A Step Towards the Development of Socio-cognitive Agent

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Abstract

The embodiment of consciousness in socio-cognitive agents play a significant role in their acceptance as co-partners. Man-machine social interaction's success is based on the agent's generated believable behaviors. In this regard, such an agent needs to generate realistic beliefs, intentions, goals, self-regulation, verbal, and non-verbal communication (including gestures) according to the context of ongoing interaction is very important. This study hypothesizes that the implementation of the Theory of mind (TOM) may allow the agent to change its intentions, beliefs, and desires by predicting the existing perspective and mental states of the other agents involved in the given social interaction. To study the complexity of dynamics in a social context we have taken the case study of the 'paper-scissor-rock' game and developed a cognitive agent capable of using gestures for non-verbal communication following the Theory of mind. This work is in progress and is being developed on the iCub robot simulation. We have used tapped delay line neural networks as the basis for reinforcement learning and strategic planning. This paper will report the cognitive model, neural network initial results obtained.

Keywords: Robots, iCub, Reinforcement Learning

1. INTRODUCTION

The popularity of motivation based cognitive systems is increasing due to behavior-based cognitive systems This is because of the

capability of motivation based agents to set goals and perform more realistically or humanlike while in man-machine interaction sessions of any daily life task [1]. Whereas behavior-based systems are only capable to perform actions according to the predefined behaviors. The man-machine social

interaction requires socio-cognitive agents to interact with other social beings like a co-partner [2]. The nature of these socio-cognitive agents allows them to observe and obey the rules organized by society to perform social interaction. These socio-agents need to interact with humans with the capability to blend in the environment [2]. Humans can interact with each other in a social environment because our brains work in a manner to trigger emotions, behaviors, and perceptions during our interactions [3]. To understand the science of our brain we need to understand how the mind works to exhibit these cognitive abilities, the Theory of Mind (TOM) helps to explain how these cognitive capacities and abilities are triggered inside the brain [4]. TOM is very helpful in explaining how a man to man interaction session is done with such cognitive abilities.

In man-to-man social interaction, the Theory of Mind plays a crucial role in successful social interaction. One can successfully interact if one understands propositional attitudes i.e. Intentions, beliefs, and desires of others and act according to them. To achieve this understanding we observe and learn about others. We observe other's behaviors and try to predict their intentions or desires behind their behavior. Infrequent social interaction, we learn the traits based on these observations and then set out motivation to act accordingly in social interaction [5].

To achieve a more natural and human-like social interaction, a socio-cognitive agent needs to understand the personality traits including the beliefs, desires, and intentions of its copartner in any routine either working or daily [6]. The Theory of Mind stresses how a human makes these interactions and

understands others to the response. Hence it is very important to implement TOM in socio-cognitive agents to achieve realistic man-

machine social interactions [7]. A socio-cognitive agent would only be able to understand the motives of its partner when it starts to communicate with him/her. For this purpose, we need to understand the phenomenon of social interactions and how communications take place. Social Interaction is performed by using Verbal and Non-Verbal communication. In verbal communication [1], it is very easy to understand the intentions beliefs, and desires of others by just listening to them and by analyzing the acoustic cues. In non-verbal communication, social interaction is performed by using body language, particularly using hand gestures and facial expressions [8]. It is very important to understand the meaning of gestures and intention beliefs and desires associated with them. Some psychology studies stress that nonverbal communication is the actual key to all kinds of communication, verbal communication does not deliver the entire message, the gestures, and facial expression provides a more realistic view about intentions and emotions at the time of communication. Hence it is also important for the socio-cognitive agents to understand the intention belief and desires associated with gestures and to perform them in non-verbal social interaction [9].

Social games are a very popular way to interact socially with each other; particularly social games are an effective way of non-verbal social interaction. In social games, one player takes decisions according to the decision of the opponent by understanding the intention, belief, or desire of the opponent by observing the strategy of the opponent [10].

