Review of Recent Trends in Measuring the Computing Systems Intelligence

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Abstract

Many difficult problems, from the philosophy of computation point of view, could require computing systems that have some kind of intelligence in order to be solved. Recently, we have seen a large number of artificial intelligent systems used in a number of scientific, technical and social domains. Usage of such an approach often has a focus on healthcare. These systems can provide solutions to a very large set of problems such as, but not limited to: elder patient care; medical diagnosis; medical decision support; out-of-hospital emergency care; drug classification among others. A recent key focus is that most of these developed intelligent systems are agent-based approaches, or in other words, they can be considered as agent-based intelligent systems (ABISs). ABISs are formally based on a set of interacting intelligent agents (IAs) in addition to the use of intelligent cooperative approaches namely forming intelligent cooperative multiagent systems (ICMASs). The main direction of study consists in the possibility to measure the artificial systems intelligence, frequently called machine intelligence quotient (MIQ). Recently, we performed some research related to the measuring of the machine intelligence. There is presented a comprehensive review of the scientific literature related to the measuring of the MIQ. We consider that the measuring of the machine intelligence is very actual and important, which could allow the differentiation of ABISs based on their intelligence, choosing of the agent-based systems able to solve the most intelligently specific problems. As the main conclusion of the performed study, we mention that cannot be given a unanimous definition of the ABISs intelligence. Even if the machine intelligence cannot be defined, it could be measured. We discuss this affirmation more in-depth in the paper. This is similar to the human intelligence that is not understood very well but can be measured using human intelligence tests.

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1. Introduction

In this study, we call generically intelligent agent-based systems (ABISs) the intelligent agents (IAs), and the intelligent cooperative multiagent systems (ICMASs). The motivation for using this generic name is based on the fact that, from the external point of view, a cooperative multiagent system can itself be viewed as an individual system. Whoever submits a problem for solving to the system maybe does not perceive that the problem is solved by an agent or cooperatively by more agents. A human or an agent submits a problem to the system, and the problem consequently is solved cooperatively by the agents' members of the system.

There are many ABISs applied for a very large variety of problems solving by different type and complexity (Iqbal, Altaf, Aslam, Mahmood, & Khan, 2016; Popescu-Bodorin, & Balas, 2010). As examples of applications of ICMASs and IAs we mention: support for automated radiology exam (Shang, & Popescu, 2000); monitoring systems (Patrut, & Tomozei, 2010); accounting education (Patrut, Varlan, Socaciu, 2008); detection and continuity perception on fish otolith images (Guillaud, Troadec, Benzinou, Bihan, & Rodin, 2002); real-time configuration of IP networks (Yang, Galis, Guo, & Liu 2003); homecare e-services for elder peoples (Campana, Moreno, Riano, & Varga, 2007); smart emergency applications based on multiagent systems (Bergenti, & Poggi, 2010); intelligent agents applied in the library environment (Liu, 2011); problems solving such as interactive e-learning and e-testing (Arif, Illahi, Karim, Shamshirband, Alam, Farid, Iqbal, Buang, & Balas, 2015); safe and effective acute care delivery (Pickering, Litell, Herasevich, & Gajic, 2012); agent-based execution of personalized home care treatments (Isern, Moreno, Sánchez, Hajnal, Pedone, & Varga, 2011); smart e-health environment for diabetes management (Kafalı, Bromuri, Sindlar, van der Weide, Aguilar Pelaez, Schaechtle, Alves, Zufferey, Rodriguez-Villegas, Schumacher, & Stathis, 2013); agent-based health monitoring of elderly people in indoor environments (Vaidehi, Vardhini, Yogeshwaran, Inbasagar, Bhargavi, & Hemalatha, 2013); integrative multi-agent clinical decision support system (Shirabad, Wilk, Michalowski, & Farion, 2012); collaborative intelligent agent-based approach for proactive postmarketing drug safety surveillance (Ji, Ying, Farber, Yen, Dews, Miller, & Massanari, 2010). In the papers (Kerti, & Nyikes, 2015; Iantovics, 2015; Nyikes, Németh, & Kerti, 2016; Albini, & Rajnai, 2018) there are treated a variety of aspects related to the security in different systems including agent-based systems.

In the scientific literature, the computational intelligence is considered as a set of fields that include: neural networks (McCulloch, & Pitts, 1943; Hebb, 1949), evolutionary computing (Fraser, 1958; Holland, 1975) and fuzzy logic (Zadeh, 1965). Methods of computational intelligence are applied to many computational hard problems solving. Applications of computational intelligence include neural networks used for handwritten zip code recognition (LeCun, Boser, Denker, Henderson, Howard, Hubbard¸ & Jackel, 1989); autonomous evolution of computer programs based on evolutionary algorithms (Koza, 1992). There are applications of the fuzzy logic for the control of the movement of high-speed trains. An example in this sense is the high-speed train in Sendai (Kosko, 1994), in which the method based on fuzzy logic was able to improve the economy, comfort, and precision of the ride.

