International Journal of Robotics
Research and Development (IJRRD)
ISSN(P): 2250-1592; ISSN(E): 2278-9421
Vol. 8, Issue 1, Jun 2018, 1-10

TRANS STELLAR
•Journal Publications •Research Consultancy

A COMPARATIVE STUDY ON ARTIFICIAL COGNITION AND ADVANCES IN ARTIFICIAL INTELLIGENCE FOR SOCIAL-HUMAN ROBOT INTERACTION

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ABSTRACT

Humans have a natural tendency to incarnate surrounding things and have been enthralled always by the generation of machines gifted with human inspired traits and abilities. Nowadays, Social-Human Robot Interaction challenges the Artificial Intelligence in some regards include: dynamic, partly unknown atmospheres, which weren't formerly devised for robots; physical communications with humans, which needs low latency, fine thus far socially suitable control policies; a wide range of situations with rich semantics to recognize and understand; and multi-model and natural interaction that authorizes common sense knowledge as well as the depiction of probably deviating mental models. This paper attempts to perform comparative analysis on artificial cognition and advances in AI for Social-Human Robot Interaction and to show core decision problems, which want to be addressed for a cognitive robot for successfully sharing tasks and space with a human. High-tech design techniques and approaches are carefully examined and compared; cases where the proposed system has been used are reported, successfully. The experiments showed the capability of the system to provide a Social-Humanoid Robot by means of human social manners and robotic emotions.

KEYWORDS: *Social-Human Robot Interaction, Artificial Intelligence, Artificial Cognition and Advances & Cognitive Robotics*

Received: Apr 16, 2018**; Accepted:** May 07, 2018**; Published:** May 23, 2018**; Paper Id.:** IJRRDJUN20181

Original Article

INTRODUCTION

Human beings have a natural tendency to incarnate surrounding things, in spite of whether they are non-living or living beings. Likewise, humans have been enthralled by the generation of machines that include not only human behaviors and traits, but also sensitive, interactive and emotional capabilities akin to the human being. This was obviously emphasized by the generation of artificial creations capable of communicating with people and to turn around social and physical spaces that have motivated producers, directors, and writers since the first light of the science invention genre. Science fiction, plays, novels and movies have shown how this creative robotic technology can cohabit with people, promoting society, but also increasing queries regarding principles as well as responsibility. In the past few decades, this image has turned into realism with huge advances in computer graphics, hardware performance, AI (Artificial Intelligence) and robotics technology. There are various reasons to create robots capable of interacting with people by means of human-centered manner [1].

AI is one of the technologies on the cusp. Whilst nothing really innovative in itself, a current convergence of raised computational power with the growing of huge datasets and refinement of available perception of the methods engaged has been viewed it as a significant differentiator in the firm, in the real world [2]. Artificial Intelligence has a tale of busts and booms, so far by any traditional success measures, the past some years have been noticeable through exceptional advancement. Many of this advancement has arrived from modern advances in 'deep learning', typified through learning huge neural network models and multiple layers of demonstration. These models have attained significant benefits in various domains spanning object detection, speech detection and control. When compared to high-tech algorithms and techniques in machine learning, human learning is differentiated through its efficiency and richness [3].

Social-Human Robot Interaction (SHRI) is an interdisciplinary analysis of communication dynamics among human beings and robots. At present, SHRI is a very widespread and varied research and design activity. Practitioners and researchers are focusing on SHRI, which arrive from various fields such as computer science (AI, robotics, HCI (Human-Computer Interaction), computer vision and natural language understanding); engineering (mechanical, design, industrial and electrical); humanities (philosophy and ethics); and social sciences (cognitive science, anthropology, human factors, interactions and psychology). In today's society, robots are suspended to fill up an increasing number of roles from factory mechanization to service applications for entertainment and medical care. While initially, robots were used in tedious tasks in which all human being direction is provided a priori, they are developing into engaging in progressively more intricate as well as less structured tasks and actions, like communication with people needed to finish those tasks. This intricacy has encouraged completely new endeavor of SHRI, the analysis of how humans communicate with robots and how finest to design and employ robot systems able to achieving interactive tasks in the human atmospheres. The basic goal of SHRI is to generate the algorithms and principles for robot systems, which create them able to secure, direct and efficient interaction with human beings. Numerous aspects of SHRI research link to and obtain principles and insights from communication, anthropology, psychology, ethics, and philosophy, creating SHRI as a naturally interdisciplinary task [4].

There are various applications of Human-Robot Interaction include: remote control of airborne, space, undersea and terrestrial motor vehicles for non-routine missions in inaccessible or hazardous atmospheres; human decision-making control of robots in the performance of everyday tasks; robotic vehicles, where a human being is a traveler; and Social Human-Robot Interaction, like robot machines to give comfort, entertainment, support and teaching for children, autistic, elderly and physically disabled persons [5].

