Big Data Research 25 (2021) 100241

Contents lists available at ScienceDirect

Big Data Research

www.elsevier.com/locate/bdr

"Brains" for Robots: Application of the Mivar Expert Systems for Implementation of Autonomous Intelligent Robots

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ARTICLE INFO

Article history:
Received 10 March 2020
Received in revised form 16 February 2021
Accepted 6 June 2021
Available online 14 June 2021

Keywords:
Artificial intelligence
Logical inference
Mivar
Mivar technologies
Robotic systems
Expert systems

ABSTRACT

Recently the contemporary robotic systems can manipulate different objects and make decisions in a range of situations due to significant advances in innovation technologies and artificial intelligence. The new expert technologies can handle millions of instructions on computers and smartphones, which allow them to be used as a tool to create "decision-making systems" for autonomous robots. The goal of this paper was to create a dynamic algorithm of robot actions that can be used in the decision module has been considered. It is proposed to use Mivar expert systems of a new generation for high-level control. The experiment results showed that Mivar decision-making systems can control groups of small robots and even an unmanned autonomous car in real time. The algorithms created in the Mivar environment can be very flexible, and their build-up depends only on engineering approaches. In addition to traditional low-level robot control systems, a Mivar decision-making system has been implemented, which can be considered as universal "Brains" for autonomous intelligent robots and now knowledge bases can be created and various robots can be trained for practical tasks.

1. Introduction

Today, due to essential progress in computer science and mechatronics, robotic systems have been developing dramatically fast and their inclusion in our life is inevitable. When it comes to robots, one usually thinks about physical agents, who perform tasks by manipulating objects in the physical world [1,2]. The contemporary robotic systems can successfully manipulate different objects in the real world, recognize those objects, and even make decisions in a range of situations [3]. This happens due to significant advances in computer vision, manipulation techniques and artificial intelligence.

Today, all of the existing robotic systems can be divided into three categories: manipulators, mobile robots and hybrid robots [4], i.e. mobile robots equipped with manipulators [1]. Scientific foundations of robotic systems are broad. Engineers and scientists use various mechatronic techniques [5–7], create expert systems, implement various planning algorithms [8] and specialized algorithms for knowledge-processing [9], computer vision techniques, etc.

Advanced robotic systems are complex devices. Main components of robotic systems can be named "effectors" (like any device that affects the environment, such as legs and hands), sensors (allowing robots to perceive their environment, like cameras, gyroscopes, etc.), and control mechanism (robot's "intellect").

Nowadays, robotic systems are seen in different areas of human activity and mostly in industry. Manipulators play a key role there. The main purpose of these robotic systems is to perform precise and repeatable actions on the assembly line [10], which play a significant role in industrial applications. Another area of active research in robotics is aimed at robot-human collaboration. Such devices are called CoBots [11]. The main difficulty here is that robot or Cobot must be human-aware because they are supposed to work in a confined working environment and thus safety requirements cannot be ignored [12].

All robotic systems also can be divided by their operational regimes. First type is semi-autonomous systems. Those systems require full-time operator. There are also fully autonomous systems designed to operate without full-time human control. The intelligent robot is a mechanical system which can function autonomously and without mindless behavior [13]. Such a robot can adapt to changes in its environment and continue to reach its goal.

The development of intelligent robotic systems is strongly linked with the field of artificial intelligence. Intelligent robots

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https://doi.org/10.1016/j.bdr.2021.100241
2214-5796/

are the implementation of AI techniques applied to robots. Here, all the traditional aspects that are inherent for artificial intelligence systems are usually considered: learning, planning, knowledge representation, computer vision [12]. Thus, the goals pursued in research in the field of intelligent robotic systems differ from those in mass industrial robotics. If the latter focuses mainly on the dynamics and kinematics of the robotic system, the former puts main emphasis on robot decision-making process. In the field of artificial intelligence, there were several different areas of research, but new advances in the Mivar technologies [14] made it possible to combine the main scientific directions to achieve a common goal: the creation of a full-fledged autonomous intelligent robot. The low computing hardware requirements make it possible to talk about creating “brains” for robots and introducing global Mivar expert systems into small autonomous robots, for example, cars, unmanned flying vehicles, uninhabited submarines, etc. Mivar expert systems [15] perform logical inference with linear computational complexity and process more than a million instructions per second [16]. Mivar technologies will allow autonomous robots to make decisions in a complex environment in real time [17].

In this study, the author focuses on the questions of robot decision making on a logical level. The author proposes to use new generation expert systems as a main decision-making mechanism. To assess the intelligence level of robots the author proposes to use the same criterion, which is used for expert systems – the decision-making time (worst case). For these purposes Mivar expert systems will be used.

2. Literature review

Integration of service robots into human life has always been hampered by many factors: low reliability, high cost of machinery, insufficient battery capacity, high cost of sensors, and low intelligence level [18].

With the growth of industry, engineers managed to solve many problems, associated with the technical components of robotic systems, but the problem of intelligence remains still relevant today. Civil service robots should easily interact with modern infrastructure, be able to communicate with a person, and the most important feature of the intelligent robots should be the capacity of “reasonable behavior”. To implement such a feature, the system must necessarily include an autonomous decision-making system. One of the approaches to creation of such a system, or, in other words, to the intellectualization of a robotic system, was considered in works [13].