In order to eliminate a frequent confusion in understanding, we outline the difference between intelligent systems and the computational intelligence. If an intelligent system uses one or more methods based on computational intelligence, this does not make it automatically an intelligent system. For illustrative purpose, we mention a very simple mobile robotic agent (mobile robot with agent properties) able of recognizing different objects based on the image of the objects using neural networks. Based just on the fact that the robotic agent uses a neural network (a field that belongs to the computational intelligence) cannot be considered an intelligent agent-based system. But, intelligent systems can use other methods based on computational intelligence for different problems (or subproblems) solving during their operation.

In spite of a large number of studies and research, there is still a lack of a universal comprehensive definition of intelligence from the agent-based system perspective. In this paper, we analyze by making a comprehensive study of the scientific literature, beginning with the biological intelligence, the possibility of giving a definition to the agent-based systems intelligence. We also outline, as a general conclusion, that such definitions are not so important in comparison to the measuring of machine intelligence. In the performed study of definition of machine intelligence, we start from analyzing the biological intelligence.

The existence of some properties of the ABISs that could be associated with the intelligence does not allow a quantitative evaluation; they just formally prove its existence. Based on the importance of the quantitative evaluation of the machine intelligence, we made a comprehensive review of the state-of-the-art of the research and studies related to measuring the machine intelligence. As one of the conclusions of our study, we mention that there is no universal view of what the machine intelligence is. There is no standardization of intelligence measuring. We consider that the evaluation of an artificial system's intelligence must be based on some metrics or tests that allow the effective measuring of the quantity of intelligence. Such an obtained measure is frequently called Machine Intelligence Quotient (MIQ). The obtained machine intelligence measure of an intelligent system should allow the comparison of the studied intelligent system with the intelligence of another system.

The upcoming part of the paper is organized as follows: In Section 2 we analyze the possibility of definition of the intelligence of ABISs, the first subsection analyses the biological intelligence, the second subsection analyzes the possibility of definition of machine intelligence; Section 3 analyses the necessity and possibility of measuring the machine intelligence of artificial agent-based systems; In Section 4 we discuss the studied subjects and Section 5 outlines the final conclusions of our study.

2. Can the intelligence of agent-based systems defined?

2.1. Biological intelligence the result of long-term evolution of life on earth

The biological intelligence of different life forms, ranging from very simple (such as plants) to very complex (such as humans) is the subject of many studies and a large amount of research. Frequent studies related to different kind of biological intelligence include: the intelligence of horses (Krueger, & Heinze, 2008; Krueger, Farmer, & Heinze, 2014; Schuetz, Farmer, & Krueger, 2016), intelligence of pigs (Broom, Sena, & Moynihan, 2009), intelligence of dogs (Coren, 1995), intelligence of primates (Reader, Hager, & Laland, 2011) and so one. Figures 1, 2, and 3 present some biological life forms that are frequently considered intelligent.

Trewavas (2002; 2005) considered that plants intelligence should be based on principles such as their ability to adjust their morphology, and phenotype accordingly to ensure self-preservation and reproduction. Figure 1.1 presents an intelligent plant (carnivorous) that uses a strategy for catching very fast flying insects. In order to eat the insect, it makes a movement. Figure 1.1 presents the catching of an insect by a carnivorous plant.

The intelligence of colonies of ants, termites and other insects that live in large colonies is considered at the colony level (Brady, Fisher, Schultz, & Ward, 2014; Johnson, Borowiec, Chiu, Lee, Atallah, & Ward, 2013). Figure 1.2 presents the coherent intelligent surviving behaviour of a colony of a species of ants. The ants make a structural reorganization in order to move on the surface of the water.

Figure 1.3 presents a very large school of fish with an intelligent coherent collective feeding and self-protecting behaviour. Each individual fish has a very simple behavior. Based on this it cannot be considered intelligent. The intelligence in large schools of fish emerges at the collective level (Shaw, 1978; Parrish, Viscedo, & Grunbaum, 2002).

Some species of birds have been shown capable of using different tools. Many studies consider the crows as very intelligent. Smirnova, Lazareva, and Zorina (2000) suggested that crows have some kind of numerical ability. Figure 2.1 presents a crow that uses a tool, a small stone in order to catch a worm from a glass of water.

