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Classifications of Intelligence Agents and Their Applications

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Abstract. Artificial intelligence agent technology occupies an increasingly important place in modern times and finds more and more applications. This article discusses the classification of intelligent agents, based on their level of intelligence and the abilities they have, which are: simple reflex agents, model-based reflex agents, goal-based agents, utility-based agents, and learning agents (utility goal-based learning agents; goal-based learning agents). Many modern applications of intelligent agents and their role in areas such as medicine, training, culture, robotics, and others are considered, which proves the relevance of the task of modeling and researching their behavior and the search for new algorithms and methods to accelerate the learning process and their self-education. The advantages and disadvantages of the types of intelligent agents and some approaches for their improvement are discussed.

INTRODUCTION

An intelligent agent is an object that can make independent decisions and take action based on the knowledge it possesses. Agents have the opportunity to learn while performing their tasks. The actions they take are in line with both the information received from the environment and/or the knowledge that the agent has already gained from his previous experience.

One of the goals of artificial intelligence is to create fully autonomous intelligent agents who can successfully cope with their environment, be able to learn, make decisions based on their own experience, update and adjust their existing knowledge depending on the dynamically changing environment, to analyze and make adequate decisions when interacting with other intelligent agents working in the same environment.

The aim of the article is to consider both the classification of intelligent agents and their latest applications in the modern world to show the relevance of the task of modeling and studying their behavior. This article is organized as follows: Section 2 discusses the basic and most commonly used classification of smart agents. The latest applications of the intelligence agents are discussed in section 3. The advantages and disadvantages of the types of intelligent agents and some approaches for their improvement are discussed in section 4.

BASIC CLASSIFICATION OF THE INTELLIGENCE AGENTS

Taking into account the degree of intelligence and abilities of the agent, it's a way of deciding what action to take when interacting with the environment there are 5 main types: simple reflex agents, model-based reflex agents, goal-based agents, utility-based agents, and learning agents [1].

The simplest type of agent is a simple reflex agent. They decide what action to take based solely on current perception, but not on knowledge gained from their previous experience. Therefore, they have great speed and are widely used everywhere in practice where an immediate reaction (reflex) and even a survival reaction are needed. Reflex agents are simpler agents. They are widely used in industry, in social and assistive robotics, and in scenarios for human-robot interaction when an instantaneous response (reflex) is required in all situations where there is no time for reflection and a survival response is required. Example EEG and EMG based algorithms, error-related potentials, ErrPs based algorithm for agents. [2]

Model-based reflex agents are similar to those described above, but there are some improvements. This type of agent has a work environment model. The actions they take are based on this model, the state they are in, the set of rules that the agent has, as well as their previous perceptions when working in the environment. The challenge these agents face is again a limited set of rules, as well as the difficulty of working in partially monitored environments. [1]

Goal-based agents have not only a model of the work environment but also a goal that they must achieve. They must anticipate not only the next action but also all the other actions they must take to reach the goal. The agent's program can combine this with the model to select actions that achieve the goal. Search and planning are part of AI, dedicated to finding sequences of actions that achieve the goals of the agent. Goal-based agents always choose the optimal path.

To choose the most optimal path, Utility-based agents use the utility function, which is an essential part of the performance measure. For agents, taking into account the utility, explicit goal setting is complemented by a utility function. It introduces a measure of the success of the agent in a given state, in the form of a number. The utility function determines the relative importance of conflicting goals and the degree of success in achieving goals when working with uncertain knowledge. The agent is expected to maximize the utility function. [1]

Learning agents have the same capabilities as other intelligent agents, but they also have the ability to learn. Learning agents have initial knowledge, which is subsequently improved and supplemented. In this way, they increase their autonomy. The training element serves to successfully adapt the agent to an unfamiliar environment. Another element of these agents is the so-called critic. It sends feedback to the agent on how successful the action has been and how it can be improved. This element cannot be changed by the agent's behavior. Another crucial component of learning agents is the problem generator, which helps the agent to enrich their knowledge by generating new proposals for action. The proposed actions may not be optimal for the specific situation but may improve the future work of the agent. Learning agents can be utility goal-based learning agents or goal-based learning agents [1].