It should be noted that when creating a robot management system, one of the most important issues is the choice of the so-called paradigm for creation of “reasonable behavior” in a robotic system. To date, the most famous are the following three classical paradigms: hierarchical, reactive (reactive planning), and hybrid. According to all of these paradigms, the basic functions that a robot should perform can be divided into three types – feel, plan, and act (or sense, plan, and act) [19]. The functional elements of the system (functions) that fall into the category of feeling produce new information potentially useful to other functional systems of the robot upon receiving signals from external sensors. The functional systems, receiving information from sensors and producing a sequence of actions that a robot must perform, fall into category of planning. The third category includes all systems that produce actions related to movements (turn around by 30 degrees, move by 30 cm, etc.) of the robotic system [20].

Historically, the hierarchical paradigm arose as the first one, since this approach is most natural when making high-level decisions. When using a hierarchical paradigm, the robotic system performs actions “from top to bottom”, namely the robot first feels, then plans, and then acts (Sense-Plan-Act). However, the use of this paradigm, at the initial stage of its existence, faced definite difficulties. Since, according to the paradigm under consideration, the robotic system explicitly plans each of its next steps and, in addition, all sensory data are accumulated in the global model of the world, the use of this paradigm at the time of its appearance entailed a long time for the robotic system to make a decision, which is unacceptable for the robotic systems.

Therefore, subsequently, by the end of the 1980s, the so-called reactive paradigm arose. In this paradigm, the planning link was excluded. That is, the rigid “perception-action” cycle was imposed. The reactive controls act on the basis of the signals received from the sensors, and are well suited for making low-level decisions in real time. Such a paradigm has proven effective in application of the so-called “reflexive” solutions [21,22] or, in other words, for making low-level decisions in real time. However, such a paradigm is not suitable for making global decisions. Therefore, in most variants of robotic architectures, a combination of reactive and algorithmic methods is used, reactive methods are used at a low level, and algorithmic ones at higher levels. This approach is reflected in the third (hybrid) paradigm. It has been the most common one since early 1990s when it appeared. This paradigm combines the achievements of the first two. Namely, in the first step, planning is carried out, and then actions, executed according to the reactive paradigm are taking place. It is worth noting that today there are also paradigms that, in addition to plan-sense-act also include the essence of learning [23].

Thus, the most popular scheme for implementing the control of a robotic system today is the hybrid one. Although the timing of robotic decisions has been sharply reduced due to division of actions into reflective and global ones, there is still a question of how quickly the system can decide on a global level.

The main problem in the development of systems that are able to find global solutions is the computational complexity associated with the logical search for such solutions [21]. After all, as it is known, the problem of constructing an algorithm for solving problems assigned to a robotic system (an action plan for solving intelligence problems) or, in other words, the problem of inference, can be a complex combinatorial problem [24,25].

In the work [16] the authors propose to use a logical kernel based on Mivar technologies as a main part of the intellectualization block. In this case, the decision is made by the system in real time, since inference search has linear time complexity with respect to number of parameters in the system. This entirely new generation of Mivar expert system [26,27] which allows processing of more than five million instructions per second.

3. Expert system as a basis for a robotic control system

Thus, to develop a robotic system, which is able to make global decisions, the author proposes to build on top of the reflex level control system a Mivar decision-making control system (DMCS), resulting in a new control meta-system (CMS). Therefore, the Mivar kernel will form the basis for CMS. This kernel uses certain pre-calculated models (knowledge base in the considered subject domain) to evaluate output parameters, which can be defined by applying some transformation to a set of input parameters. As the simplest examples of such models, the author cites the model of traffic laws analysis (TLA), the model of the movement of a small robot over the field, different models of manipulations with objects (see the example below).

The structure of Mivar DMCS is shown in Fig. 1. The practical realization of Mivar-based DMCS is shown on the MIVAR channel on YOUTUBE via (Mivar pilot system video test) [28].

According to the presented scheme on Fig. 1, the task (in various formats) enters the system. Further on, the obtained information is converted into the format of parameters suitable for the

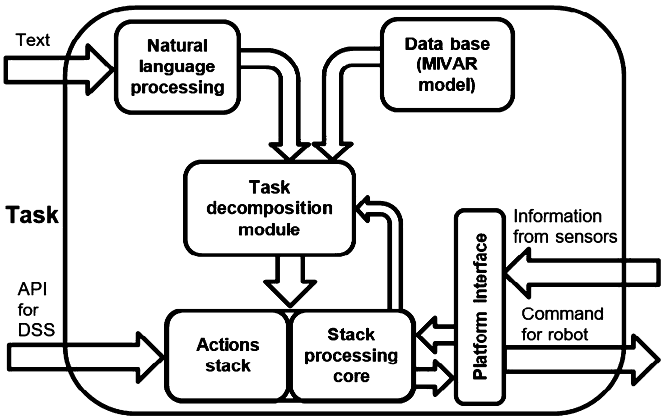

Fig. 1. Mivar decision-making control system.