Figure 1. Intelligence of different simple living creature (accessed 01.11.2017).
1.1. A carnivorous plants catching an insect (https://phys.org/news/2016-05-colombia-peace-reveal-jungle-species.html); 1.2. A colony of ants solving a very complex task (https://mappingignorance.org/2016/05/27/rafting-ants); 1.3. The collective behaviour of a school of fish (https://simple.wikipedia.org/wiki/Shoaling_and_schooling)

The dolphins in many studies are considered intelligent at the individual level. An advanced ability of dolphins is the self-awareness. Marten and Psarakos (1995) presented an interesting study based on self-view television to distinguish between self-examination and social behavior in the Bottlenose dolphin. The most well-known abilities of dolphins are to teach, learn and cooperate. Dolphins have a complex communication and social behaviour. Figure 2.2 presents the image of a common group of dolphins.

Some studies prove that primates are one of the most intelligent in the class of animals (Reader, Hager, & Laland, 2011). Orangutans are one of the most intelligent primates. The ability of orangutans to use different types of tools in order to perform tasks is well-known. Figure 2.3 presents an orangutan that uses a spear to catch fish. The orangutans can be considered intelligent at individual level.

Figure 2. Intelligence of different living creature (accessed 01.11.2017).
2.1. A crow solving a complex task (https://www.disclose.tv/spooky-genius-crow-had-to-be-removed-from-scientific-experiment-314886). 2.2. A group of dolphins with a social behaviour (http://www.sciencemag.org/news/2012/04/teamwork-builds-big-brains); 2.3. An orangutan that use a spear to fish (https://primatology.net/2008/04/29/orangutan-photographed-using-tool-as-spear-to-fish)

Elephants are large mammals of the Elephantidae family that are frequently considered very intelligent. One of their impressive ability is the very good long-term memory. Elephants exhibit mirror self-recognition, which is an indication of self-awareness and cognition (Plotnik, de Waal, & Reiss, 2006). Figure 3.1 presents an elephant named Suda painting a picture in the Chiang Mai, Thailand.

The study of the intelligence of Cephalopods is very interesting based on the fact that they have a very complex nervous system fundamentally different from that of vertebrates. It's interesting that only a part of it is localized in the brain (Hochner, 2012). They represent one of the most intelligent invertebrates and an important example of advanced cognitive evolution in animals.

Many observations proved that octopus species have an impressive spatial learning capacity, advanced navigational abilities, and advanced predatory techniques. The dexterity is important for using and manipulating tools. Zullo, Sumbre, Agnisola, Flash, & Hochner, (2009) studied the successful dexterity of octopuses. They have highly sensitive suction cups and prehensile arms, squid, and cuttlefish. This allows them to hold and manipulate objects. The motor skills of octopuses (Figure 3.2) do not seem to depend upon mapping their body.

Some species of parrots are able to mimic very well the human speech. There were performed many studies with parrots that shown that some individuals are able to associate words with their meanings. Another observed ability is to form simple sentences. It has been shown that some grey parrots perform at the cognitive level of a 3-year-old child in some tasks. Pepperberg (2006) proved that some parrots can count up to 6. Figure 3.3 presents a frequently studied species of parrots, called African grey parrot.


Figure 3. Intelligence of different living creature (accessed 01.11.2017).
3.1. A painting elephant (http://www.wittyfacts.com/suda-the-painting-elephant/); 3.2. A common octopus (https://en.wikipedia.org/wiki/Octopus). 3.3. An African grey parrot (https://en.wikipedia.org/wiki/Grey_parrot)

Considering humans, the intelligence consists in the cognitive abilities that allow them to perform tasks such as to learn, to understand, and to reason (Neisser, Boodoo, Bouchard, Boykin, Brody, Ceci, Halpern, Loehlin, Perloff, Sternberg, & Urbina, 1996). Intelligence enables humans to experience and think. They have capacities such as: recognizing complex patterns, comprehending ideas, making complex planning, solving difficult problems, and making complex decisions. Such highly advanced cognitive abilities are very few evolved in other living creatures. This makes the humans more intelligent than any other species on earth.

As a conclusion to the performed study related to the biological intelligence, with some of the studied references presented in this subsection, we mention that the biological intelligence is the result of the very long-term evolution of life on earth, and it emerged in different forms, observable in different living creatures. The evolution of life on earth is by a 0.5 billion of years (Bell, Boehnke, Harrison, Mao, & 2015). Also, it should be mentioned that supported by some of the studied works mentioned in this section, we consider that the biological intelligence generally, and biological intelligence of different life forms particularly, cannot be uniquely defined. The biological intelligence cannot be completely understood. The biological intelligence is a very good source of inspiration for the design of intelligent systems. For example, we mention the learning ability of different species used as inspiration for the design of machine learning algorithms.

