dimensionality reduction (to reduce the complexity of computation after feature extraction), and semantic understanding (to infer the objects or human behaviours from the extracted features). Moreover, ML methods used in semantic understanding tasks such as object recognition, object tracking, object segmentation, and speaker localization are reported.

The ability to perceive emotion has been widely studied in HRI, as it is a critical component in social interactions. Emotions can be expressed verbally, e.g. vocal and speech, or non-verbally, e.g. facial, gait and/or posture, and touch. In the following, studies in which emotion recognition is performed through vocal and speech, facial, gait and/or posture, and touch based on ML methods are introduced. Speech recognition is also an important aspect of SP, but we believe that a complete coverage of speech recognition advances would be beyond the scope of this review. However, we can note one paper that proposes an approach to train models for HRI-specific scenarios [5].

In Yu et al. [6], multimodal data from thermal facial images and human gait data were used to recognize four emotions (neutral, happiness, angry, and sadness), while in Boucenna et al. [7], happiness, sadness, anger, and surprise are recognized online with the help of a realistic baby-learning model. In the learning phase, the human mimics random facial expressions created by a robotic head; then, the robotic head mimics the human's facial expression. Another interesting contribution consists in a proposed face/non-face internal supervision based on a neural network which learns to predict the rhythm of the HRI; hence, the robot can recognize a human presence or absence in front of the camera.

Several studies are reviewed in Crumpton et al. [8] which used vocal prosody to transmit emotions between humans, to convey emotions from robotic systems to the human users, and to use vocal prosody in robot speech synthesizer with ML methods. Still, the main contribution of the previous survey consists in the raised and discussed issues such as embodiment effects of robots, avoiding confounding factors when portraying emotions, and generation and validation of emotional robot speech.

Reliable recognition of four emotions, e.g. anger, joy, sadness, and neutral, due to the fusion of six emotional models in parallel was reported by Devillers et al. [9]. The fusion was generated between two training corpora and three acoustic feature sets on with ML classifier were applied, and a performance improvement was reported due to the performed fusion.

Even if emotion recognition from gait and posture still seems to be at an early stage, a thorough review on the matter is presented by Stephens-Fripp et al. [10] as well as cultural similarities in emotional recognition by people from different backgrounds. ML methods reported in this review can be found in Table 1.

ML methods can be used to recognize emotions, and also to express them. The ability to express emotions through touch is investigated by Andreasson et al. [11] where both female and male conveyed eight emotions (five primary emotions: anger, disgust, fear, happiness, and sadness, and three prosocial emotions, gratitude, sympathy, and love) by touching a small humanoid robot. The provided data was used as training set by the support vector machine (SVM) classifier and the reported results are quite similar with observations found in human-human interactions, for example squeezing and pressing were found as the dominant touch used for communicating fear, while stroking was the most frequently used when communicating sympathy [[12], p. 570]. Furthermore, while expressions are often used to express a simulated, internal emotion model of the agent for interaction purposes only, Feldmaier et al. [13] propose a novel approach to express the state of the simultaneous localization and mapping (SLAM) system of a robot.

Finally, according to Fischer et al. [14], emotions in human interactions can be conventionally defined and activity-specific, and emotional displays in HRI should follow such expectations towards the activities the robot is carrying out. Thus,

Table 1 Review studies on social perception (SP) and explainable behaviours (EB) based on machine learning published in ACM/IEEE International Conference on Human-Robot Interaction, ACM Transactions on Human-Robot Interaction, and *International Journal of Social Robotics* since 2014