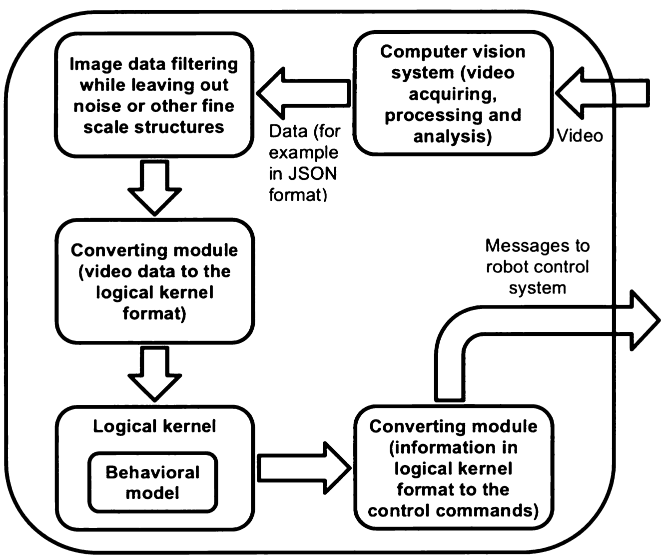

Fig. 2. Decision-making process.

existing model. With the assistance of the existing model, an algorithm for solving the problem is constructed, each step of which is placed on the action stack. Subsequently, information from this stack is converted into a command format.

As an example, the decision-making process for the source information in the form of a video is further considered in more detail. First, the video sequence enters the system of technical vision, where processing of the video stream takes place and thus the properties of the environment are determined. Further, in the form of an intermediate data structure (e.g., JSON message), the information enters the filtering unit, where noise is eliminated and bounce signals are taken into account. Next, the information from the camera is converted to a form required for the operation of the logical core. This information enters the logical core (with the model already loaded), for example, as a formatted JSON message with a set of input parameters for the calculation. The output parameters are calculated. A formatted JSON message with a set of output parameters, obtained after the calculation of the model, enters the conversion unit, which converts the output signals to control commands in accordance with the protocol of interaction with the equipment (see Fig. 2).

Integration of the intellectualization block, as described above, into a robotic system can be implemented, for instance, according to the scheme from Fig. 3.

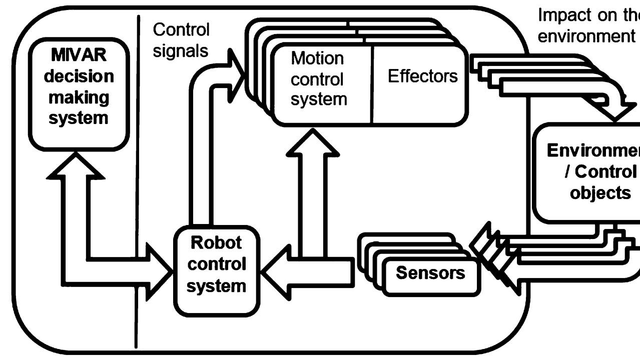

Fig. 3. DMCS in the robotic system.

The unit of intellectualization appears as a separate module, which, using various interfaces receives information about the environment, performs calculations according to the available model and translates the resulting data into commands for the control module.

4. Robot control systems and decision-making systems for robots

As was already mentioned above, the main part of Mivar decision-making control system is a logical kernel. This kernel works with the models which can be obtained using Wi!Mi shell [14]. As an example, a model implementing the management of a robotic cafe, or "Robocafe", highlighting the power of Mivar management system, is considered. The main purpose of the model is to organize the functioning of the office robotic canteen, namely, the reception of orders for servicing, the formation of relevant orders, and their delivery. The algorithm is not specified initially, but is constructed on the basis of the order parameters and variable initial conditions.

4.1. Formulation of the problem

Further, the following task of controlling the behavior of a multi-agent robotic system is described. It is required, using robots of two types, namely robot-cooks and robots-waiters, to organize the functioning of the office robotic buffet, namely, to plan the assignment of roles, prepare the incoming order and deliver the corresponding order (Fig. 4). Management at the group level is assumed to be centralized. In this paper, the author considers a model with a limited number of input parameters, a known displacement map (a map with static obstacles) and without any constraints limiting the time of order creation. The algorithm itself is not specified initially, but is constructed on the basis of order parameters and initial conditions. The presence, location and other parameters of the status object are set at the beginning of the calculations.

The variability of robot chain of actions depends on the initial conditions mentioned above.

For the execution of an order from the available list, one of unoccupied robot cooks is assigned. If the lack of objects in general or in the kitchen is detected, an order is formed and will be issued for the delivery of the necessary goods from the storeroom (Fig. 5). The main stages of the model are as follows:

1. Distribution of roles between the robotic chefs;
2. Selection of the main robot;
3. Sending a job to run in a service area;
4. Performing tasks;
5. Serving a tray;
6. Delivery of a tray to the customer.

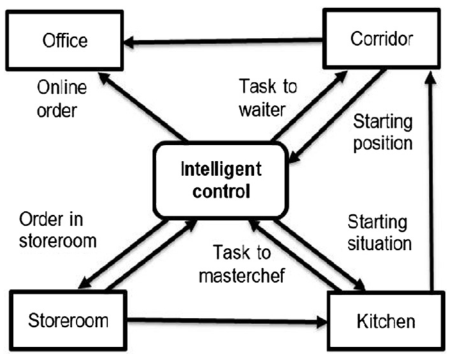

Fig. 4. Operation scheme of the robotic cupboard.

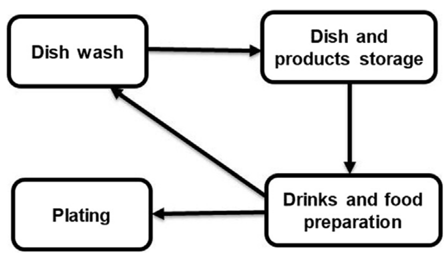

Fig. 5. Manipulating objects.

Thus, it is necessary to develop a model for control system that, based on the initial state of the environment, will produce an action plans for the robot system when executing an order. The Action Plan will be considered satisfactory if the order is delivered on the tray to the specified table or cabinet.