For this study, we choose a "Paper-Scissor-Rock" game as a way of Interaction between man and socio-cognitive agents in a cybernetic environment. Paper scissor rock is a social game that is played between two or more players. If one player performs the gesture of

paper and other rock then the player with the gesture of paper wins because paper the meaning to wrap the rock. If one player gives the gesture of Paper and other scissors then the player with the gesture of scissor wins because scissor gives the meaning to cut the paper. If one player shows the gesture of scissor and others gives the rock then the player, showing the gesture of rock wins because rock here gives the meaning to break the scissor or simply scissors cannot cut a rock. Socio-Cognitive agents while playing with a human can learn the strategy of a human player by observing his/her gestures through series of interactions then it can predict the intention and based on this intention, it performs a suitable gesture to win.

2. RELATED WORK

This paper presents a quick direction to the basics of social interaction and the involvement of the theory of mind in social interaction. These models review some problems that exist in man-machine social interaction, human cognition, and game theory.

2.1 Social Interaction and Theory of mind

During social interaction, the human can always conclude other human beings whether the conclusion is right or wrong. These conclusions are based on intents, desires, beliefs, knowledge, and most importantly emotions. Furthermore, the attribution of mental states based on these conclusions refers to the theory of mind (TOM) [11]. An individual can perceive the behavior of other counterparts through its own beliefs, however, these anticipations may not depict the actual reason behind the cause [12]. In these circumstances, one can consider a false belief [12]. Whereas, in another example, one can also place itself to understand the attributions of other humans and try to collect evidence of the reason for the counterpart's behaviors. These attributions give rise to the ability of

empathy in TOM and it can mature with each new interaction [13].

2.2 Human Cognition

The human brain is involved in various types of simple and complex cognitive processes like perception, sensory interaction, emotions, and action selection. The most important one is the memory which can store, encoding, recalling, and learning mechanisms. The memory include: short-term memory (STM), medium-term memory (MTM) and long-term memory (LTM). Signals are transferred from short-term to medium-term and then to long-term in bottom-up attention (Miller, 1956) [14].

Working memory has the executive control of the system and its processes are based on language understanding, reasoning, perceptual analysis, momentary storage, and learning [15]. Given Baddeley [16] short-term maintenance is the responsibility of working memory along with the integration of stimuli coming from other memories. Working memory works as a preconscious buffer for internal activities [17]. According to Cowan, working memory can be divided into two parts: one is based on the attention mechanism and the second contains the representation of long-term memory [18].

Long-term memory (LTM) is composed of semantic memory and episodic memory [19]. Semantic memory contains the experiences of objects, which is mostly general in nature [20]. Whereas, episodic memory stores events related to contents stored in semantic memory [16]. Information can be retrieved (recall), stored, and encoded in LTM. Retrieval is the process of recalling past experiences, storing is the process of transferring the information from medium-term or short-term memory to long-term memory, whereas encoding is based on indexing the information according to their meanings [19] [20].

Some of the researchers have a different opinion than LTM and STM are separate memories; they consider memory as a single

unit (Brown, et al., 2007). Likewise, some others have described the association between STM and working memory as several researchers assume that working memory is an extension of STM [19].

2.3 Game Theory

A socially interactive game's agent requires the property to attain equilibrium in the game. Introducing equilibrium in the game can prevent the game from being complex for players. Through equilibrium, any agent can do self-assessment in any particular state. This self-examination can achieve when the rules of the game, the rationality of the player, and player payoff functions are all in the common knowledge of every agent. According to [21] when two rational players have the same information, they must draw the same interpretation and draw the same conclusion.

2.3.1 Machine in the Learning Process:

In man-machine social interaction, it requires providing ability in the machine to do learning from the environment. Learning from the environment consists of two parts a learner and an environment. An active agent is referred to as a learner if it has some deterministic and unpredictable characteristics. It can use these characteristics to achieve its goals, through performing actions in the environment. Whereas the environment is a passive agent, which can change its internal states according to the actions, performed by active agents on it or by any other source [22]. There are various types of machine learning techniques: supervised learning (classification or regression), unsupervised (clustering), and reinforcement learning.