Paper	Year	Semantic understanding task	Learning algorithm	Robotic system
[4]	2014	Survey on perception methods: visual-, audio-, tactile-, range sensor-based	Template matching Clustering Nearest neighbour Neural network Boosting Hidden Markov model	
[7]		Emotion recognition (facial expressions)	Neural network architecture	Robotic head (minimal facial expression capabilities)
[23]		Familiarization, e.g. human learns from the robot's demonstration	Functional gradient optimization	Herb
[60]		Collaborative task: puzzle	Bayesian network	Keepon
[47]	2015	Learning by observing an assistant	Probabilistic approach: GP binary discriminative classifier and GP regressor	Smart wheelchair
[9]		Emotion recognition (audio signals)	Linear support vector machines (SVM)	
[46]		Modeling of polite approach behaviour	SVM	
[65]		Learning by teaching (writing)	Principal component analysis (PCA)	Nao
[59]		Learning from demonstration	Hierarchical task networks	PR2
[40]		Robots learn to collaborate with humans through cheap talk [36]	Repeated stochastic games	Nao
[8]	2016	Survey on of using vocal prosody to convey emotion in robot speech	Hidden Markov models Deep belief networks Deep neural networks	
[48]		Socially adaptive path planning	Inverse reinforcement learning	Smart wheelchair
[54]		Programming by demonstration	Incrementally assisted kinesthetic teaching	KUKA LWR4+
[56]		Affordance learning	Hidden Markov models	Curi
[61]		Integrated affective tutoring system that uses an integrated child-tablet-robot	Reinforcement learning	Tega
[64]		Fully autonomous robotic tutor	Decision trees, neural networks, clustering algorithms	Nao
[58]		Learning from demonstration; human-robot collaborative	Gaussian process (Gaussian process latent variable model)	Jaco robotic arm, Nao
[33]		Head pose estimation	Discriminative random regression forest	RGB-D camera
[10]	2017	Survey on emotion recognition from gait and posture	Logic regression Naïve Bayes Decision tree Artificial neural network Support vector machine Gaussian mixture model Random forest SMO classifiers Adaptive boosting with naïve Bayes *k*-Nearest neighbour Adaboost with naïve Bayes Multilayer Perceptron	
[13]		Expressing the state of a simultaneous localization and mapping (SLAM) algorithm with a model of emotion	SLAM, component processing model (CPM)	
[30]		Generating natural language instructions that allow humans to navigate a priori unknown environments	Markov decision process via inverse reinforcement learning	
[24]		Obtain legibility via a model-free approach	Model-free reinforcement learning	Baxter
[31••]		Synthetizing natural language explanations of controller policies	Markov decision processes, reinforcement learning, deep learning	PR2
[62]		A tutor robot helps people learning how to solve grid-based logic puzzles called nonograms	Exponential-weight algorithm for exploration and exploitation: decision tree model with a multi-armed bandit (MAB) algorithm	Pepper
[43]		Adapt the robot proxemics behaviour with respect to the human users' personality	Fuzzy logic, neural networks, and Bayesian classifiers	

Table 1 (continued)