2.2. Machine Intelligence and Intelligent Systems

One of the major branches of the design of ABISs consists of the intelligent agent-based robotic agents. The intelligent robotic agents are robots with properties of intelligent embedded agents that could be static (they are not able to move in the physical environment) or mobile (able to move in the physical environment). There have been developed many robotic agents at worldwide able to perform simple tasks (as an example we mention the scenario of a robotic agent composed of complex sensors, able to identify objects in the physical environment) as well as very complex problems (for example, out of the next-generation developments that could be designed in the near future, we mention the intelligent autonomous flying drones able to transport goods and passengers).

Figure 2.1 presents Erica, a well-known more than 23-year-old humanoid robot developed by Professor Hiroshi Ishiguro from Osaka University. Erica understands spoken Japanese not only with audio; but also with body language, such as blinking, moving the head, and raising the eyebrows.

Atlas is a highly advanced bipedal humanoid robot developed by the American robotics company Boston Dynamics. The 1.8-meter high robot is designed for a variety of search and rescue tasks. Atlas robot was unveiled to the public on July 11, 2013. Figure 2.2 presents the photo of the Atlas robot that is more recent then the Erica robot.

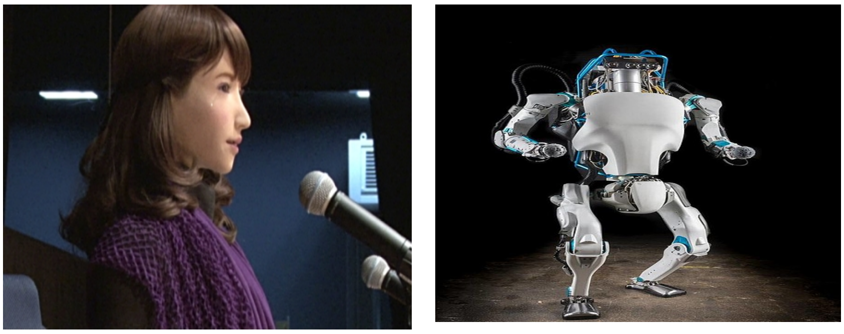

Figure 4. Intelligent robots (accessed 01.11.2017).
4.1. Erica, a humanoid robot (https://www.tech-review.com/erica-is-the-latest-japanese-robot-with-human-appearance.html). 4.2. Atlas, a bipedal humanoid robot developed by Boston Dynamics (https://en.wikipedia.org/wiki/Atlas_(robot))

One of the most highly quoted and interesting definitions of machine intelligence was presented by Alan Turing (1950). Turing considered a computing system intelligent if a human assessor could not decide the nature of the system (being human or artificial) based on questions asked from a room hidden from a human assessor. Until recently there were performed different discussions and comments on the Turing test. Hernández-Orallo (2000) presents an interesting study related to the Turing Test. Dowe and Hajek, (1998) propose a computational extension of the Turing Test. The design and development of intelligent systems are historically very recent. But, even if the advance of hardware and software is very fast, it will take a longer time until the artificial computing systems will attain a similar intelligence with the humans. Based on this fact, we consider that is not appropriate to formulate the problem of the direct comparison at a general level of human intelligence with the machine intelligence.

Different definitions were proposed for the intelligence of the agents (Russell, & Norvig, 2003; Iantovics, & Zamfirescu, 2013). Many authors (Russell, & Norvig, 2003; Iantovics, 2005) argue that the intelligence of the agents cannot be defined universally. The impossibility to give a universal definition to the human intelligence is based mostly on the enormous complexity of the human brain and complexity of the human thinking and decision making. Similarly, we may consider the impossibility of universal definition of intelligence of the agents based on the very large variety (by type and complexity) of intelligent agents. The machine intelligence frequently is defined based on different abilities such as (Iantovics, 2005; Sharkey, 2006): autonomous learning, self-adaptation, and evolution. These principles of considering the intelligence are inspired by biological life forms able to learn autonomously during their life cycle, to adapt to the environment and to evolve during more generations. We would like to outline that not all the designed agents are intelligent. There is not a required property of an agent to be intelligent.

Beni and Wang (1990) introduced the concept of Swarm Intelligence (*SI*), which is widely used in Artificial Intelligence. *SI* was introduced in the context of cellular robotic systems. *SI* at a general level can be defined as the collective behavior of self-organized, decentralized, natural or artificial systems.