4.2. Building the model

For the development of robotic cupboard control system described above, a special framework (or shell) Wi!Mi is used.

To represent knowledge about subject area, a Mivar network is built and used internally by the shell. The Mivar network is a way of representing domain objects and rules for their further use in the form of a bipartite directed graph G (P, R, E), where the set of vertices is composed of objects (P) and rules (R). Together, these objects and rules form the domain model. Edges E connect rules and parameters (and vice versa). An important feature of the Mivar network is that for each variable from the set P the network explicitly stores information about all the rules from the set R, for which it is the input (X) or output (Y) variable, with a clear indication of that fact. Mivar network is constructed by connecting two sets of different type according to the rules: “object-rule” and “rule-object”. Relationships (i.e., edges) of the type “object-object” and “rule-rule” are not allowed. Based on this representation, Wi!Mi shell builds the inference route. Thus, when creating a model of robot control system, the key point is the generation of a network for a subject domain. To achieve that, one defines (or marks out) all objects of the subject area, and then links (or edges, in terms of graph theory) between the relevant objects are being established.

When designing the Mivar network for a particular subject area, the author, in the first phase, highlights the main objects, which, for convenience, are combined into classes. Examples of these classes include the following ones, see, for example, Fig. 6:

1. Customer order - a class that allows one to enter a job for robot groups.
2. Stockroom - a class that contains the list and the number of items in stock.

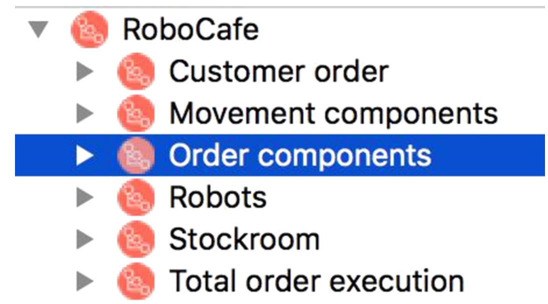

Fig. 6. The main classes in the control system model “Robocafe”.

Fig. 7. The subclasses and parameters of the “Order components” class.

3. Total order execution - a class that is used to calculate the complete algorithm. It is created due to the nature of the simulation environment.
4. Movement Components - a class used for the organization of movement.
5. Order Components - a class that is used to perform the task by robotic chefs.
6. Robots - a class that contains information about the status of robots and their names.

Further, the class named “Order components” is considered. This class contains a few subclasses: “Stuff in a dishwasher”, “Stuff in a cupboard”, “Stuff on a tray”, “Stuff on a table”, “Served dishes”. Each of the respective subclasses contains parameters used for the calculations (Fig. 7 a, b, c).

In this way, all necessary parameters are being defined to describe the knowledge base for multi-agent systems. The model described in the article contains 64 classes, 264 variables and 266 edges. The objects (products and dishes), location (functional, spatial), performers (robot waiters, robot cooks) represent here classes, while the properties of objects (the presence, quantity, purity (for dishes), readiness (for beverages), serving (for tray), etc.) act as the parameters.

In the second stage, all parameters obtained during the first stage are linked among themselves. Relations between objects are the targeted actions (e.g. generation of an order for the supply, dish cleaning, serving trays, etc.). Targeted actions that are required for the transfer of objects from one state to another are presented in Mivar model in the form of instructions. For example, in order to

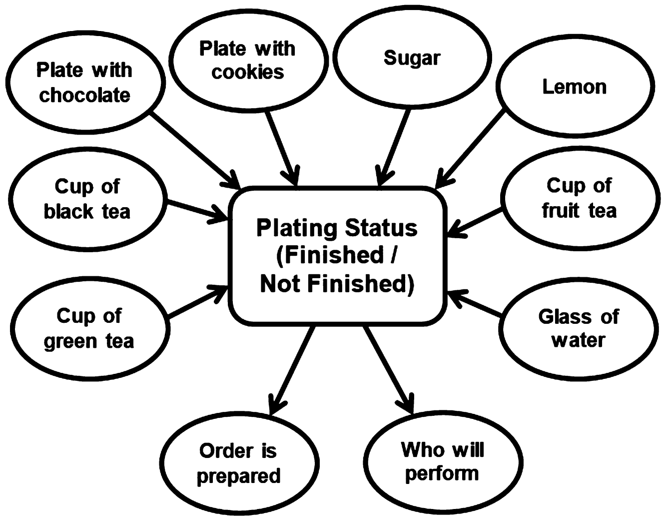

Fig. 8. The rule for order status generation.

have water in the empty teapot – it must be filled with water. When adding a purposeful action to the model one "teaches" the robot to interact with the object, transforming it from one state to another. An example of "Generation of the order status" instruction is shown in Fig. 8.

4.3. Formation of the system functioning algorithm

The logical kernel for constructing the functioning algorithms of the multi-robot system uses a model of knowledge representation obtained in this fashion. Receiving the input parameters, the system builds an algorithm of system functioning according to the existing rules in the knowledge base.

This mechanism is illustrated on the following example. The current state of the system is determined by the following condition parameters: "Robot Chef: Chef robot A: employment status" = busy; "Robot Chef: Chef robot B: employment status" = busy; "Robot Chef: Chef robot C: employment status" = not busy; "Customer order: black tea" = 1; "Stuff in a cupboard: platter" = 1; "Stuff in a cupboard: a bottle of water" = 7; "Stuff on a table: empty teapot" = yes; "Stuff on a table: cup" = 6; "Stuff on a table: teaspoon" = 2; "Stuff on a table: black tea bags" = 25. It is required to obtain "Brewed Black Tea", "Cup of Tea, exposed on the tray". In this case, the solution algorithm, constructed by the logical kernel will consist of six following steps (see Fig. 9).