Paper	Year	Semantic understanding task	Learning algorithm	Robotic system
[11]	2018	Emotion recognition (touch)	SVM classification	Nao
[28]		Learning card game	Reinforcement learning used in three versions: basic, advance, and generalized learning algorithm	Nao
[49]		Create intelligent agents	Interactive machine learning: Newtonian action advice and critique-driven policy shaping	
[53]		Teach socially assistive robots personalized behaviours	Combines learning from demonstration and reinforcement learning	Casper
[27]		Learning the desired objective function for a robot from comparative queries	Probabilistic model	
[55]		Learning robot objective functions from human guidance	Kinesthetic teaching	7-DoF robotic manipulator
[25]		Enable robots to express their incapability	Sequential convex optimization	
[66]		Learning by teaching (writing)	Inverse optimal control	Nao
[5]		HRI-specific speech recognition training	Deep neural network and Hidden Markov model	PR2
[36]		Activity recognition system	Long-term recurrent convolutional networks	Pepper
[34]	2019	Generate demonstrations via a virtual reality system	Deep neural network	Virtual reality system and Sony Play Station 3 controller
[37]		Infer and correct a collaborator's task understanding during joint task execution	Partially observable Markov decision process coupled with a family of hidden Markov models	Rethink Robotics Sawyer
[38]		Dyadic storytelling interactions and emotion recognition (attentiveness)	Bayesian Theory of Mind	
[45]		Learning a robot short-term memory representation of interaction history between shopkeeper and customer	Gated recurrent unit (GRU) neural network architecture	
[39]		Grounding unknown synonymous object and action names	Bayesian learning model	Toyota Human Support Robot (HSR)
[52••]		Comparison between three ML in an autonomous drive domain	Model-based reinforcement learning Theory of Mind Model-free based reinforcement learning	
[29]		Automated rationale generation	Recurrent neural networks	
[26]		Goal communication, favourizing user anticipation	Inverse reinforcement learning	
[63]		Training personalized policies for teaching	Model-free affective reinforcement learning	Tega
[67]		Teaching a robot to learn toy names and the locations	Reinforcement learning	Kasper
[42]		Robot approaching behaviour to groups of humans	Proximal policy optimization	Pepper
[35]		Adaptively decide a monitoring distance and an approaching direction to improve user activity recognition performance	Reinforcement learning	Pepper
[6]		Online emotion recognition	Random forest	Pepper
[44]	2020	Predict shopkeeper reactions from customer	Attention network Interaction network	
[51•]		Rethink the Boltzmann model	Limiting errors due to similar selections (LESS)	7-DoF robotic arm

the expression of emotions can play a key role in producing explainable behaviours.

Explainable Behaviours

Along SP, explainable robotic behaviours (EB) are also critical for proper and successful human-robot interactions. Without having studies which understand how human beings interpret the behaviour of robotic systems and what are their expectations of such systems, it would be impossible, for example, to help humans trust their robot counterparts in critical and non-critical situations [15].

On this subject, Han et al. [16] proposed a literature review, while interesting studies from a computer science, artificial intelligence, cognitive psychology, and philosophical perspective can be found in a recent full-day workshop [17]. For example, the Theory of Mind (ToM) model is used by both human and robot in order to understand each other in an autonomous car driving on the highway scenario [18]. Moreover, Bekele et al. [19] introduced the MAResNet system, as well as an analytic pipeline that provides a blueprint which is very useful in making the operations of deep learning techniques comprehensible to human operators. Hastie et al. [20] provide the Offshore Robotics for Certification of Assets (ORCA) interface which will be later on applied to both black-box (e.g. convolutional neural network) and grey box (e.g. Bayesian network) reasoning to provide explanations of the robot perception and robot planning and action including the causal structure of the plan that is being carried out.

An interesting study by Mohammad et al. [21] focused on back imitation familiarization before learning from demonstration sessions shows that people prefer a robot that they previously imitated in terms of imitation skill, naturalness, and motion human-likeness compared with the robot that they did not imitate. Another study by Zanatto et al. [22] suggests that humans can strategically imitate robots while playing an economic investment game with a robot banker. Furthermore, it is reported by Dragan et al. [23] that while familiarization with a robot will lead to a better understanding of its behaviour, predictable and natural motion is still necessary to promote this familiarization. Thus, the goal of producing predictable and legible motion is an important trend that can be identified in relation with EB. In Busch et al. [24], model-free reinforcement learning is used to learn legible motion in human-robot joint tasks. In Kwon et al. [25], the authors study the expression of incapability to reach a motion goal as an optimization problem. The proposed approach can automatically generate trajectories that approximate the motion that would have been performed in other conditions, and data suggests that it better communicates the intent of the robot compared with previous approaches. Furthermore, Huang et al. [26] propose that the robot models how people infer the objectives from observed behaviour, and Basu et al. suggest that it can optimize its objective function based on comparative queries [27].While there is more than one way to learn behaviours, Rosenthal-von der Pütten et al. [28] implement multiple different ones on a humanoid robot based on user feedback to play a card game, and results suggest that a simpler human-like learning behaviour can reach a sufficient performance level with acceptable evaluations, rather than a complex and more human-like learning behaviour.