Cooperative multiagent systems are composed of two or more agents that cooperatively solve undertaken problems. The members agents of a cooperative multiagent system are not necessarily intelligent but, at the system's level, many times is emerging an increased intelligence. Frequently, the intelligence of a cooperative multiagent system is considered at the system's level.

There are many developed cooperative systems composed of very simple agents that at the system's level are considered intelligent. Yang, Galis, Guo, and Liu (2003) presented an intelligent cooperative mobile multiagent system composed of simple reactive agents. The mobile agents are specialized in a computer network administration. They are endowed with knowledge retained as a set of rules which describe network administration tasks. The multiagent system could be considered intelligent based on the fact that it simulates the behavior of a human network administrator.

In some cooperative systems, the member agents can organize themselves into cooperative coalitions/groups. Each coalition being able to solve cooperatively problems. Iantovics and Zamfirescu (2013) presented such an adaptive cooperative multiagent system, able to reorganize autonomously the coalitions in order to solve more intelligently problems.

The biological and artificial intelligence are by a completely different type (Figure 5). Recently, the biological intelligence is the source of inspiration for the development of many intelligent artificial systems and different problem-solving algorithms.

Figure 5. What machine intelligence is (accessed 01.11.2017)
http://www.ibmbigdatahub.com/blog/measuring-artificial-intelligence-quotient)

For example, we mention the very well-known problem-solving based on the behaviour of natural ants which are in search for food. Marco Dorigo (Dorigo, Maniezzo, & Colorni, 1991; Colorni, Dorigo, & Maniezzo 1991; Dorigo, 1992; Dorigo, Maniezzo, & Colorni 1996) proposed the problem-solving based on simple computing cooperative agents that mimic the behavior of natural ants. There are many such algorithms and systems (swarms of mobile robots) applied for different problems solving, such as the Min-Max Ant System (Stützle, & Hoos, 2000), Ant Colony System (Dorigo, & Gambardella, 1997), Best Worst-Ant System (Cordon, Herrera, Viana, & Moreno, 2000). Applications of the problem-solving based on natural ants include: post-rolment course timetabling problem-solving (Jaradat, & Ayob, 2010), quadratic assignment problem-solving (Stützle, 1997) and many others.

3. Measuring the machine intelligence

Even if there is no unique definition of the human intelligence, there are different tests used to measure the human intelligence called Intelligence Quotient (IQ) (Chase, 2005; Kaufman, 2009; Nicolas, Andrieu, Croizet, Sanitioso, & Burman, 2013; Raven, 1936; Bilker, Hansen, Brensinger, Richard, Gur, & Gur, 2012; Wechsler, 1939; Kaufman, & Lichtenberger, 2006; Kaufman, & Kaufman, 1983; Kaufman, & Kaufman, 2004). There are some critics of human IQ measuring, arguing that IQ test scores alone ignore many important aspects of human mental ability (Neisser, Boodoo, Bouchard, Boykin, Brody, Ceci, Halpern, Loehlin, Perloff, Sternberg, & Urbina, 1996). Schmidt and Hunter (2004) accentuate the importance of IQ for school and job performance.

Schreiner (2000) presents a study realized by the National Institute of Standards and Technology from US (NIST). The study was related to the creating of standard measures for intelligent systems. NIST's initial approach for establishing metrics attempts to address different theoretical and pragmatic subjects. Schreiner accentuates the important open research question related to how precisely intelligent systems can be defined and how to measure and compare the cognitive capabilities that intelligent systems should provide.

Fox, Beveridge, and Glasspool (2003) present a research focused on agents with cognitive capabilities. They consider very important the agents with Belief-Desire-Intention architecture (*BDI*) as a class of cognitive agents. There was designed a benchmark agent model appropriate for comparing agent-based systems. PROforma is an agent technology for modeling medical expertise. The benchmark was realized is order to carry out a case study analysis of this technology. The analysis was realized based on three points of view: object-oriented programming, logic programming and agent-oriented programming. There were presented different strengths and weaknesses of PROforma.

Legg and Hutter (2006) proposed a formal measure of intelligence. The authors appreciate that the performance in easy environments counts less toward an agent's intelligence that does performance in difficult environments.

An interesting study related to the intelligence of computing systems is realized by Legg and Hutter (2007). They show that a fundamental problem in AI is that the notion of intelligence cannot be uniquely defined. Based on the researchers' affirmation, nobody really knows what the intelligence is. There is outlined that the artificial cognitive systems are significantly different from humans. In the presented study, were considered some definitions of the human intelligence. Based on these definitions there were established some essential features, which later are mathematically formalized in order to produce a general measure of intelligence for artificial cognitive systems. The main objective was to capture the concept of machine intelligence. It is also realized a survey of other tests and definitions of the machine intelligence.