Supervised learning is known as "learning with the teacher", in such type of learning whenever the input vector is applied in the system the desired output is defined by the teacher [23]. It is a comparison between the system output and

the desired output. Unsupervised learning does not depend on any target values, it takes input pattern and finds out the association between the patterns without any teacher [24]. Reinforcement learning is based on the evaluation of training based on the right or wrong decisions and up-gradation of the learning model accordingly [25].

2.3.2 Implicit and Explicit Learning and Knowledge:

Knowledge is vital for an intelligent agent. It can be divided into implicit and explicit. Implicit knowledge is generated from insight based on experiences and intuitions and transforms beliefs, perceptual and mental models [26]. Implicit knowledge is produced through implicit learning in which one does not know explicitly what is going on inside [27]. Implicit learning is to find out the regularities in the world and then express them explicitly [27]. Furthermore, rules are generated through the identification of reason behind definite actions. The knowledge extracted from implicit learning is explicit knowledge.

Implicit knowledge is procedural knowledge whereas explicit is declarative knowledge. As compare to implicit knowledge explicit knowledge can be directly accessed and install. Explicit knowledge gets more elaborative with the extension in the implicit knowledge [28].

2.4 Man-Machine Social Interaction

2.4.1 WAP-based Game Engine:

An artificial player is presented for the PSR game [29]. The problem defines that to predict the opponent's next move it is required to takes all previous moves of the player and opponent's instead of making a prediction based on only one previous move. A move of each player is represented by three units associated with paper, scissors, rock. The player predicts the next move of the opponent

based on the previous five moves of both players. The focus of this application was to attract a large number of players for the gathering of realistic data.

A WAP-based engine designed for this game. The main server with which all the clients are going to attach. This server also behaves as the main memory to memorize players and opponent moves for the training of neural networks. The major point of this application is server predicts the opponent move before the opponent plays his/her move.

Figure 1 : WAP-based-Game Engine [29]

2.4.2 PSR-EAL Framework:

The reference [30] provides a theoretical framework based on game theory to ensure the assessment of the opponent moves in the game. This framework is based on the ANN and genetic algorithm, Evolutionary Neural Network for the training artificial player and genetic algorithm to get the optimal option for this prediction. It uses TDNN in an artificial player for the memorization of previous moves of both players. This framework consists of three components Gaming Server, Human Player Terminal, and Artificial Player. For the artificial player, two environments exist there Observatory Environment and Combat Environment. Firstly, the game will be played between human players and Artificial Players in their Observatory Environment mode mimics the game played between the human

players. After learning human strategy in the game, Artificial Player transfers to the Combat Environment mode where it plays against human players.

Figure 2 : PSR-EAL Framework [30]

2.5 Man-Machine Social Interaction Issues

2.5.1 Trust:

One of the numerous issues that ensure successful communication among humans is based on the trust factor between them [31]. Therefore, it's important and challenging to program a setup that could trigger and build trust between a man and a machine having social interactions.

2.5.2 Comprehension of Non-verbal Cues:

The social interactive machine can understand and perceive the nonverbal cues of humans in a social setup. The machine can perceive the activities and behaviors in any situation. Such a machine can classify and observe these activities. The machine can perceive human gesture and posture and respond accurately to humans [32].

2.5.3 Age groups:

A socially interactive machine can interact with a large number of humans. Which have different ages, cultures, and social standards of different genders according to their viewpoint [32]. A socio-cognitive agent may have to

interact with different age groups of people and this becomes a challenge as the behaviors of children and adults are different. Children can develop false beliefs and may not be able to comprehend but adults on the hand are immune to it.

2.5.4 Long-term Interactions:

A long term interaction with the human can be attained by providing a large memory in the machine for the storage of human activities and behaviors. [32].Data storing and handling has become an issue of the 21st century. For long term interactions, we require a big storing medium for storing the interactions for future interactions.