Still, the control policies resulting from machine learning can be difficult to understand, even from domain experts. Producing explanations to learned behaviour is studied by the larger field of explainable AI. For instance, Ehsan et al. [29] propose an automated method to explain the behaviour of an agent playing the Frogger videogame based on an encoder-decoder network that learns from a corpus of natural language explanations. Similarly, inverse reinforcement learning is used to generate natural language instructions in a navigation task [30]. For collaborative robots, Hayes et al. [31••] propose multiple algorithms to synthesize policy explanations that are applicable to various types of robot controllers, including some based on RL and deep RL. The fact that it generalizes to multiple types of controllers suggests that it would apply to a large range of interactive applications.

Machine Learning in HRI

Machine learning methods are often used to analyse data gathered from human-human to improve HRI. Therefore, the goal is to learn models from human-human interactions, apply them to HRI, and obtain more human-like and hopefully natural robot behaviours. For instance, human social activities such as handshake, hug, help walking, help standing-up, fight, push, talk, and draw attention were recognized from a continuous stream of RGB-D data, combining temporal segmentation and classification, as well as a model for learning the proximity-based, on Gaussian mixture models (GMM), priors of the social activities [32]. In Rossi et al. [33], head pose from RGB-D data was used to estimate users' focus of attention via a discriminative random regression forest algorithm.

Three successively harder tasks, e.g. the cleanup task, the handover task, and the block-stacking, were investigated in Jackson et al. [34] to validate a system which uses a virtual reality system display and a Sony PlayStation DualShock 3 wireless controller. It was suggested that the use of such system generated superior demonstrations for a deep neural network without introducing a correspondence problem. In Raggioli et al. [35], RL is used to improve user activity recognition performance adaptively, while in Sorostinean et al. [36], RL addresses activity recognition for a robot that monitors elderly people by applying the long-term convolutional network approach.

A complex collaborative puzzle game, in which a framework based on a partially observable Markov decision process (POMDP) coupled with a family of hidden Markov models (HMM) to infer and correct a collaborator's task understanding during joint task execution, is presented in Tabrez et al. [37].

Bayesian ToM was used to model dyadic storytelling interactions in Lee et al. [38], in which the storytellers are modeled as a POMDP planning problem and the listeners are modeled as a dynamic Bayesian network with a myopic policy. The Bayesian learning model is used in a multimodal framework for grounding unknown synonymous object and action names as reported in Roesler et al. [39]. The model is learned through the robot visual perception and proprioception during its interaction with a human tutor. Online learning of repeated stochastic games has also been suggested [40] as an efficient method to learn to collaborate with people through cheap talk [41]. In Gao et al. [42], proximal policy optimization (PPO) was used to learn robot approaching behaviour, while in Vitiello et al. [43], the robot proxemics is adapted with a neuro-fuzzy-Bayesian system.

An interesting application of ML methods is to predict shopkeeper reactions from customer actions and interaction context [44]. The proposed system utilizes neural networks to first learn, through an attention network, which customer actions are important to respond to and then learn via an Interaction network how the shopkeeper should respond to those important customer actions. In a similar application, Doering et al. [45] went further and exceeded the capabilities of a previous approach by Nanavati et al. [46], by having a robot learn a short-term memory representation of interaction history within a simulated camera shop scenario. The interest in having a short-term memory can be more realistic as the shopkeeper interacts with customers only for short periods of time. Previously, in a scenario where a robot had to meet strangers, support vector machines (SVM) were used to model a polite approach behaviour [46]. An online probabilistic model which learns both when and how to assist iteratively was tested by users of a smart wheelchair platform with paired haptic controllers [47]. Another framework tested on a smart wheelchair is reported by Kim et al. [48]. The latter framework is composed of a feature extraction module, an inverse RL module, and a socially human-like adaptive path planning, represented through a cost function that respects social variables, in dynamic environments.