Anthon and Jannett (2007) consider the agent-based systems' intelligence based on the ability to compare different alternatives by various complexities. In the study ,it is considered an agent-based system one that perceives the environment via distributed sensors. For measuring the machine intelligence, a specific approach is applied. The proposal was tested by comparing the MIQ on different agent-based scenarios.

Hibbard (2009) proves that a constraint on universal Turing machines is necessary for Legg's and Hutter's formal measure of intelligence to be unbiased. The measure proposed by Legg and Hutter, defined in terms of Turing machines, is adapted to finite state machines. A No Free Lunch result is proved for the finite version of the measure.

Hernández-Orallo and Dowe (2010) present the idea of a general test called universal anytime intelligence test. The authors of the study emphasize that such a test should be able to measure the intelligence level of any artificial or biological system. The proposal is based on the C-tests and compression-enhanced Turing tests developed in the 1990s. There are presented different tests highlighting their advantages and limitations.

Hibbard (2011) proposed an intelligence metric based on a hierarchy of sets of increasingly difficult environments. An agent's intelligence is measured according to the ordinal of the most difficult set of environments that it can pass. The proposed measure is defined based on Turing machine and finite state machine models of computing.

Legg and Veness (2013) analyze the formal definition of machine intelligence that they call Universal Intelligence Measure (UIM) based on Hutter's Universal Artificial Intelligence theory. It is an extension of Ray Solomonoff's work called universal induction (Solomonoff, 1964a, 1964b; Solomonoff, 1978). Legg and Veness consider that the UIM is asymptotically computable. Building a practical intelligence test based on this principle is not appropriate. Legg and Veness study some practical issues involved in designing an applicable UIM. They developed a prototype implementation that was used in order to evaluate different intelligent artificial agents.

Frequently swarm systems are considered intelligent. Winklerová (2013) the collective intelligence of particle swarm system assess according to a proposed Maturity Model. The proposed model is based on the Maturity Model of C2 (Command and Control) operational space and the model of Collaborating Software. The aim of the study was to obtain a more thorough explanation of how the global intelligent behavior of the particle swarm emerges.

Besold, Hernandez-Orallo, and Schmid (2015) studied some difficult problems for the humans that could be used as benchmark problems for intelligent systems. Detterman (2011) proposed a challenge for the *MIQ* measuring by well-known human *IQ* tests. Sanghi and Dowe (2003) presented a computer program that was evaluated successfully on some standard human *IQ* tests. It surpassed the average human intelligence on some tests, by scoring above 100 (Sanghi and Dowe, 2003). 100 is the average human IQ value. Even if this computer program performed very well on some standard IQ tests developed for humans, we consider that the artificial and human intelligence cannot be directly compared. This is based on the fact that they are by a completely different type and are not directly comparable.

Chmait, Dowe, Green and Li (2015) presented a study related to the intelligence of CMASs. The researchers consider that the intelligence of the CMASs is influenced by the communication and observation abilities of the member agents. The authors formulate the research question, which of the factors from a considered set of factors has a more significant influence on the intelligence. The solving of the research question is approached using an information-theoretical approach. Using some tests, collaborative agents are compared considering different kind of communication and observation abilities. Based on the obtained results, Chmait, Dowe, Green and Li formulate the conclusion, that the effectiveness of CMASs with low observation/perception abilities can be significantly improved by increasing the communication efficiency.

Chmait, Dowe, Green, Li and Insa-Cabrera (2015) presents an interesting study related to the intelligence of cooperative coalitions of agents. It is proposed a metric considered universal, appropriate to empirically measure intelligence of different agents. The study presents different situations over which a coalition of agents can be more intelligent than other coalitions. There are discussed different influencing factors to the collective intelligence of cooperative coalitions of agents.

Some studies focus on measuring the machine intelligence using intelligence testing frameworks. Chmait, Li, Dowe, and Green (2016) elaborated some dynamic intelligence tests for measuring the collective intelligence. They presented a technical description of a proposed testing framework, design, and implementation. It is presented how it can be used to quantitatively evaluate the machine intelligence.

Zitnick, Agrawal, Antol, Mitchell, Batra, and Parikh, (2016) analyze tasks that are easy for humans but difficult for computing machines. There is presented a case study that explores the very popular problem by image captioning, analyzing its limitations in the context of a task for measuring machine intelligence. As an alternative task, there are analyzed the Visual Question Answering tests, that included a machine's ability to reason about language and vision. There is described a dataset unprecedented in size created for the task that contained more than 760,000 human generated questions about images.