2.5.5 Emotions:

Emotions play important role in human-machine interaction in social setup [5]. Emotions cause changes in cognitive states and psychological excitements through the perception of objects and persons [5]. This emotional aspect of the machine will present truth factors in the machine's output value for humans. To improve human-machine interactions and decision making, emotions and feelings can play a vital role [5].

3. MODEL

3.1 COGNITIVE MODEL SOCIAL INTERACTION [CMSI]

The purpose of CMSI (Cognitive Model for Social Interaction Machine) is to socially interact with the human in PSR games and learn their playing mix strategies to improve the responses. In-game, the Machine can learn and understand the playing strategy of its opponent by using two techniques. One is, to perceive its opponent playing policy during a game. Another is to understand the opponent playing policy through his/her experience, in addition to current experience, which can be

obtained by playing the game multiple times with its opponent. This learning can improve the responses of the machine towards its opponent as it starts to play the game accordingly to change its playing strategy in any game, through predicting or understanding the moves of humans.

Figure 3 : Cognitive Machine Social Interaction

3.3 Sensory Memory:

In-game playing social robots primarily through its software sensors get initial necessary information about opponents and rules of the game. Sensory memory is a storage area, temporarily store sensory stimulus, and try to develop elementary understandings about the opponent.

3.3 Perception Evaluation:

This module is based on earlier sensed information checks that the artificial agent has any past playing experience with that human. If an opponent is unknown and playing the first time then profile information is stored in his/her memory for future games. In another case, it will recall the human memorized profile for the validity of perception.

3.4 Working Memory:

Working memory works as a buffer for internal activities and provides temporary storage. In working memory based on the output generated by the perception evaluation module, the agent performs the identification of an interacting person. If it recognizes that human then it

recalls its previous learned implicit knowledge from long-term memory, to currently choose its moves in-game in a better way through predicting the playing mix strategy of humans. In another case, if an artificial agent plays a game first time with a human then it will be able to observe the playing techniques of humans and predict the next move. This module is also responsible to check if during the game it senses any new person entry then how to manage both interactions.

3.5 Long Term Memory (LTM):

It is an everlasting memory of social robots. It is responsible to provide any memorized learned implicit knowledge of humans after the identification process. The last part which an agent does in its observation is, to memorize this predicted implicit knowledge in its memory for future games with that person.

3.6 Social Response:

Predicted implicit knowledge will help any social robot to decide its move towards another human. The more accurate prediction will generate responses that are more approved and help an agent to reach equilibrium state in-game.

4. RESULTS

4.1 Experimental Setup

Social interaction between man and machine firstly working setup is defined to interact with the machine. Application is played in two modes: profile-based playing and generic playing. A group of four persons is chosen to play the game with an agent designed in the application. Initially, two players using observation features of the profile-based mode of application play games with each other for 10 rounds, and during their play Agent observe the game. After observation, each player will play 10 games of different rounds separately with Agent. These 10 games are consist of the following number of rounds as 1st game is of 25 rounds, 2nd is of 35, 3rd of 50 rounds, 4th one is of 60 rounds, 5th of 80, 6th of 90, 7th of 50 rounds, 8th with 40 rounds and last game is

consist of 20 rounds; performance of Agent in each round noted automatically in a file. Then the same player plays 10 games with the same number of rounds in each game with the generic mode of Agent.

Some dissimilarities are noticed in the performance of gameplay by Agent within profile-based and generic playing. These variations in performance occur due to the different playing strategies of human players. Sometimes this player play game entirely in the random way with Agent, which decreases Agent performance, sometimes player play game with define strategy, and sometimes he/she play with Agent using mix strategy. Therefore, considering these different scenarios it is needed essential to check out the performance of Agent in these different states. For the Analysis of Agent performance three groups each, at least four people of different ages are designed to interact with the application. Each person plays both modes of application, in the same way, define previously against Agent with two games of a different number of rounds individually. 1st game is of 20 rounds and the second game of each mode is 40 rounds. This playing gave a brief view of the Agent's performance for each experiment.