NEURAL INSPIRATION AND COGNITIVE IN ARTIFICIAL INTELLIGENCE

The report from Science, Robotics AAAS Report (2016) found that inventing robots with very flexible manipulation, raised intellectual perception and enhanced learning capability will attain the target of creating these devices more human -like. One feasible way to success in creating next-generation robots are by brain-inspired smart robotics, an interdisciplinary field, which brings together investigators from neuroscience, Mechatronics, robotics and informatics between other regions. Brain-inspired smart robotics targets to provide robots with human-like intelligence, which may be either mechanism-based or application-based robotics. Mechanism-based robotics aims to enhance the performance of robots by imitating the mechanisms, structures and basic standards of human cognitive movement and function. Application-based robotics concentrates on imitating human operations with the help of new algorithms or models borrowed from the information science. Though, such robots are normally devised for particular tasks as well as their learning capability is poorer than that of human beings. Hence, it needs the close relationship between investigators from both robotics and neuroscience [6].

Researchers in [7] have identified that the growth of Brain-inspired computing system provides challenges in the basic theory and in the growth of software atmospheres, system integration, and hardware systems. Nowadays, the robotics field is the most dynamic regions of technological growth. Though, the shortage of intelligence in present service and industrial robots restricts severely their applications. Hence, the major problem in advancing this robotics field is providing robots with cognitive capabilities. Eventually, researchers view the most vital imperatives as providing robots with insightful abilities drastically decreasing their power usage. If robots need an insightful ability in a dynamic and complex atmosphere, then it will be complex for them to assist other cognitive operations, let unaided to learn and operate autonomously.

A report by PWC (2017) has established that AI indicates to the capability of computer or computed-based robotic system to practice information and attain results in a way akin to the image process of human beings in decision making, solving problems and learning. AI will identify the application in a wider variety of cognitive domains like language, learning, creativity, planning, and reasoning. Extensively, the collaboration of human and AI may consider the following types:

- AI carries out beside human beings in a helpful mode, aiding human judgment through giving resources like predictive results;
- AI conducts actions that surpass the cognitive capabilities of human beings in applications, where it is cognitively or physically not possible for humans to do accurate analysis (i.e. Large scale genome analysis in bio-informatics); and
- AI operates instead of humans – supremely in atmospheres, which are possibly risky to human beings or need a phenomenal reaction time (i.e. Toxic atmospheres and fast system response in the nuclear reactors) [8].

In [9], researchers have found that transfer learning is an enhancement of learning in a novel task by the knowledge transfer from an associated task, which has been learned already. Whilst most machine learning techniques are proposed to address single tasks, the growth of techniques that make ease the transfer learning is a concept of enduring interest in machine learning community. Transfer techniques have a tendency to be greatly reliant on machine learning techniques that were employed to study the tasks and may frequently be assumed expansions of those techniques. Some analysis of transfer learning is concernedto inductive learning and includes expanding well-known inference and classification techniques like Markov Logic Networks, Bayesian networks, and neural networks.

IMPLEMENTATION CHALLENGES IN HUMAN LIKE MACHINES

Recent advancement in AI has rehabilitated attention in developing systems, which study and imagine like people. Lots of advances have arrived from employing deep neural networks, skilled lengthwise in tasks like video games, board games, and object recognition, attaining performance that even beats or equals humans in several respects. In spite of their biological stimulation and performance attainments, these systems vary from the human intelligence in critical ways. Hence, the review steps forward in cognitive science recommending that really human-like thinking and learning devices will have to accomplish ahead of present engineering trends in both how and what they learn it. Especially, the researchers have argued that these devices must a) create casual models of the universe, which support elucidation and perceptive, more willingly than simply solving, pattern recognition issues; b) ground learning in intuitive theories of psychology and physics for supporting and enriching the knowledge which is learned; and c) control compositionality and learning to learn to quickly obtain and simplify knowledge to innovative tasks and situations [3]. There are two challenging issues for AI and machine learning includes:

- Learn to play Atari games Frostbite [10]; and
- Learn Simple Visual Concepts [11].

Character Challenge

A character has proven to be a classic problem for comparing different types of machine learning algorithm. The first challenge issues, handwritten character detection, a typical issue of comparing various kinds of machine learning techniques.

