

DOI: 10.18721/JCSTCS.11206

UDC 004.81

## **COMPARISON ANALYSIS OF KNOWLEDGE-BASED SYSTEMS FOR NAVIGATION OF MOBILE ROBOT AND COLLISION AVOIDANCE WITH OBSTACLES IN UNKNOWN ENVIRONMENT**

*V.N. Sichkar*

Peter the Great St. Petersburg Polytechnic University, St. Petersburg, Russian Federation

Developing systems for intelligent navigation is one of the major problems in world of modern robotics. This problem is particularly urgent when the environment is unknown. It means that a mobile robot meeting unpredictable obstacles on its way and has to react according to the current situation fast and in real time. That is why developing such a system is always a big challenge. This paper studies different techniques for storing and using the knowledge in order to avoid collisions with obstacles. Most attention is paid for developing two types of Knowledge Bases to help the mobile robot to avoid possible collisions and continue its way. A comparison analysis is provided for these two different types of Knowledge Bases. The advantages and disadvantages were analyzed and described.

**Keywords:** mobile robot, intelligent navigation, obstacle avoidance, symbolic knowledge base, neural network knowledge base.

**Citation:** Sichkar V.N. Comparison analysis of knowledge-based systems for navigation of mobile robot and collision avoidance with obstacles in unknown environment. St. Petersburg State Polytechnical University Journal. Computer Science. Telecommunications and Control Systems, 2018, Vol. 11, No. 2, Pp. 64–73. DOI: 10.18721/JCSTCS.11206

## **СРАВНИТЕЛЬНЫЙ АНАЛИЗ СИСТЕМ, ОСНОВАННЫХ НА ЗНАНИЯХ ДЛЯ НАВИГАЦИИ МОБИЛЬНОГО РОБОТА И ПРЕДОТВРАЩЕНИЯ СТОЛКНОВЕНИЙ С ПРЕПЯТСТВИЯМИ В НЕИЗВЕСТНОЙ СРЕДЕ**

*В.Н. Сичкар*

Санкт-Петербургский политехнический университет Петра Великого,  
Санкт-Петербург, Российская Федерация

Разработка систем интеллектуальной навигации – одна из основных проблем в мире современных роботов. Окружающая среда, в которой будет работать мобильный робот, не постоянна. Он будет встречать препятствия на своем пути и при этом должен реагировать в соответствии с текущей ситуацией быстро и в реальном времени. В статье рассмотрены различные методы хранения и использования знаний для того, чтобы робот смог избежать столкновений с препятствиями. Особое внимание уделено разработке двух разных типов баз знаний, на основе которых мобильный робот избегает возможных столкновений с препятствиями и продолжает свой путь. Проведен сравнительный анализ двух разных типов баз знаний. Проанализированы и описаны их преимущества и недостатки.

**Ключевые слова:** мобильный робот, интеллектуальная навигация, предотвращение препятствий, символьная база знаний, нейросетевая база знаний.

**Ссылка при цитировании:** Сичкар В.Н. Сравнительный анализ систем, основанных на знаниях для навигации мобильного робота и предотвращения столкновений с препятствиями в неизвестной среде // Научно-технические ведомости СПбГПУ. Информатика. Телекоммуникации. Управление. 2018. Т. 11. № 2. С. 64–73. DOI: 10.18721/JCSTCS.11206

## Introduction

Creating an autopilot for cars, autonomous vehicles, mobile robots, rescue robots, etc., is currently an important task. Autopilot systems were first developed exclusively for aircraft, but later automatic control systems were also switched to land vehicles. Nowadays, there are three main types of navigation algorithms for movement control of mobile robots in an unknown environment [1]:

- algorithm based on separation of functions for processing the information received in the process of “recognition-modeling-planning-action”;
- algorithm based on the strategy of targeted behavior of the mobile robot, which includes training under supervision, fuzzy logic, neural networks, and behavior planning based on the data obtained from sensors;
- hybrid system based on integration of the two previous types of algorithms, which

allows to overcome difficulties in modeling and ensure adaptability of behavior in real time and in uncertain environment.

Navigation in the field of mobile robotics also can be classified in two types: global navigation and local navigation [2]. In the part of global navigation, the preliminary knowledge of the environment should be available. With the help of the local navigation the mobile robot can orient itself using ultrasonic sensors, camera, lidar sensors, and variety of other sensors according to the real task.

## Problem statement

The study is aimed at comparing different types of Knowledge Bases for navigation system of a mobile robot in an unknown environment in order to avoid possible collisions with obstacles. For comparison analysis, two types of Knowledge Bases were chosen and they are a Symbolic Knowledge Base and a Neural Net-

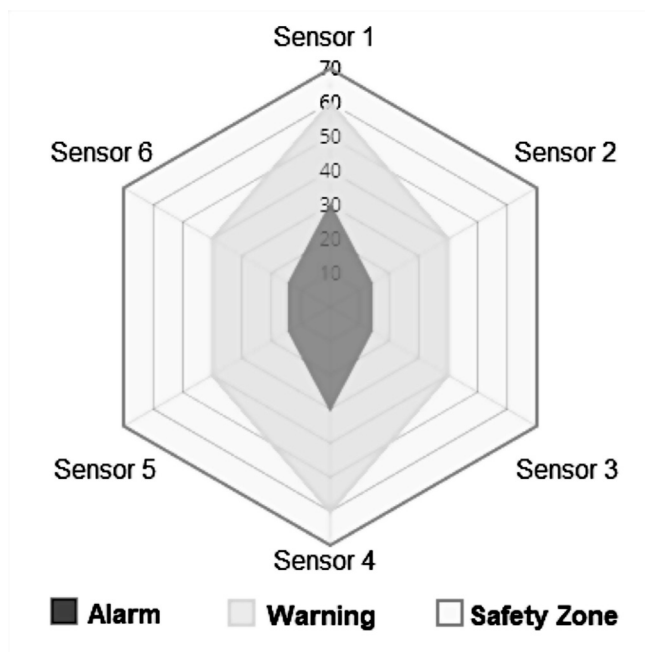


Fig. 1. Radar chart with zones

work Knowledge Base. This study shows the implementation of two types of Knowledge Bases and provides analysis of advantages and disadvantages of both of them.