Figure 4 : Overview of the System

Figure 5 : Robot Behaviors

4.2 Experimental Results

Many experiments were conducted to check the performance of an agent in different social interactions. Different rounds played between humans and agents to check the profile based social behavior learning of it with numerous socially interactive humans.

4.2.1 Agent Performance in Profile Based and Generic Social Interaction

In the first heaps of games of different rounds are played between humans and Agents to check Agent performance. The graph below shows the Agent's performance in profile-based social interaction.

Figure 6 : AgentPerformance inProfile Based Social Interaction

Four humans selected to play different rounds of games with Agent on an individual basis. For 25 rounds game the average performance of Agent remains 39%, then for 35 rounds game with the same players average performance of Agent is 25.57%, for 50 rounds average performance is 32.84%, for 60 rounds average performance is 31.89%, for 80 rounds it is 30.76%, for 90 rounds average performance is 30.67%, for 50 rounds 30.33%, for 70 rounds average performance is 35.08%, for 40 rounds average performance is 35%, for 20 rounds it is 46.25%.

To validate the results of profile-based social interaction of Agent plays similar rounds

games with the same human players using generic social interaction application.

The average performance of the agent in each round for these four players is defined next. In 25 rounds game, the average performance of Agent is 23.5%, for 35 rounds game with the same players average performance of Agent is 19.1%, for 50 rounds average is 20.48%, for 60 rounds performance is 23.24%, for 80 rounds it is 22.31%, for 90 rounds average is 22.77%, for 50 rounds 20.08%, for 70 rounds average performance is 25.07%, for 40 rounds average performance is 18.57%, for 20 rounds it is 35%.

4.3 Social Interaction Parameters:

The evaluation parameters can be seen below.

Figure 7: Agent performance in profile base insertion

Table 1 . Social Interaction - Profile Based and Generic

Social Interaction		Random Behavior	Mix strategy Behavior	Strategy Behavior
Profile Based	An agent can recall its previous experience with humans.	Random behavior in moves; performance 28.75%	Person behavior never remains the same; performance 31%	The opponent can easily predict the behavior; performance 34%
	Plays 20 Rounds			
Generic	Every player is unknown.	Random behavior in moves; performance 25%	Person behavior never remains the same; performance 24%	The opponent can easily predict the behavior; performance 31%
	Plays 20 Rounds			

Table 2 . Phases of Interaction

Phase	Robot's behavior	Failures to be moderated
Finding an interaction target	Selecting a likely interaction target	Unreachable/ Rejected
Interaction at public distance	Announcing its presence and intention to talk	Unaware
Initiating a conversation at a social distance	Nonverbally showing intention to interact	Unsure

5. DISCUSSIONS

The entire concept of a socio-cognitive agent is to have an agent intelligent enough to have social interactions with a human and most importantly like a human. An agent that lacks the ability of social interaction with humans is not as useful as one with social interaction abilities. Such agents are truly a bridge forward to a more realistic man-machine relation. This work has described a model that allows the agent to learn the opponent's strategy by observing his /her playing strategies. Just like humans first, observe and then start to make strategies on how to counter and argument or how to respond to a certain behavior, it is very important to note here that the socio-cognitive agent described in this model, does follow the same principles of TOM as they are executed in a human mind. The agent does this job using its submodule which imitates its opponent. When observing the human player, Agent tries to learn their behavior and patterns in current decision making. This task is performed through learning using tapped delay line neural networks.