The issue of recognizing characters by all ways people make both printed and handwritten - consists of for the most part if not all the basic challenges of Artificial Intelligence. Whether or not this declaration is correct, it emphasizes the unexpected complexity that underlies a ‘simple’ human level concept such as letters [11]. There are at a minimum of two significant variations include: and people learn from some instances and they learn more affluent depictions, a comparatively accurate for both learning of more general classes of objects and handwritten characters. Additionally, in order to recognize new instances, people may also create new instances; parse the character into its major parts as well as relations; and create new characters provided a small group of relative characters [12]. For simple visual concepts, humans are still more and more sophisticated learners when compared to finest algorithms for recognizing characters. People learn more and capturing these human level learning capabilities in machines is said to be Characters Challenge. Recently, researchers have reported enhanced on this challenging issue by probabilistic program induction, yet aspects of complete human cognitive capability to stay out of reach.

The Frostbite Challenge

The second challenge issues ‘Atari game Frostbite’ that was the control issues managed through DQN (Deep Q-learning Networks). DQN was considered as an important advance in the reinforcement learning, revealing that a solitary technique may study to play a broad range of difficult tasks. In Frostbite challenge, player’s manager an agent like Frostbite Bailey tasked with building an igloo within certain time constraints [13].

Start Up Software Development

Human beings have an initial understanding of various core domains. The domains such as space (navigation and geometry); psychology (groups and agents); number (set and numerical operations); and physics (mechanics and inanimate objects), in development. These key domains cut cognitions by the side of its conceptual joints and every domain is planned through a group of units and abstract standards concerning the units. The basic cognitive depictions may be recognized as ‘intuitive theories’, with causal structure similar to a scientific theory [14].

HUMAN INTELLIGENCE CORE INGREDIENTS

The ingredients have been considered in contrast with the current state of neural network modelling. These ingredients are considered to be key building blocks and integrating them produces powerful and human like learning and thinking abilities in AL system. The key ingredients required are as follows:

Intuitive Physics

Newborns have primal object concepts, which permit them to trace objects over time as well as permit them to reduce physically improbable trajectories. Organized with these common standards, people may learn more quickly and create more precise forecasts. Whilst a task can be novel, physics works the similar way still.

Intuitive Psychology

Newborns recognize that human beings have psychological conditions such as beliefs and goals. This understanding powerfully limits their forecasts and learning. These kinds of suppositions additionally intensify the learning of novel tasks.

Learning in Model Building Stage

Next, the model building stage is the hallmark of human level learning or elucidating observed data by the creation of world's casual models. Under this viewpoint, the current capabilities for intuitive psychology and physics are also considered as the world's casual models. An initial task of learning is to expand and augment these models, as well as to create parallel casually structured theories regarding other domains.

Compositionality

Compositionality is considered as a typical concept that new depictions may be built by the mixture of primal components. The primal functions may be merged together to generate new tasks and these new tasks may be additionally merged to generate even more complex tasks, in computer programming. This task hierarchy offers an effective description of greater level functions, such as a partial hierarchy for explaining complex scenes or objects.

Causality

In scene understanding and concept learning, causal models indicate imaginary real world methods from the perceptual remarks. In reinforcement and control learning, causal models indicate the environment structure, like action or modelling state to state transitions.

Learning to Learn and Fast Thinking

A way in which people obtain former knowledge by 'learning to learn', a word established by Harlow (1949) as well as closely linked to machine learning concepts of 'multi task leaning', 'representation learning or 'transfer learning'. These words indicate two ways in which learning a novel concept or task may be intensified by parallel or former learning of other linked concepts or tasks.

Model Free Reinforcement Learning

Model free reinforcement learning algorithms learn a control strategy with no explicitly creating a model of atmospheric (state and reward transition distributions). Model-based techniques, learn environment models and employ it to choose activities through planning.

MACHINE LEARNING TECHNIQUES

This section provides reviews on various deep learning techniques and machine learning algorithms used in developing efficient human machine interface models. The various algorithms used are as follows:

Fuzzy Systems

Researchers, in [15] said that managing problems linked to secure NPP (Nuclear Power Plants) is of great significance and priority for guaranteeing non-stop energy production. In order to improve safety, upgrade and modernizing of aging installations through integrating computerization processes is inevitable for various reasons between them, lifetime extension and environmental safety of presently functioning NPP. Hence, this analysis has aimed to propose a mechanism for estimating the HMI efficiencies in the safety of NPP. The developed evaluator was devised by using Fuzzy logic techniques. The results have shown that the proposed mechanism using fuzzy logic was more efficient and safety.

A research was carried out by researchers in [16] to concentrate on implementing HMI in the crane control using fuzzy logic technique. HMI application was generated from monitoring, visualization and dealing with transportation process recognized through crane. TSK (Takagi-Sugeno-Kang) model was more efficient in devising on PLC (Programmable Logic Controller) due to its result of fuzzy rules.