TABLE 1. Types of intelligent agents and their applications

Types of intelligence agents	Applications
Simple reflex agents	Vacuum-cleaner Robot[3] EEG and EMG based algorithms, error-related potentials, ErrPs based algorithms for agents [2]
Model-based reflex agents	MaSMT4[4] Agent-Based Methods in Support of Adaptive Instructional Decisions[5]
Goal-based agents	Modeling Behavior Change using Cognitive Agent Simulations [6]
Utility-based agents	Socially Intelligent Agents[7] Hurricane Emergency Identification [8] ECAs [9]
Learning agents (Utility goal-based learning agents; Goal-based learning agents)	Intelligent Software Web Agents[10] Smart Shopping Cart[11] BARICA system[12] A Dynamics Perspective of Pursuit-Evasion Games of Intelligent Agents with the Ability to Learn[13] Learning to Incentivize Other (LIO) Learning Agents [14]

In situations and scenarios where planning, reasoning, inference schemes, prioritizing and deciding in conflict situations, and seeking compromises need to be implemented, the types of smart agents used are goal-based agents, utility-based agents, and learning agents.

APPLICATIONS

Intelligent agents are widely used in the modern world. Their ability to learn, make independent decisions, comply with consumer requirements, compromise when there are conflicting goals [15], reason, and draw logical conclusions makes them essential in many areas, including training [14][16-19], medicine [20-25], e-commerce, sales of smart shopping agents [11], industry, tourism, games, disaster relief [9] and many more.

Application of Intelligent Agents in the Process of Student Education

The application of cognitive agents in the learning process of pupils, students, or other intelligent agents is advancing with each passing day. In [12] developed Beautiful Artificial Intelligence Cognitive Agent the goal is to support students in their various tasks and training. It receives voice commands, and then the BARICA system generates video with audio or text as output.

Visiting virtual museums in the modern world is not new. Anyone could visit the Louvre, the Metropolitan, and others virtually without traveling. On the other hand, the remote use of virtual museum collections for educational purposes is relevant [26]. Depending on the level of knowledge of the user, and his preferences in a particular area or specific exhibits, the virtual learning agent can choose the appropriate arrangement and way of presenting the information. The aim of the authors in [13] is to improve the dynamics and self-learning techniques of intelligent agents in Pursuit-Evasion Games. Both goal-based agents and utility agents are used. In [14], some of the intelligent agents can reward other agents who are trained with incentives and thus direct them towards achieving a certain goal.

Application of Intelligent Agents in the Process of Building Autonomous Cars

Autonomous vehicles are expected to contribute to safer and more efficient driving. Intelligent learning agents developed for this purpose usually work in a multi-agent environment and must be able to predict the behavior and trajectory of the agents around them in order to learn about the environment and the ability to make high-level decisions. This would lead to greater driving safety for autonomous vehicles [27].

The authors in [28] use a jointly learning agent, which is trained by the JAL-MTP method, based on multimodal trajectory prediction when driving in complex multi-agent environments. JAL-MTP prepares an example model of the possible current traffic on the lanes, in order to predict based on the selected trajectory and to adapt more easily to the road map. The future movement of agents is multimodal and requires the generation of multiple trajectories with probabilities. Stochastic models are used. It has been experimentally proven that accurate forecasts can be made in complex road conditions. The use of heuristic methods in the design of neural networks is recommended [28].