The agent's ability to imitate humans develops neural networks in its internal memory to increase the learning process. The learning process depends upon the strength and efficiency of the neural networks. It has been reported that by evolving neural networks, the learning process increases [33]. Once an agent is in playing mode, plays a game with the human player, whose behavior, it has already learned by observing the player's playing strategies, Agent will load learned knowledge. In the first move, Agent selects a random move to play its dominant strategy and also to learn what dominating strategy does human players have to play. It is to be noted that our agent selects a random move on purpose at the start of the game, this exhibits the behavior of "not showing trunk card" at the start, also by doing

so our agent observes the player one more time upon how the player decides at the start. As we know the agent already knows the player's strategies so for the next move, the agent looks into the opponent's all previous game moves which he/she has played with other humans and tries to predict his/her next move. This entire phenomenon of predicting how the player may response is very well defined in "The simulation theory", it is also a part of TOM, it simply states that it is human behavior to observe someone and imagine one's self in their position and try to predict how the other person would respond, it also states that person can develop more than one predictions about a certain strategy at a certain amount of time. Following the same principle, our agent predicts two moves for an opponent human player, one based on the current game and the other based on previously observed. These two predicted moves are then compared, if the difference between these moves exists, then Agent computes beliefs for both moves. A move with a maximum belief is selected. This process goes on until the game or interaction session stops and our socio-agent responses every time by following the same process of a human mind. The work in this paper shows that socio-cognitive agents are a reality and they can provide a basic platform to strengthen man-machine relationships.

6. CONCLUSIONS

Cognitive architecture CMSI is working as an autonomous agent for social interaction with a human. CMSI manipulates it's neural correlates implicitly to predict the human internal state of mind based on its observation and experience. The model can predict the internal state of mind of the human through its observation and experience. It can predict implicit knowledge better in subjective learning as compare to generic learning. An agent can understand the strategic and mix strategic behavior of any

human through its interaction increases over time.

In social interaction, emotions play a significant role in understanding the behavior of its opponent as in human-human game playing if the opponent is sad/happy then his/her playing logic is mostly simple one or if he/she is in an aggressive mood then mostly it will play the game with complex logic. This application is not currently able to understand the emotions of its opponent in a future version this application would be able to predict human strategy by understanding the emotions of humans in any particular situation. It would be an attempt to make this architecture more dynamic and consistent to work in different environments. For this purpose, some modifications would be required in the robotic setup.

Reference

- [1] J. Kennedy, P. Baxter and T. Belpaeme, "Nonverbal Immediacy as a Characterisation of Social Behaviour for Human–Robot Interaction," *International Journal of social Robotics*, p. 20, 2016.
- [2] T. J. Wiltshire, S. F. Warta, D. Barber and S. M. Fiore, "Enabling Robotic Social Intelligence by Engineering Human Social-Cognitive Mechanisms," *Science Direct*, p. 53, 2016.
- [3] S. Lemaignan, M. Warnier, E. A. Sisbot, A. Clodic and R. Alami, "Artificial Cognition for Social Human-Robot Interaction: An Implementation," *Science Direct*, p. 29, 2016.
- [4] A. I. Goldman, "Theory of Mind," *Oxford Handbook of Philosophy and Cognitive Science*, p. 25, 2012.
- [5] B. Duffy, "Fundamental Issues in Affective Intelligent Social Machines," vol. 2, no. 21-34, 2008.
- [6] J. Hartwell, "Access Denied: An Investigation of the Impact of Aphasia on Social Inclusion in Long-term Care Facilities," ProQuest Dissertations Publishing, University of Louisiana at Lafayette, 2015.
- [7] A. Aly, S. Griffiths and F. Stramandinoli, "Metrics and Benchmarks in Human-Robot Interaction: Recent Advances in Cognitive Robotics," *Science Direct*, p. 20, 2016.
- [8] T. Fong, I. Nourbakhsh and K. Dautenhahn, "A survey of socially interactive robots," *Robotics and Autonomous Systems*, p. 24, 2003.
- [9] C. D. Kidd, W. Taggart and S. Turkle, "A Sociable Robot to Encourage Social Interaction among the Elderly," in *IEEE International Conference on Robotics and Automation*, Orlando, Florida, 2006.
- [10] C. F. Manski, "Economic Analysis Of Social Interactions," *National Bureau of Economic Research*, p. 43, 2000.
- [11] D. Liu, M. Sabbagh, W. Gehring and H. Wellman, "Neural Correlates of Children's Theory of Mind Development," vol. 80, no. 2, 2009.
- [12] H. L. Gallagher and C. D. Frith, "Functional Imaging of 'Theory of Mind'," vol. 7, no. 2, 2003.
- [13] A. N. Meltzoff and J. Decety, "What Imitation Tells Us About Social Cognition: A Rapprochement between Developmental Psychology and Cognitive Neuroscience," vol. 358, no. 491-500, 2003.
- [14] T. Madl, S. Franklin, J. Snider and U. Faghihi, "Continuity and the Flow of Time—A Cognitive Science Perspective," in *Philosophy and Psychology of Time*, Springer, Cham, 2016, pp. 135-160.
- [15] W. M. Qazi, S. T. S. Bukhari, J. A. Ware and A. Athar, "NiHA: A Conscious Agent," in *COGNITIVE 2018, The Tenth International Conference on Advanced Cognitive Technologies and Applications*, Barcelona, Spain, 2018.
- [16] A. D. Baddeley, "The Episodic Buffer: A New Component of Working Memory?," *Trends Cogn. Sci.*, vol. 4, pp. 417-423, 2000.
- [17] T. Madl, S. Franklin, K. Chen and R. Trappl, "A computational cognitive framework of spatial memory in brains and robots," *Cognitive Systems Research*, vol. 47, pp. 147-172, 2018.
- [18] N. Cowan, "Activation, attention, and short-term memory," *Memory & Cognition*, vol. 21, no. 22, pp. 162-167, 1993.
- [19] S. Franklin, B. Baars, U. Ramamurthy and M. Ventura, "The Role of Consciousness in Memory," 2005.
- [20] S. T. S. Bukhari, A. Kanwal and W. M. Qazi, "Machine Imagination: A Step Toward the Construction of Artistic World Through Storytelling," in *Recent Trends and Advances in Wireless and IoT-enabled Networks*, Cham,

