How Learning Capabilities Can Make Care Robots More Engaging?

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Abstract— **This paper explores how learning can be employed at different levels of the robot intelligence. It discusses psychomotor learning where machine learning is used to perform motor tasks; followed up by cognitive learning where machine learning is used to give robots the ability to learn understand the environment and human; and finally followed up by affective learning where robots can learn how to improve their social interaction with their human counterparts. Further, it discusses why learning is important for care robots and how it can make robots more acceptable to humans.**

I. Introduction

One of the dreams of social robotics is to give robots the ability to develop new skills and to acquire new knowledge and skills from experience by time in the same way humans do when growing up. Human's ability to learn has been addressed for a very long time in the field of life sciences and particularly in its disciplines of neuroscience and psychology. Humans as well as other organisms possess the ability to learn from experiences and by that to adapt to their social or physical environment and to ensure their own survival. Since the time of Jean Piaget, the field of Developmental Psychology has focused on understanding how humans learn from contact with the environment as well as from their parents and society[1]. Especially in early-age, humans go through several stages of development where they learn different skills and behaviours and develop their own personalities. Seeing such learning and adaptation capabilities in robots has always been fascinating to many. Learning can make robots better understand their environment and their human counterparts. It can help them to gradually improve their execution of physical and cognitive tasks. Additionally, it can help robots improve their (social) interaction skills with humans. This paper explores the idea of learning in robots, discussing in the first four sections how human learning works and how it can be implemented on different level of robot intelligence to improve its capabilities, followed up by a discussion about why robot really need learning and how to make it acceptable by humans.

II. Different Levels of Learning

In life sciences, a distinction of three categories of learning can be made, namely psychomotor, cognitive and affective learning [2]. Through psychomotor learning, humans learn to perform motor skills such as walking, dancing, swimming, and driving; through cognitive learning human are able to learn cognitive skills such as problem solving, language acquisition, learning concepts; while through affective learning humans learn emotional judgements towards persons, objects and events which is the basis of social skills. The inspiration by human (and other organisms) capabilities of learning led to the development of many life sciences inspired computational approaches for learning leading to the emergence of a domain we nowadays know as *Machine Learning* [3].

III. Psychomotor Learning

The problem of teaching robots to perform tasks such as walking or grasping among other more complicated tasks, such as opening a bottle of water, has had a few different solutions. Early methods of teaching a robot have been to either program the action on the robot, or use reinforcement learning or genetic algorithms to let the robot learn the action on its own. However, programming can be very time consuming and much work is needed to program the complex motions that are involved in a task while keeping some room for error adjustments and generalizations adds many more hurdles. Using reinforcement learning techniques, while theoretically robust, is not ideal due to the suboptimal conditions in which the robot has to learn actions with very little information. The most popular method for the past two decades has been learning by imitation: observing the action in question by an able and similar agent and imitating it. This method has vastly overshadowed the other methods. The potential of imitation learning for robots was quickly realized soon after its introduction[4][5]. Since then, imitation methods have been implemented by modelling brain functions or techniques observed in humans and animals when learning from their peers to teach robots tasks such as limb control [6][7][8].There are also methods that use more abstract and primitive concepts of imitation that may be more suitable to the computational nature of robots and may take advantage of the extra sensory capabilities of robotic systems [9][10][11]. The way humans interact when teaching has also been taken into account in the research to allow humans to use more natural ways of teaching robots and reduce the need to follow specific instruction in order to train robots [12][13][14][15][16]. There is also the daunting task of teaching robots how to manipulate objects. This involves two main concepts: learning object affordances (functionalities), and learning how to do the specific manipulations on the objects. There are algorithms to tackle both of these issues involving observation of humans using objects or by physical experience of the robot itself using the object in order to get the affordances[17][18][19][20][21], and using imitation techniques after watching humans manipulating objects in

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order to learn how to do it themselves as described in [22] and [23] among many others.

IV. Cognitive Learning

Machine learning has been used to enable computers (and hence robots) to also emulate human cognitive abilities such as speech recognition, image recognition, emotion recognition, and behavior analysis. In speech recognition, there has been significant success using hidden Markov models (HMM) on appropriate features of processed speech waveforms [27]. The feature extraction itself has had many innovations to provide robustness from noise and variations of speech between speakers[28][27]. A more hot-topic is natural language processing, which gives the ability to understand speech, a very important ability for successful HCI [27]. Image recognition algorithms used for object recognition/tracking, and even face recognition have also become very usable in the past decades due to innovations in the learning algorithms themselves, innovations in image processing techniques and feature extraction, and even innovations in hardware architectures (GPUs used for parallel image processing) [29][24]. Image analysis has also been used for emotion recognition by extracting features from an image of a face such as eyebrow positions, eyes open/closed, mouth corners stretched, and others (FACS) and analyzing them to determine the emotion of a person from a facial image [30]. Emotion recognition as a whole does not have only the facial image modality, there have been works to enable emotion recognition using modalities such as vocal features (dynamics of tone, pitch, etc.), language usage, and even the dynamics of how the person moves[31][25]. Machine learning has also been used to analyze the behavior of a person (or groups) to understand habits and general dynamics of the behaviors which enable machines to predict or expect certain behaviors much like a person might expect certain behaviors from someone else[32] [33][34][35][36][26].