Application of Intelligent Agents in the Medicine

Intelligent agents are often used in medicine to diagnose certain diseases. The authors in [20] use goal-based learning agents to diagnose and predict heart disease. Autonomous agents must be responsive, proactive, and social. Not only do they perceive the environment, they react adequately to any change in it, but they can also interact with other agents or people in order to reach a solution to a problem. It is necessary to use filtering agents that remove unnecessary information and increase accuracy in training and analysis of results. One possibility is to use the Bayesian classification algorithm to classify the symptoms. The relationship between symptoms and disease can be calculated by applying information entropy theory in order to classify all symptoms according to a significance index [20].

The intelligent agent who plays an important role in rescuing people from natural disasters [8] must be able to gather information from various social media networks in real-time and identify messages that require rescue. The agent needs to retrieve the address and location of the victims and display them on an interactive map. It is appropriate to use deep learning for its training. There is an opportunity to build a concrete model of the world through messages on social networks related to natural disasters, which will lead to updating existing knowledge and deriving new rules [8].

Utility-based agents that visually mimic human behavior and image, not only reproducing but also responding to human speech, gestures, and facial expressions are, for example, Embodied Conversational Agents (ECAs). They use different ways of communicating, such as natural language, gestures, or facial expressions [9]. An example of the ECA is Webot, which is an automated conversational agent designed to provide cognitive-behavioral therapy through short conversations or tracking participants' moods. An experiment was conducted with students proving that Webot contributes significantly to reducing depression [29]. Conversational agents are entering widely into modern technology. Their ability to have a dialogue with people, and their ability to be constantly on the line, give those many advantages, especially in the field of e-commerce, healthcare, and others. They can give advice, and recommendations, and answer questions [30]. The application of conversational agents even reaches the stock exchange, where agents can give investment advice, and provide information about companies, stocks, and breaking news. In this way, consumers have a kind of personal, intelligent assistant [31].

Application of Intelligent Agents in Shopping and Services

Intelligent agents are an important part of the shopping world. They provide guidance to consumers by helping them find the products they want, navigate consumers in large stores or malls, inform them about active promotions [11], perform online shopping tasks [32], and help salespeople develop more profitable marketing strategies based on the behavior of their customers [33]. Customer convenience is very important during shopping. This is one of the reasons intelligent voice assistants are rapidly entering the realm of shopping. They can recognize and analyze consumer voice requests, as well as direct / recommend/assist them with a wide range of desired purchases [34].

Amazon Alexa is a voice assistant that is based on artificial intelligence. It provides users with personalized recommendations according to their needs and assists them in making decisions as well as in seeking information [35]. Such intelligent voice assistants are Apple Siri, Microsoft Cortana, Google Assistant, and Samsung Bixby. Although they can be good helpers in diagnosing diseases, there is still not enough research to assess the quality of health information provided by these technologies [36-37]. The constant need of users for a variety of information, as well as easier access to it, makes voice assistants a key technique for future intelligent systems [38].

DISCUSSION OF THE ADVANTAGES AND DISADVANTAGES OF THE TYPES OF INTELLIGENT AGENTS

From the considered features and examples of the use of the technology "artificial intelligent agents," it can be summarized that it is developing rapidly as new structural elements are added to the architecture of agents, which give them more and more options to solve increasingly complex scientific and practical problems. On the other hand, their complexity is growing and requires:

- More and more computing resources;
- High-performance processor architectures [39] and cloud technologies (Cloud computing) [40][41], utilizing multiple GPUs - graphic processor units with 10 million connections (2008), HPC - high performance computing [42] with many GPUs and 100 billion connections (2015) i.e. already used for parallel loads;
- Efficient use of memory through new ways of presenting and processing data [43-45];
- New faster algorithms and methods for extracting knowledge from data [46-48];
- Application of heuristics to accelerate finding the best solution for multivariate tasks such as Evolutional algorithms [49-50] and in particular Genetic algorithms [51-53], Imitation learning [54-56]; Deep learning [54][57];
- Using the knowledge and experience of experts as well as metaheuristics to make the proposed heuristics certainly useful and lead to a solution instead of a delusion [58];
- It is necessary for agents not only to be trained but the training process to be accelerated and improved;
- Decision-making to take into account even more circumstances and more moves forward [59-60];
- To achieve an understanding of the requirements of the users, so that the way proposed by the system to achieve the goal is accepted by them; even when compromises are needed, they are still acceptable to the consumer; when there is a conflict situation to find a goal that balances the existing advantages and disadvantages of the circumstances [61];
- Communication and dialogue skills with the consumer are required in order to achieve trust and effective mediation. This requires knowledge of the theory of mind, knowledge of human psychology, application of technologies for speech comprehension, speech synthesis, text reading, modeling of expression of emotions and gestures, skills of agents to understand emotions, facial expressions, and gestures [62-63];
- Production robots need to be increasingly safe to prevent accidents at work. In order to achieve this, security clearance methods must be developed for all actions to be performed by the production robot. Examples of

such activities are catching and moving parts that are in danger of being dropped; assembly, arrangement, and other activities in which the robot works in the same environment with the workers and are at risk of accidents [64-66];

- When working in a hazardous environment, in observations or situations where it is necessary to avoid dynamic obstacles, new approaches are needed to analyze the images from the cameras and recognize the events that occur, and recognize the context to predict the situation in its development [67].

For example, we are witnessing the greatest achievements of neural networks in speech recognition, image interpretation, and robotics. One of the reasons for this is the development of the idea of understanding the architecture of neural networks and being able to design them in such a way as to understand how they work. A useful idea in this direction is to decompose the task into subtasks. Each subtask is tonally decomposed into subtasks and this process continues until a set of elementary tasks is reached, the answer to which can be given by a hidden layer in the so-called deep neural networks. The use of filters, several different feature maps, local receptive fields, pooling, and techniques to reduce the number of connections that connect hidden layers are other successful methods for accelerating learning in deep neural networks, convolutional neural networks, and shared weights.

Another example is the social robots created by Honda, Aldebaran, and other leading companies [68-71]. They have even more degrees of freedom. For example, the smallest robot NAO has 25 degrees of freedom. If only three commands are used in his training to perform a task, such as: go forward, go backward, stop, then 325 possible actions will be obtained. The space of conditions is so large that the learning process will be slow and difficult and needs to be significantly reduced. In this regard, the optimization of the Reinforcement learning method known as Learning by demonstration or Imitation Learning is very successfully applied. In it, a teacher shows the robot the movement he needs to learn in a straight line, and thus the space of states is drastically reduced. Training is much faster this way.

In the field of data acquisition, the greatest achievements include the construction of decision trees, where the convergence is logarithmic; the construction of the smallest identification tree in the subject area, from which rules are derived, the most important prerequisites for an event to occur are determined; the construction of the version space, which further accelerates the process of building a generalized model of objects or events; the construction of probabilistic Markov and hidden Markov models of the nth order; the construction of Bayesian Models, which allow the interpretation of the causal relationships between the states in the model.

Social agents are required to recognize the hidden emotions, including masked emotions and gestures, to express emotions, engage in dialogue by following the rules of conversation, deliver an emotional speech, and sound different each time.

CONCLUSION

This article discusses the basic classification of intelligent agents based on their level of intelligence and the abilities they possess, which are: simple reflex agents, model-based reflex agents, goal-based agents, utility-based agents, and learning agents. Some of the numerous applications of the technology of artificially intelligent agents in medicine, the construction of autonomous cars, and communication with consumers in their daily activities are discussed. All these numerous applications confirm the relevance of the task of modeling and studying the behavior of intelligent agents; the need to look for new methods to accelerate the training of intelligent agents; the benefit of implementing new algorithms to improve the way agents achieve a goal and choose a goal to achieve; the importance of improving the way intelligent agents and humans communicate. The advantages and disadvantages of the types of intelligent agents and some approaches for their improvement are discussed.

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