- Springer Nature Switzerland AG 2019, 2019, pp. 197-206.
- [21] S. Heap and Y. Varoufakis, *GAME THEORY: A Critical Introduction*, Routededge, 1995.
 - [22] W. Shed, *Autonomous Learning from the Environment*, 1994.
 - [23] J. Zurada, *Introduction to Artificial Neural System*, West Publishing Company, 1992.
 - [24] K.-L. Du and M. Swamy, *Neural Networks in a Softcomputing Framework*, London: Springer-Verlag, 2006.
 - [25] J. Tebelskis, *Speech Recognition using Neural Networks*, 1995.
 - [26] H. Nemati, D. Steiger, L. Iyer, Herschel and R.T., "Knowledge Warehouse: An Architectural Integration of Knowledge Management, Decision Support, Artificial Intelligence and Data Warehousing," vol. 33, no. 143 - 161, 2002.
 - [27] Z. P. J. Dienes, "A Theory of Implicit and Explicit Knowledge," vol. 22, no. 735-808, 1999.
 - [28] R. Sun, "The Importance of Cognitive Architectures: An Analysis Based on CLARION," 2006.
 - [29] L. Niklasson, H. Engström and U. Johansson, "An Adaptive 'Rock, Scissors and Paper' Player Based on a Tapped Delay Neural Network," 2001.
 - [30] M. Khan, W. Qazi and S. Lodhi, "Theoretical Framework to Learn Opponents Mixed Strategy Playing 'Paper, Scissor, Rock' by Evolving Adaptive Neural Networks," vol. 61, no. 1, 2009.
 - [31] B. Becker, "Social robots – Emotional Agents: Some Remarks on Naturalizing Man-Machine Interaction," vol. 6, 2006.
 - [32] T. Fong, I. Nourbakhsh and K. Dautenhahn, "A Survey of Socially Interactive Robots," vol. 42, no. 143–166, 2003.
 - [33] T. Vogl, J. Mangis, A. Zigler, W. Zink and D. Alkon, "Accelerating the convergence of the backpropagation method," vol. 59, no. 256-264, 1988.