V. Affective Learning

Recent developments in neuroscience suggest that emotions are at the core of every rational decision making [37]. They assist the decision-making process of humans by highlighting actions based on their future positive or negative consequences. Thus, based on these emotional judgments humans decide which actions to take and which not. Next to emotions as judgement, experienced emotions can also trigger the so-called action tendencies [38], where certain emotions push us towards performing certain actions. Furthermore, emotion regulation process might also trigger actions if they serve the goal of inhibiting or intensifying an experienced emotions [39]. One might feel the tendency to take revenge at a moment of anger. However, if taking revenge would result in a more regrettable future consequences (e.g. losing the job) than when not taking revenge, the emotion regulation process would attempt to inhibit the felt emotion. The possession of such emotional intelligence is what enables humans to interact socially with each other. However, such social behaviour would have never been achieved without certain mechanisms of learning. Humans learn from previous life-experiences whether certain event is desirable or not [40]. Previous physical and emotional rewards and punishments determine how we would feel toward an event [41]. Emotions also influence the way information is stored in our episodic memory [42]. We might remember emotionally loaded events more clearly than the ones that are not. Similarly, it is more likely that we remember events that are coherent to the emotion we are experiencing at a moment than the ones that are not.

All the aspects mentioned in the story above show that emotional intelligence involve different affective and cognitive components of the human brain. In the fields of robots and virtual humans, different biology-inspired computational cognitive and affective systems have been developed with each of them covering certain aspects of emotions. Systems such as ALMA [43] and EVA [44] have focused on the relationship between emotions, mood, and personality, and on how to simulate the interaction between these three components. Other systems such as FLAME [45] and ParleE [46] have focused on appraisal models, where emotions are automatically elicited based on the perceived events or actions and their contextual information. EMA [47] and Silicon Coppelia [48] have focused on the regulation of emotions. In the second version of EVA, Kasap and colleagues have focused on the simulation of episodic memory and its interaction with emotions and mood [49], [50]. Conscientia [51], TAMER [52] and MAMID [53] have focused on the influence of emotions on the decision making and learning from previous experiences. Although the discussed approaches clearly define the concept of emotions and attempt to implement certain aspects of it, it should understood that other implementations of decision-making that employ learning also implement certain aspects of emotions, even though they do not mention it. The whole philosophy behind rewards and punishments in basic reinforcement-learning techniques in AI can be considered as inspired by the human affective system and the use of these techniques in developing statistical dialogue management can be compared to the use of emotions. These kind of systems have often been implemented using probabilistic techniques such as (fully observable) Markov Decision Process (MDP) or a Partially Observable Markov Decision Process (POMDP)[54]. Learning is then used to dynamically optimize the dialogue by allowing change of the dialogue strategies based on some kinds of reward. Using reinforcement learning the system learns the optimal strategy[55]. In most cases, such systems employ designer-defined rewards, where high rewards are assigned to the achievement of tasks or the satisfaction of agent goals and low rewards (punishments) when a task is failed or a goal is violated[56].

VI. The Need for Learning

As illustrated in this paper, a lot of work has been conducted in employing learning in the field of robotics and other related fields such as virtual humans, natural language and dialogue management. These advancements in learning have also contributed to the development of many robotics solutions that have been introduced to the care sector in the last decades. Leaning is also used in projects that aim at developing robots that would care for humans, help them in performing tasks and assist them at home. By learning, robots can learn to understand their human counterparts better and to perform certain tasks better. However, to achieve robustness, robot developers have often limited the learning capabilities of robots focusing more on simple but robust solution resulting in predictable robot behaviour. Furthermore, in contrary to the field of virtual humans, the field of robotics has been for the most of times avoiding the use of learning in social interaction with the human. On the other hand, it is understandable why some of these topics have been avoided. Unpredictability if gone wrong can cause disappointment for many end-users. However, too much predictability also can make robots quite boring and not so much engaging. Human-like behaviour needs a certain level of predictability.

When robots start to show intelligence, human become less tolerant towards its mistakes and would not always accept errors. However, a good implementation of learning would still make robots engaging, even if it makes mistakes. The trick of making learning robots more acceptable is by making humans see the robots more as infants. Cynthia Breazeal, who has been working on social robotics for the last two decades, has shown that robots are more likely to be liked and accepted by humans when they are modelled as infants [57]. Humans do not easily accept robots that look and behave like all knowing superior intelligent beings and especially when these robots cannot achieve what is expected from them due to the current technological limitations [58][59]. Humans are more likely to forgive infant-like robots for mistakes made because of technological limitations than by robots pretending to be more intelligent and developed.

CONCLUSION

The paper have shown how different levels of learning can be used in making robots behave more intelligently. It started with psychomotor learning, followed up by cognitive learning and then affective learning. It has also discussed on how learning can make robots more engaging if the robot is perceived as an infant. A lot of work still has to be conducted in this approach and we see the direction of having robots as infants as the way to go.

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