MetrIntMeas metric (Iantovics, Emmert-Streib, Arik, 2017) is able to measure the machine intelligence of an evaluated swarm system and compare it with a considered reference machine intelligence value. The metric makes also a classification of a studied swarm system, by verifying if it belongs to the class of swarm systems with the considered reference machine intelligence value. There is given a definition to the swarm systems' evolution in intelligence. The evolution of a swarm system in the intelligence is defined as an increase in intelligence, measurable by using the *MetrIntMeas* metric.

Arik, Iantovics, and Szilagyi (2017) propose a method called *OutIntSys* for the detection of the systems with a statistically extremely low and extremely high intelligence, from a set of intelligent systems that solves the same type(s) of problems. The proposed method can be applied in choosing the most intelligent systems from a set of intelligent systems able to solve difficult problems.

Iantovics, Rotar and Niazi (2018) proposed a novel metric called *MetrIntPair* for measuring the machine intelligence of *CMASs*. The *MetrIntPair* is able to analyze two CMASs at an application of the metric. It makes an accurate comparison of the intelligence of the two studied

CMASs, and at the same time verifies if they can be included in the same class of intelligence. Systems that can solve problems with the same intelligence from the statistical point of view are classified in the same class. The intelligence comparison of two CMASs is based on specific pairwise problem-solving intelligence evaluations.

Recently (ACM Technews, October 18, 2017) at the Chinese Academy of Sciences have been developed a universal intelligence test that can be applied to both machines and humans. According to the researchers, it is appropriate to rank intelligent assistants such as Google Assistant and Siri on the same intelligence scale that can be used for humans. According to a case study performed using the proposed intelligence test, it has been shown that even a six-year-old human outperforms the very advanced digital Google Assistant.

During our study, we identified that an important aspect that should be treated at the development of intelligent systems is the analysis of the necessary intelligence. The analysis of necessary intelligence is important because sometimes an increased intelligence may even have disadvantages. For instance, if we have to consider an extremely intelligent agent as one that uses complex specializations for data processing and analyzing, but solves very simple problems, it would probably have to make considerably more complex computations (e.g. verification of numerous conditions) than would actually be necessary.

There are very few intelligence metrics presented in the scientific literature related to the importance of intelligent systems in solving problems. In this subsection, we presented some of the studies related to the machine intelligence measuring that we considered relevant. Only few designed metrics are able to make an effective comparison of more agent-based systems' intelligence. Comparisons should allow the classification of intelligent systems in classes of intelligence. Many designed metrics are dependent on some aspects, such as the intelligent system's architecture that is the most frequent. Based on this fact, their effective practical utilization is limited. Agent-based systems for solving the same type of problem could have a very large variety of architecture (reactive, BDI, subsumption and any other). This fact motivates the necessity to design metrics able to make an accurate comparison of the intelligence of more intelligent systems (two intelligent systems or any number of intelligent systems). We appreciate that such intelligence metrics must be universal, and should not depend on some relatively particular aspects such as the agent-based systems architecture. In previous studies (Iantovics, Emmert-Streib, & Arik, 2017; Iantovics, Rotar, & Niazi, 2018) we proved that the intelligence of the artificial systems, similarly with the intelligence of the humans have a variability. This is a suggestion to the researchers that would like to develop intelligence metrics to include in the analysis of the design of the metrics the treating of the aspect related to the variability of the intelligence of an agent-based system in problem-solving.

4. Discussions

Many difficult problems solving require computational intelligence or intelligent systems. We have discussed in the introduction section the difference between the notions computational intelligence and intelligent computing system. The importance of design intelligent systems is proved by the existence of many problem-solving solutions based on them. Most of the intelligent systems are agent-based, that could be intelligent agents or intelligent cooperative multiagent systems. The intelligence of the agent-based systems, IAs or ICMASs cannot be unequally defined. Sometimes it is necessary to give some relatively particular definition to ABISs in order to make them understandable. Such definitions of machine intelligence by our opinion must be based mostly on different kinds of problem-solving abilities such as: solving difficult problems; or could include some other aspects of problem-solving such as the efficiency, flexibility, and accuracy. Difficulties in problem-solving could consist in aspects such as they are NP-hard; present different types of uncertainty, such as missing or erroneous data. Image analysis (that could include medical images among others) consists in the extraction of some meaningful information from digital images (Solomon, & Breckon, 2010). Image analysis can range from the reading of bar-coded tags to identifying a person based on its photo. Many image analysis problems are computationally difficult.