Krening et al. [49] investigated how to create intelligent agents by using interactive ML methods such as the Newtonian action advice and the critique-driven policy shaping which can easily be taught by non-specialized individuals in training. Along with traditional ML performance metrics such as cumulative reward, the previous study Krening et al. used the human factor metrics such as frustration and results suggest that the action advice performed better than the critique one.

Until recently, a lot of studies which modeled the human behaviour utilized the Boltzmann noisily rational decision model [50]. This decision model makes the assumption that people approximately optimize a reward function and choose trajectories in proportion to their exponentiated reward. Even if the Boltzmann model has been successful in a variety of robotics domains, Bobu et al. [51•] reformulated the Boltzmann model and proposed another one called limiting errors due to similar selections which supposes that human trajectories lie in a continuous space rather than the supposition made by the Boltzmann model. The study reported an inference improvement while using the new proposed decision model.

A quite interesting debate in HRI is whether a robot should be built on an explicit model or it should learn a policy directly. Choudhury et al. [52••] did not have interest in responding to this precise research question, but instead report a first comparison between three HRI paradigms: two based on explicit modelling (model-based RL and ToM) and one on model-free-based RL in an autonomous driving domain. Among the reported results, it was found that model-free methods require several orders of magnitude more data and that the ToM one is robust to small changes, but with large enough differences, the model-based methods can vastly surpass the ToM method.

Another appealing idea is to combine ML algorithms, as done, for example, by Moro et al. [53], where a robotic learning architecture was developed based on learning from demonstration (LfD) and RL to effectively teach personalized behaviours to a social assistive robot such as Casper. To teach robot motion using LfD, multiple ML approaches have been proposed, notably incremental kinesthetic teaching [54, 55] and HMM to learn affordances [56]. Kinesthetic teaching is also compared with other approaches such as teleoperation in Fischer et al. [57]. Furthermore, to learn from observations instead of physical guiding, a Gaussian process latent variable model has been proposed [58]. In Mohseni-Kabir et al. [59], the use of bidirectional communication between a robot and a human is introduced to interactively learn hierarchical tasks from demonstrations.

Beyond emotion recognition, a Bayesian network is introduced in Leyzberg et al. [60] for skill assessment of students to personalize the behaviour of a robot tutor. Similarly, Gordon et al. [61] use automatic facial expression recognition to personalize the motivation strategies of a social robot learning companion. In Gao et al. [62], a tutor robot utilizes RL and helps people solve grid-based logic puzzles called nonograms. Furthermore, Park et al. [63] propose a model-free RL approach to produce a personalized policy shaping the behaviour of a tutoring robot. Results suggest that a personalized policy improves engagement of the child and the outcome of the lessons in a literacy education setting. In a similar educational scenario, decision trees, neural networks, and clustering algorithms are used to learn from social interactions [64]. Other machine learning approaches have also been used in learning by teaching scenarios with children, notably principal component analysis (PCA) [65], and inverse optimal control [66] to model handwriting and RL to learn toy's names and locations [67].

Table 1 reports all studies investigated in this paper which are based on ML methods. As expected, ML methods were widely used in socially assistive and collaborative robots, with increasing complexity as time passes. Indeed, in the last 2 years, more advanced ML and computationally intensive methods were used, notably deep learning. Finally, recent studies which compare the performances of multiple ML methods on the same scenario open the door for the idea of using "hybrid" ML methods, e.g. the use of multiple ML methods, such as model-based RL, ToM, and model-free-based RL, which can be "activated" in the scenario in which a better performance was observed.

Discussion

We provided an overview on studies which investigated ML method-based SP and EB reported since 2014 in the ACM/IEEE International Conference on Human-Robot Interaction, ACM Transactions on Human-Robot Interaction, and the *International Journal of Social Robotics*. Even with a relatively small number of analysed references, this study covers some important aspects for future HRI research, such as studies which try to bring some light in what which SP methods are the most effective and how to obtain robots with EB while using both classic and new ML methods. However, in the following, some limitations that were encountered and that we believe are worth discussing are presented for each of the SP, EB, and ML methods' directions.