It is worth noting that in the subject area described by 264 parameters and 266 links, the search for 10 parameters and calculation of the algorithm took just three milliseconds, and the memory footprint was about 9456 KB.

5. Practical examples of the use of Mivar "Brains" (Roborazum) for robots

The practical realization of Mivar-based DMCS is shown on the MIVAR channel on YOUTUBE via Mivar pilot system video test [28].

This video and Fig. 10 show the results of practical implementation. Fig. 10 shows a stand demonstrating the capabilities of a Mivar decision-making system for managing autonomous robots.

At the top of the picture is a video camera that collects information about the state of the site. These data contain information about type and position of obstacles as well as the data about robots' locations.

In the center of the figure, one can see the laptop, which runs the control RoboRazum software which is driven by MIVAR decision-making system.

At the bottom of the picture, there is a test platform, on which obstacles and autonomous mini-robots are placed.

To simplify the problem of pattern recognition, the author used special markers (RUCO - markers) for robots and obstacles. Autonomous mini-bots were made independently. The camcorder monitors the test site and transmits information via the cable to a laptop operated by RoboRazum.

On the laptop, at the beginning of the test, a job is specified for robots to carry out varying tasks. For example, the first task is to move the robot from the initial position to a given target point; second task may be to line up three robots along a certain direction. Third task is to ask all three robots to surround a given point, etc. The author specifically notes that with the help of Mivar technologies [26,27] and the software product TELMI, one can give commands to robots in plain text. After receiving the task, RoboRazum analyzes where the robots are located and builds the movement routes for each robot, taking into account the obstacles. All three robots move at the same time, and RoboRazum transmits real-time motion commands to each robot via a Wi-Fi radio channel and tracks the robots' paths and changes in the environment. If the obstacles change their position, the new ones are added or if existing obstacles disappear, then RoboRazum re-routes the robots in real-time until the target position is fully reached. In the author's experiments a regular notebook (Core i5 3.0 MHz processor with two cores, 8GB RAM) was able to control simultaneously in real time five robots in environments with variable obstacles. On the video clip mentioned above, all three robots are moving simultaneously.

On Fig. 11, two types of obstacles are added:

1) "passable", for example, grass and bushes for cars and tractors - these obstacles are indicated by markers on posts;
2) "impassable", for example, houses and trees for cars and tractors - these obstacles are indicated by markers that lie on the floor.

The video above shows how RoboRazum manages with two types of obstacles and robots that drive through "passable" obstacles, but go around "impassable". It is important to note that at the request of one Customer, the separation of obstacles into two types was carried out in the conditions of the exhibition by adding several rules to the Mivar decision-making system and it took no more than two hours. The author is not aware of any other examples of solving such problems. Besides, the author can quite easily add other types of obstacles and different types of robot activity in the process of moving across the field. For example, in the field of agriculture, a combine, which operates under the control of RoboRazum, not just moves around the field, but also performs various types of work, taking into account the real-time features of the soil and other decision-making parameters.

As can be seen on Fig. 11 the RoboRazun controls Bluetooth channel for children's toys - robots. An additional difficulty in this experiment was that these children's robots perform all actions with very large errors, for example, they cannot go straight, turn to the required angles within 15 degrees' accuracy, etc., so RoboRazum constantly monitors their position on the pitch. RoboRazum specified the corrected displacements and refined robots' rotation angles.

These experiments were conducted back in 2016 [28], when, for the first time in the world, the author showed that the Expert System could control the movement of robots in real time. Then these experiments were conducted on the unmanned vehicle, which was created by the scientific group of Prof. Shadrin et al. [13]. Partially, the results of the author's experiments are shown in Figs. 11–12. The author emphasizes that in these studies, as shown in Figs. 11, 3 different systems have been used:

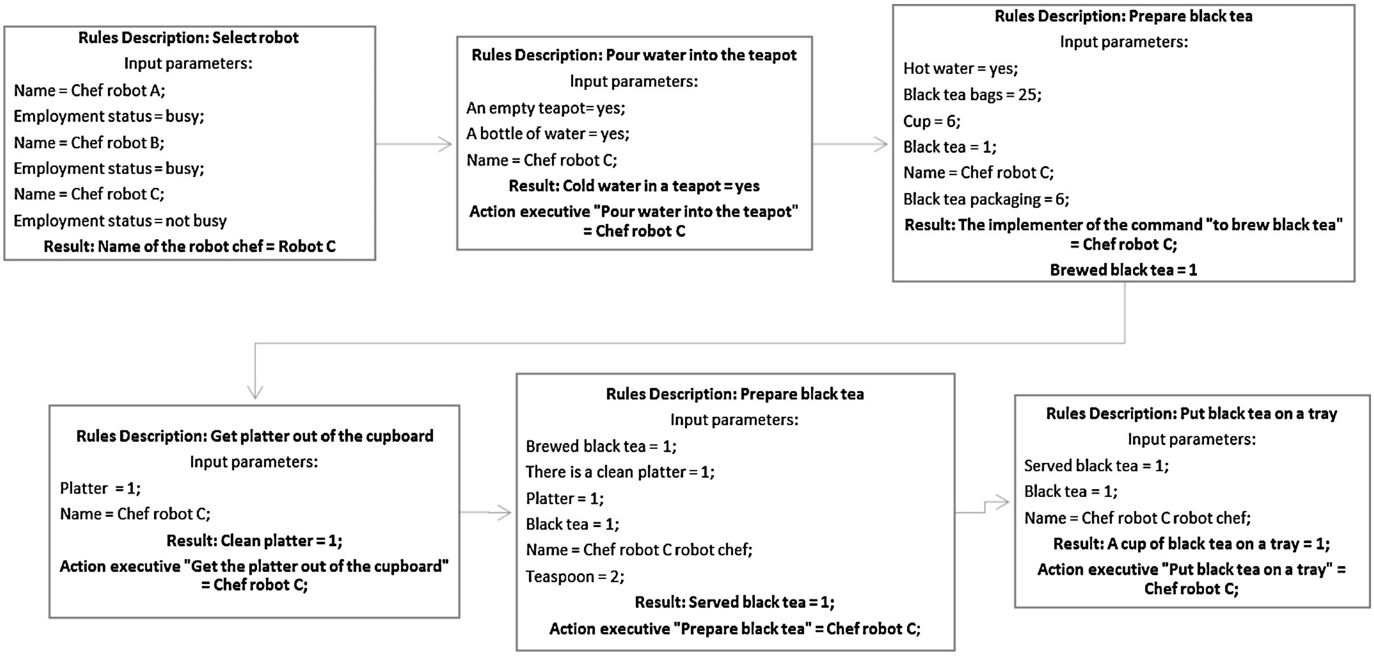

Fig. 9. The algorithm of multi-robot system functioning constructed by the logical kernel.

Fig. 10. A stand demonstrating the capabilities of the mivar decision-making system for managing autonomous robots. The Mivar expert system RoboRazum manages a group of mini-tractor robots.

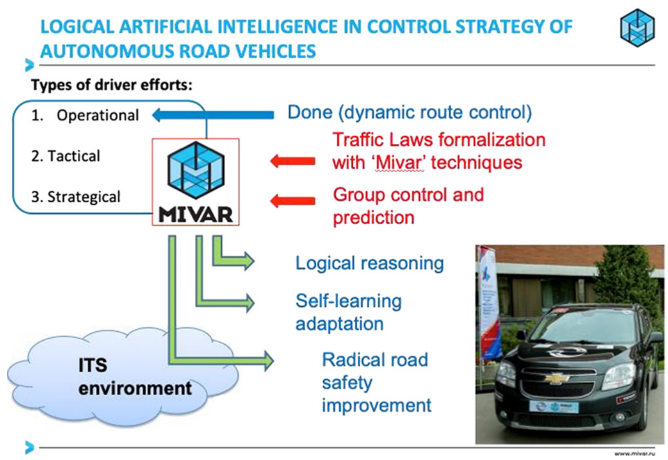

Fig. 11. Role and positioning of Mivar decision-making systems in the overall driving.

1) system of trajectory control;
2) vision system;
3) decision-making system RoboRazum.

Thus, in January 2017, the Mivar expert system, implemented as a RoboRazum decision-making system, began to drive a full-fledged unmanned vehicle.

6. Discussion

Mainly in the field of navigation of mobile robots, there are grid and topological studies. Thus, according to Suo et al. [29], when studying the problem of real-time navigation and obstacle avoidance by mobile robots in difficult conditions, a new structure of perception and navigation of the local environment was used on the basis of information about altitude. For this, a map of the area was used, on which obstacles were drawn. With the help of local elevation maps, the level of terrain passability was determined, and on the basis of these data, a two-dimensional grid map was created for navigation and creating a route for the robot.

According to the results of the review of achievements in the field of navigation of mobile robots [30], it is shown that geometric and topological models of space are used in a structured environment. At the same time, for unstructured environments, optical flow and paradigm methods are used to recognize specific objects in the environment. The review [31] of methods for integrating sensors in the navigation of robots with a different set of sensors showed that machine intelligence is a more efficient method for integrating multisensory signals, including algorithms such as fuzzy logic and neural networks. Over the past decade, Mobileye, NVIDIA, and Google have been using hybrid CNN-RNN methods in real-time vision and navigation systems for smartphones, cameras, robots, and self-driving cars [32]. The main advantage of this method is the detection and tracking of moving objects in images. Thus, based on CNN, a system has been developed in the work of Caltagirone et al. [33] that is able to perceive and generate driving paths from real driving sequences using input data from LIDAR and GPS. There is another example of the application of intelligent methods [34], where the authors used the DeepSense learning environment to classify input data from sensors in order to perform tracking, object recognition, and user identification. The above research results are in good agreement with the results of this work. The authors Chuvikov et al. [30] conclude that it is possible to create decision-making systems for autonomous robots using Mivar expert systems as a firm basis. These systems are capable of managing groups of robots in real time based on Mivar technology [16]. Significant speed-up of processing and decision making is achievable due to the linear computational complexity of the logical inference in Mivar knowledge bases. These knowledge bases operate under control of the software product called RAZUMATOR Wi!Mi [26]. Consequently, it is theoretically substantiated [27] and proved by practical experiments [16] that expert systems can be used to control robots. These ESS, together with Mivar technologies, are capable of processing more than five million instructions per second, which is several orders of magnitude greater than human capabilities.

The author's approach to the intellectualization of robots differs from others since for the first time it is proposed to add Mivar expert systems, in addition to the usual low-level (trajectory) control systems, for creation of decision-making systems, i.e. RoboRazum.