Convolution Neural Network

CNNs (Convolutional Neural Networks) are a category of deep neural models, which may perform directly on raw inputs. Though, such models are presently restricted to manage 2-Dimensional inputs. In [17], the researchers have proposed a new 3-Dimensional CNN model for recognizing of human activities. This model has extracted features from both temporal and spatial dimensions through conducting 3-Dimensional convolutions, by this means capturing motion information to encode in the multiple adjacent frames. The proposed model has created multiple information channels from input frames and last feature representation merges information from all channels. Findings have revealed that proposed model was outperformed other techniques and shown better performance in the real world atmospheres.

Deep Neural Network

Deep neural networks want more data than that of people to perform to solve the similar kinds of issues, whether it learns to play, an innovative game or learn to detect a new kind of object. It can be complex to incorporate physics-oriented primitives and object into DNN, but the payoff with respect to learning speed and performance might be high for various tasks. Assume the condition of ‘learn to play Frostbite’. Though, it may be complex to distinguish precisely how a system learns to solve a specific task, the DQN possibly doesn’t parse Frostbite screenshot with respect to stable things or sprites moving along with intuitive physics rules. But integrating a physics-engine-oriented representation might assist DQNs ‘learn to play games’ like Frostbite in quicker and more commoner manner, whether knowledge of physics is captured explicitly in the simulator or implicitly in a neural network [18].

Genetic Algorithm

In [19], researchers have designed a new HMI interface of cabin depends on GA-ACA and cognitive ergonomics. To assume the psychological, cognitive features influencing operating comfort and recognize cognitive ergonomics, automatic layout design and Genetic Algorithm and Ant Colony Algorithm (GA-ACA) were established in layout design of HMI interface. Initially, in accordance with information processing practice, cognitive model of HMI interface was established from the cognitive psychological perspectives. For justification, the layout design of HMI interface of the drilling rig center of operations was considered as an instance. The optimization finding has revealed the effectiveness and feasibility of the proposed technique.

Hidden Markow Model

Intelligent HMI derived from the multi-model interaction are proposed separately in various application regions. There is no combined opinion subsists regarding the problem of what features most these interfaces have to give a natural as well as intuitive interaction. Having performed a methodical review of the articles, which tackle with intelligent interactions a group of features are given that are required for intelligent interactions among a human and an information system. The features include: justification, training, adoptiveness, absolute response, training, collectivity, personification, portability, security, filtering, portability and hidden persistence [20]. Currently, hidden persistence features of IHMI have appeared in the kind of inter-operational and operational persistence.

Support Vector Machine

Humans intuitively and naturally employ facial expression as a powerful and significant modality to share their emotions as well as to intermingle socially. There has been sustained study interest in allowing computer systems to recognize expressions and to employ the emotional information entrenched in them in HMI. This poster has presents the application of machine learning system of SVM (Support Vector Machines) to the detection and categorization of facial expressions in both live video and still images [21]. By developing and using the automatic SVM model is the most probable one to attain the enhanced performance and raise the accuracy of SVM-oriented expression detection techniques in creating socially intelligent and effective HMI.

COMPARATIVE ANALYSIS

Since the origination of AI, people have required to create devices that learn and imagine like themselves. If SHRI systems are devised, then their impact on humans and society are progressively assumed, at large. Presently, it is very complex to compare robotic systems developed for various issue domains; thus far it is significant to perform so to initiate benchmarks for ethical and efficient SHRI design. It has been argued for proposed tasks and comparative techniques for SHRI, with specific concentration on attaining a better perceptive humanoid robot devised for SHRI. The most challenging factors of establishing such tasks are that various facets of SHRI are complex to measure. Most of the advancement arrives from modern advances in ‘deep learning’, typified through learning huge neural network models and multiple layers of demonstration. The results found that DNN and SVM were outperformed than that of other techniques in performing specific tasks with learning the speed of human beings.

CONCLUSIONS

A new SHRI architecture was initially implemented using AI and machine learning technique like Fuzzy systems, CNN, DNN, Genetic algorithm, Hidden Markov Model, and SVM. Artificial Intelligence has a tale of busts and booms, so far by any traditional success measures, the past some years have been noticeable through exceptional advancement. Analysis and design in Social-Human Robot Interaction demandmuch higher involvement of the human society that has happened in the past, excluding for several contexts like military and commercial aviation systems, in which human factors experts have long involved. Many of this advancement has arrived from modern advances in ‘deep learning’, typified through learning huge neural network models and multiple layers of demonstration. Here, some key ingredients like Intuitive Physics, Intuitive psychology, Learning in the model building stage, Compositionality, Causality, Learning to learn and fast thinking and Model-free reinforcement learning for developing computational models were suggested with more human-like thinking and learning. These ingredients may prompt the evolution on key AI issues with real-world applications. In future, there will be a hope that SHRI is the most stimulating growths of social robotics that is creating a novel generation of emotional devices and sequentially turning into human-design centered interactions of the forthcoming smart world.

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