Social Perception

There is a serious issue that can occur when performing online learning of emotions, namely the fact that humans usually have a non-immediate reaction time to robot "facial" expressions. Still, Boucenna et al. [7] propose to solve this thanks to the detection of the statistical contingency in order to obtain statistically correct results.

Another possible problem while investigating facial recognition in real-time situation can be related to the fact that some people are less expressive than others, cases in which the robot will certainly have some difficulties in recognizing facial expressions. Moreover, it seems to be difficult to recognize the sadness emotion through both facial recognition [7] and touch [11]. This can be linked to a lack of context and maybe this raise the necessity on having a fusion of multiple ways in which emotions can be recognized, as it is the case in Devillers et al. [9] where a fusion of multiple speech systems is discussed. However, the multiple fusion reported in Devillers et al. [9] is a complex process and the obtain performance was only of 38.7%, which clearly shows the difficulty in working on spontaneous emotional data, especially with subjects with particular voices, such as elderly people and children.

Explainable Behaviours

While the influences of culture on expectation and responses to robot have been studied in HRI [68], it is less common in EB-specific studies. For example in Johnson et al. [69], all participants were from the Netherlands, thereby increasing the chances of representing a common culture. This same limitation can apply to the study reported in Obaid et al. [70]. Indeed, it can be of great advantage to the research community if the mentioned future work in EB that the synthetized explanations or legible motions can be understood by people coming from a wide range of cultural and social backgrounds.

Machine Learning

The work reported in Bobu et al. [51•] improved the Boltzmann learning model in order to learn more accurate human models. Still, feature misspecifications can be a possible limitation of the new method due to the reliance on a pre-specified set of robot features for similarity selection. Even if the results reported in Soh et al. [47] were very positive from the part of the participants, a validation of the model with the targeted population and in real-world situations needs to be performed in order to obtain accurate feedback. As the work proposed in Roesler et al. [39] seems to be the first to investigate grounding unknown synonymous object and action names, it can be interesting to go further and be able to update the learning parameters in case of new objects and actions.

Conclusion

The studies published since 2014 revealed that a large amount of research was done in the studies of social assistive robots and collaborative robots involving SP and EB based on ML methods. Still, as many of the user studies are performed in a laboratory environment and with participants which are not the targeted users for the robotic systems, a lot of effort need to be put in order to have models validated in real world with non-trained and/or non-specialist users.

From an application point of view, a trend towards increasing complexity and computational requirements was definitely found in the ML methods that were applied since 2014. Furthermore, as it was reported in this Table 1, the investigated studies report a great use of classical ML methods since 2014 and some recent studies (from the last 3 years) combine different approaches in order to explore the advantage and good performance of each in order to cover as many different data sets as possible. Still, from a methodology perspective, classical ML methods are being rethought and new methods are emerging which make more human-like assumptions. As reported in the investigated studies, different ML methods were used over the years and some limitations of these methods were found. These limitations can only open other research venues such as the use of different approaches while performing HRI. Hence, being able to take only the advantages of each approach may only lead to further improvement.

Studies involving SP and EB responded to appealing questions for the HRIs, such as humans are capable of imitating a robotic system and the imitation and interaction with the robot are more naturally performed when the human was already familiarized with the robot. As human SP is complex, and little is known about the “real” models used by humans to perceive them, it is important to keep in mind that first, robots should utilize simple models which can explain human behaviour rather than complex ones which can make humans overestimate the robot’s capabilities. Finally, as people have the ability to switch between their behaviours and perception approaches, it can be a good practice to imitate this adaptability and use multiple models or techniques to make robots better perceive their environments and react in a more human-like way, leading towards more natural HRI.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

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