As it is known, Mivar technologies allow solving problems during development of the whole spectrum of artificial intelligence systems [30]. These systems, in addition to expert systems and automated control systems, may include software kernels aimed at understanding natural language and semantic understanding of images. Therefore, in the author's further work, it is planned to build systems capable to understand text in natural (Russian) language and insert them into autonomous robots. Besides, in the longer term the author plans to improve technical vision systems by adding the possibility of a semantic understanding of images and traffic conditions.

7. Conclusion

In this paper, one of the possible methods to create a dynamic algorithm of robot actions that can be used in the decision module has been considered. It is proposed to use expert systems of a new generation for high-level control, and to organize the control system of the "top level" as a decision-making system. The resulting systems can work successfully using one computational module, since it allows processing subject areas with more than million instructions in less than a second. The experiments showed that Mivar decision-making systems can control groups of small robots and even an unmanned autonomous car in real time. The algorithms created in the Mivar environment can be very flexible, and their build-up depends only on engineering approaches. In addition, the system has a kind of flexibility in terms of simplicity and naturalness of changing its behavior.

Indeed, there are a number of problems associated with the use of the proposed method. Those are the purely technical difficulties associated with the need for rapid modeling and third-party input tools, and the laboriousness of the process of creating a model. In general, the author expects that this method can be widely used in modern robotic systems.

Mivar technologies expand the sphere of application of expert systems and allow creating decision-making systems for autonomous intelligent robots and cobots at the logical level.

In the further work, the author is going to build the new Mivar systems for understanding natural language and semantic understanding of images into autonomous robots so that, for example, an unmanned vehicle or tractor can be assigned tasks with text or voice. The author already has some developments in this area that will be described in the following publications. It is important to emphasize that a qualitative transition based on Mivar networks in the speed of logical processing of causal instructions made it possible to combine all areas of research in the field of artificial intelligence at the logical level.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Fig. 12. A demonstration of the work done by RoboRazum: movement is allowed (left) and you must stop and let another car pass (right).

Availability of data and materials

Data will be available on request.

Acknowledgement

The author would like to thank Dr. Larisa Adamova, Dr. Lyudmila Artemyeva and Dr. Boris Strokopytov for help in preparation of the manuscript. The author would like to thank Panferov Alexei, Novikov Dmitrii, Miftahov Timur, Trofimov Ilja, Kassym Vlad and Zhdanovich Elizaveta for practical implementation and completion of the tasks.