We would like to outline the problem-solving difficulty from human and computational point of view. A problem-solving could be difficult to humans but easily solvable by computing systems. For example, we mention the search in a very large collection of data. A problem-solving could be easy to humans but difficult to solve by computing systems. In this category of problems can be mentioned some image processing in different domains such as the healthcare. Image processing could present different difficulties to computing systems (Georgieva, Kountchev, Draganov, 2014; Draganov, 2014; Georgieva, Draganov, 2016). There are many approaches of image processing based on intelligent agents such as: medical image segmentation based on intelligent agents (Bensag, Youssfi, Bouattane, 2015). A problem could be difficult to be solved to human specialists and computing systems in the same time. For example, we mention the comorbidities in humans. A comorbidity (Maj, 2005) is the presence of one or more additional diseases or disorders co-occurring with a primary disease or disorder. In many cases, comorbidities are so difficult that should be solved by more physicians and frequently claim for the support, or even a stronger assistance of medical information and/or decision support systems. Expert systems are classically well known for problem solving that would require human specialty knowledge. MYCIN (Shortliffe, & Buchanan, 1975; Buchanan, & Shortliffe, 1984) is an example of classical well-known medical expert system. There are some developments of intelligent agents who extend the classical expert systems with agent properties allowing them additional intelligence. López-Ortega and Villar-Medina (2009) presented a multiagent system able to construct production orders that combine/hybridize an expert system and a neural network.

We would like to outline that our consideration related to the artificial intelligence consists in the fact that the intelligence of artificial systems could not be uniquely defined, but could be measured. In analogy, we mention the human intelligence that cannot be precisely defined. Nobody knows what the human intelligence is, but there are intelligence tests able to measure the human intelligence. As examples of the best-known human IQ tests we mention *Stanford-Binet* (Chase, 2005; Kaufman, 2009; Nicolas, Andrieu, Croizet, Sanitioso, & Burman, 2013), *Raven's Progressive Matrices* (RPM) (Raven, 1936; Bilker, Hansen, Brensinger, Richard, Gur, & Gur, 2012), *Wechsler Adult Intelligence Scale* (Kaufman, Lichtenberger, 2006; Wechsler, 1939) and *Kaufman Assessment Battery for Children* (Kaufman, & Kaufman, 1983; Kaufman, & Kaufman, 2004). Such evaluated test results at humans have applicative value, based on the fact that the intelligence influences how the humans solve complex problems at the job, the students how easily could learn. We would like to outline that intelligence is not the only influencing factor in efficient solving of less or more complex problems. Problem-solving by the humans is influenced also by other aspects such as the detained problem-solving specialty knowledge.

Based on a comprehensive study of the literature, we can conclude that there is no universal view of what an intelligence metric should measure. An important subject that could be derived consists in the standardizations of the intelligence metrics. There are very few reported metrics for the measuring of the machine intelligence which are based on different principles of measuring the machine intelligence.

We consider the measuring of the machine intelligence as an open direction that should be focused on the principle of problem-solving ability. Elaborated metrics must be able to measure the machine intelligence of an artificial system and the obtained intelligence measure must be comparable (should allow the comparison with the intelligence of other systems). If a metric is able to obtain the MIQ value of ABISs, it should indicate which system how intelligently can solve problems. As an important property that an intelligence metric should possess, we mention the requested necessary universality. This is based on the fact that a type of problem (or more types of problems) could be solved by agent-based systems with a very large variety of architectures. For example, we mention an intelligent agent able to autonomously pilot a flying drone, which could have a large variety of architecture such as: hybrid, stratified, subsumption etc.

Some studies (Hernández-Orallo, & Dowe, 2010; Legg, & Veness, 2013) consider the notion of universal intelligence metric at the general level, considering the capability to measure the intelligence of computing systems and the humans. We consider the universality in the context of computing systems. We consider the notion of universality as not dependent on the intelligent system architecture. In our study, we have not considered appropriate the comparison measuring of the intelligence of humans and computing system with the same metric/test.

5. Conclusions

The intelligence of artificial systems cannot be unanimously defined. There can be formulated just relatively particular definitions. Even though the evolution of intelligent systems is very fast, at this moment the artificial systems intelligence cannot be compared with the intelligence of the humans. We consider that it is just a matter of time when the artificial systems will become more intelligent than the humans. This moment we cannot predict it but it could come sooner than is expected. As a simple motivation, we mention a principle of complex systems that we call hiding of the complexity; this allows the handling higher and higher complexity tasks more and more easily by different computing systems.

We indicate as a very important research direction the measuring of the machine intelligence by universal metrics that could allow the differentiation between systems based on their intelligence. Elaborated effective intelligence metrics will have a large applicability. There are lots of systems whose intelligence should be measured. As examples, we mention intelligent agents able to drive autonomously or semi-autonomously cars, collaborative flying drones able to inspect distant lands, complex moving swarms of robots and many others.

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