References

[1] S.J. Russel, P. Norvig, Artificial Intelligence: A Modern Approach, Pearson, Boston, 2010.
[2] A. Ostroukh, N. Surkova, O. Varlamov, V. Chernenky, A. Baldin, Automated process control system of mobile crushing and screening plant, J. Eng. Appl. Sci. 16 (2018) 343–348, https://doi.org/10.5937/jaes16-15586.
[3] G.H. Lim, Shared representations of actions for alternative suggestion with incomplete information, Robot. Auton. Syst. 116 (2018) 38–50, https://doi.org/10.1016/j.robot.2019.02.005.
[4] X. Li, K. Guo, T. Jia, X. Zhang, Visual perception and navigation of security robot based on deep learning, in: 2020 IEEE International Conference on Mechatronics and Automation (ICMA), IEEE, 2020, pp. 1216–1221.
[5] I. Kresse, M. Beetz, Movement-aware action control – integrating symbolic and control-theoretic action execution, in: IEEE International Conference on Robotics and Automation (ICRA), 2012, pp. 3245–3254.
[6] A.N. Ostrikov, A.A. Ospanov, A.A. Shevtsov, N.Z. Muslimov, A.K. Timurbekova, G.B. Jumabekova, Mathematical model of high-temperature tube-shaped pasta drying in a conveyer belt drier, Int. J. Food Eng. 1 (ahead-of-print) (2020), https://doi.org/10.1515/ijfe-2020-0101.
[7] A. Ospanov, A. Timurbekova, New hypothesis of energy of crushing, J. Hyg. Eng. Des. 27 (2019) 87–89.
[8] M. Leonetti, L. Iocchi, P. Stone, A synthesis of automated planning and reinforcement learning for efficient, robust decision-making, Artif. Intell. 241 (2016) 103–113, https://doi.org/10.1016/j.artint.2016.07.004.
[9] M. Tenorth, M. Beetz, KnowRob: a knowledge processing infrastructure for cognition-enabled robots, Int. J. Robot. Res. 32 (2013) 566–590, https://doi.org/10.1177/0278364913481635.
[10] A.R. Sadik, B. Urban, An ontology-based approach to enable knowledge representation and reasoning, Future Internet 9 (4) (2017) 90, https://doi.org/10.3390/fi9040090.
[11] S. El Zaatari, M. Marei, W. Li, Z. Usman, Cobot programming for collaborative industrial tasks, Robot. Auton. Syst. 116 (2019) 162–180, https://doi.org/10.1016/j.robot.2019.03.003.
[12] A.M. Djuric, R.J. Urbanic, L.J. Rickli, A framework for collaborative robot (CoBot) integration in advanced manufacturing systems, SAE Int. J. Mater. Manuf. 9 (2) (2016) 457–464, https://doi.org/10.4271/2016-01-0337.
[13] S.S. Shadrin, O.O. Varlamov, A.M. Ivanov, Experimental autonomous road vehicle with logical artificial intelligence, J. Adv. Transp. 1 (2017) 2492765, https://doi.org/10.1155/2017/2492765.
[14] O. Varlamov, Wi!Mi expert system shell as the novel tool for building knowledge-based systems with linear computational complexity, Int. Rev. Autom. Control 11 (2018) 314–325, https://doi.org/10.15866/ireaco.v11i6.15855.
[15] O. Varlamov, MIVAR: transition from productions to bipartite graphs MIVAR nets and practical realization of automated constructor of algorithms handling more than three million production rules, preprint, arXiv:1111.1321, https://arxiv.org/abs/1111.1321, 2011, 23 p.
[16] D.V. Aladin, O.O. Varlamov, L.E. Adamova, D.A. Chuvikov, D.V. Saraev, Control of vehicles and robots: creating of knowledge bases for mivar decision making systems robots and vehicles, IOP Conf. Ser., Mater. Sci. Eng. 747 (2020) 012099, https://doi.org/10.1088/1757-899X/747/1/012099.
[17] O.O. Varlamov, A.M. Khadiev, M.O. Chibirova, G.S. Sergushin, P.D. Antonov, Russian Federation Patent No. RUS 2607995, 2015.
[18] B. Demin, S. Parlati, P.F. Spinnato, S. Stalio, U-LITE, a private cloud approach for particle physics computing, Int. J. Cloud Appl. Comput. 9 (1) (2019) 1–15, https://doi.org/10.4018/IJCAC.2019010101.
[19] R. Gervasi, L. Mastrogiaconno, F. Franceschini, A conceptual framework to evaluate human-robot collaboration, Int. J. Adv. Manuf. Technol. 108 (2020) 841–865, https://doi.org/10.1007/s00170-020-05363-1.
[20] A. Lager, G. Spampinato, A.V. Papadopoulos, T. Nolte, Towards reactive robot applications in dynamic environments, in: 2019 24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), IEEE, 2019, pp. 1603–1606.
[21] H. Ahmadzadeh, E. Masehian, Modular robotic systems: methods and algorithms for abstraction, planning, control, and synchronization, Artif. Intell. 223 (2015) 27–64, https://doi.org/10.1016/j.artint.2015.02.004.
[22] J. Bidot, L. Karlsson, F. Lagriffoul, A. Saffiotti, Geometric backtracking for combined task and motion planning in robotic systems, Artif. Intell. 247 (2017) 229–265, https://doi.org/10.1016/j.artint.2015.03.005.
[23] A. Agostiny, C. Torras, F. Wörgötter, Efficient interactive decision-making framework for robotic applications, Artif. Intell. 247 (2017) 187–212, https://doi.org/10.1016/j.artint.2015.04.004.
[24] P. Gangadhar, A.K. Hota, M.V. Rao, V.V. Rao, Performance of memory virtualization using global memory resource balancing, IJCAC 9 (1) (2019) 16–32, https://doi.org/10.4018/IJCAC.2019010102.
[25] K. Sambrekar, V.S. Rajpurohit, Fast and efficient multiview access control mechanism for cloud based agriculture storage management system, IJCAC 9 (1) (2019) 33–49, https://doi.org/10.4018/IJCAC.2019010103.
[26] O.O. Varlamov, D.V. Aladin, L.E. Adamova, D.A. Chuvikov, D.V. Saraev, Creation of autonomous groups of combine harvesters and tractors for agriculture based on the Mivar decision-making systems "ROBO!RAZUM", IOP Conf. Ser., Mater. Sci. Eng. 819 (2020) 012002, https://doi.org/10.1088/1757-899X/819/1/012002.
[27] M.P. Bulat, P.V. Bulat, The history of the gas bearings theory development, World Appl. Sci. J. 27 (2013) 893–897, https://doi.org/10.5829/idosi.wasj.2013.27.07.13718.
[28] Mivar pilot system video test, https://www.youtube.com/watch?v=o_0K_fdCaBk, 2020. (Accessed 10 December 2020).
[29] C. Suo, W. Xu, Y. Guan, L. He, Y. Yang, Real time obstacle avoidance and navigation with mobile robot via local elevation information, in: 2019 IEEE International Conference on Robotics and Biomimetics (ROBIO), IEEE, 2019, pp. 2896–2901.
[30] D.A. Chuvikov, O.O. Varlamov, D.V. Aladin, V.M. Chernenkiy, A.V. Baldin, Mivar models of reconstruction and expertise of emergency events of road accidents, IOP Conf. Ser., Mater. Sci. Eng. 534 (2019) 012007, https://doi.org/10.1088/1757-899X/534/1/012007.
[31] M. Khairudin, S.P. Herlambang, H.I. Karim, M.N.A. Azman, Vision-based mobile robot navigation for suspicious object monitoring in unknown environments, J. Eng. Sci. Technol. 15 (1) (2020) 152–166.
[32] S. Parasuraman, Sensor fusion for mobile robot navigation: fuzzy associative memory, Proc. Eng. 41 (2012) 251–256, https://doi.org/10.1016/j.proeng.2012.07.170.

[33] L. Caltagirone, M. Bellone, L. Svensson, M. Wahde, LIDAR-based driving path generation using fully convolutional neural networks, in: 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), IEEE, 2017, pp. 1–6.

[34] S. Yao, S. Hu, Y. Zhao, A. Zhang, T. Abdelzaher, Deepsense: a unified deep learning framework for time-series mobile sensing data processing, in: Proceedings of the 26th International Conference on World Wide Web, 2017, pp. 351–360.