A mobile robot acts in unknown environment inside a building with static obstacles such as furniture, walls and doors. The surface of the floor is smooth with a small number of low obstacles like thresholds in door frame which are not higher than two centimeters.

The navigation system uses six ultrasonic sensors that monitor different directions while the mobile robot is moving. The type of the sensors is HC-SR04 that can measure distance in the range from 2 to 400 cm and with a step of 1 cm. This range is sufficient for recognition of obstacles in the room. Based on this data (types of obstacles and features of sensors), three zones were developed: Alarm, Warning and Safety. Each zone covers its own space around the mobile robot. Fig. 1 shows a radar chart with zones and Table 1 shows intervals for each of three zones.

The sensors are located along the perimeter of the mobile robot creating a kind of bubble around it. System sends requests to the Knowledge Bases and asks for the current statement for all sensors each time when an obstacle penetrates inside this bubble. For getting results, system uses two types of the Knowledge Bases in parallel. Each sensor works independently and shows in real time the current value which is the distance to the nearest object. The navigation system processes data from all sensors and with the help of Knowledge Base obtains the three statements in each of the six directions. These statements are safety zone, warning zone and alarm zone. After getting this information,

the system slows down the mobile robot and applies an algorithm for maneuvering to avoid the obstacle, or completely stop the mobile robot if there is not enough space to turn left or right.

As shown in Table 1, the range for the alarm zone is between 2 and 30 cm for sensors number 1 and 4 that are front and back sensors, and between 2 and 14 cm for four side sensors. The minimum distance was set to 2 cm due to the blind zone of the chosen ultrasonic sensors. It means that if an object approaches closer, a collision happens. Since the step with which the sensors can measure distance is 1 cm, the three zones have a gap of 1 cm between each other. That is why, for example, the alarm zone for sensor 1 ends in the 30th cm and warning zone begins with the 31st cm. There is no maximum limit for the safety zone because the system does not consider everything that is far from the warning zone as an obstacle.

### Symbolic Knowledge Base

The Symbolic Knowledge Base can be shown graphically and parametrically. For the parametric method of representation, the Semantic Web Language (SWL) is used. This technique allows not just to save the database but to show the relationships between the data. In symbolic representation by SWL, the Knowledge Base consists of ontology [3, 4] which includes individuals and their properties. Ontology describes state-independent information, the logical component concept model with particular syntax, ontology class graph. The core of this Knowledge Base contains state-independent information, the actual data component contains all individual instances,

Table 1

Intervals for each zone

| Sensor   | Alarm min, cm | Alarm max, cm | Warning min, cm | Warning max, cm | Safety, cm |
|----------|---------------|---------------|-----------------|-----------------|------------|
| Sensor 1 | 2             | 30            | 31              | 60              | > 61       |
| Sensor 2 | 2             | 14            | 15              | 40              | > 41       |
| Sensor 3 | 2             | 14            | 15              | 40              | > 41       |
| Sensor 4 | 2             | 30            | 31              | 60              | > 61       |
| Sensor 5 | 2             | 14            | 15              | 40              | > 41       |
| Sensor 6 | 2             | 14            | 15              | 40              | > 41       |

the ontology instance graph. To use information from the ontology instance graph, the Resource Description Framework (RDF) triples [5] are used. For this study, the RDF store was developed with triples in order to have an opportunity to query the Knowledge Base and get the resulting information from it. The queries will be provided by SPARQL query language [6] and the system will get the current statement of each ultrasonic sensor in real time.

A flowchart with a graphical representation of the Knowledge Base is shown below in Fig. 2. For this flowchart, the graphical tool was used and it is called Concept Map. It helps to organize and represent knowledge by concepts with boxes or circles of specific types. Relationships between concepts are connected by line and words on the line. The words or phrases specify the relationship between the two concepts [7].

This flowchart describes the intervals in which the system has Alarm and Warning statements. Alarm and Warning here are the concepts that are connected with the State concept by the linking phrase «a kind of» (AKO). These two concepts describe statements of the system and they are connected with the

concepts of intervals by the appropriate sensor. These sensors are represented here as P1, P2, P3, P4, P5 and P6. Each interval has its own value for maximum and minimum. The intervals are different for Alarm and Warning concepts. Using the Symbolic Knowledge Base is easy because it is easy to change values, add more concepts and link them all together.

### Neural Network Knowledge Base

There is another way how to store and query the Knowledge Base of the system by using the Knowledge-Based Neural Network. It means that all data of the system will be inside the Neural Network and asking for the current state of the system is done through the Neural Network. The Neural Network for the system is shown in Fig. 3 below.

The designed Neural Network has an input layer, a first layer, one hidden layer and an output layer. The input layer represents signals from sensors S1–S6 and sends this information to neurons N1–N24 in the first layer. The first layer processes the received data and sends the results to neurons H1–H12 in the hidden layer. The hidden layer also processes data and sends it further to the final output layer. The chosen

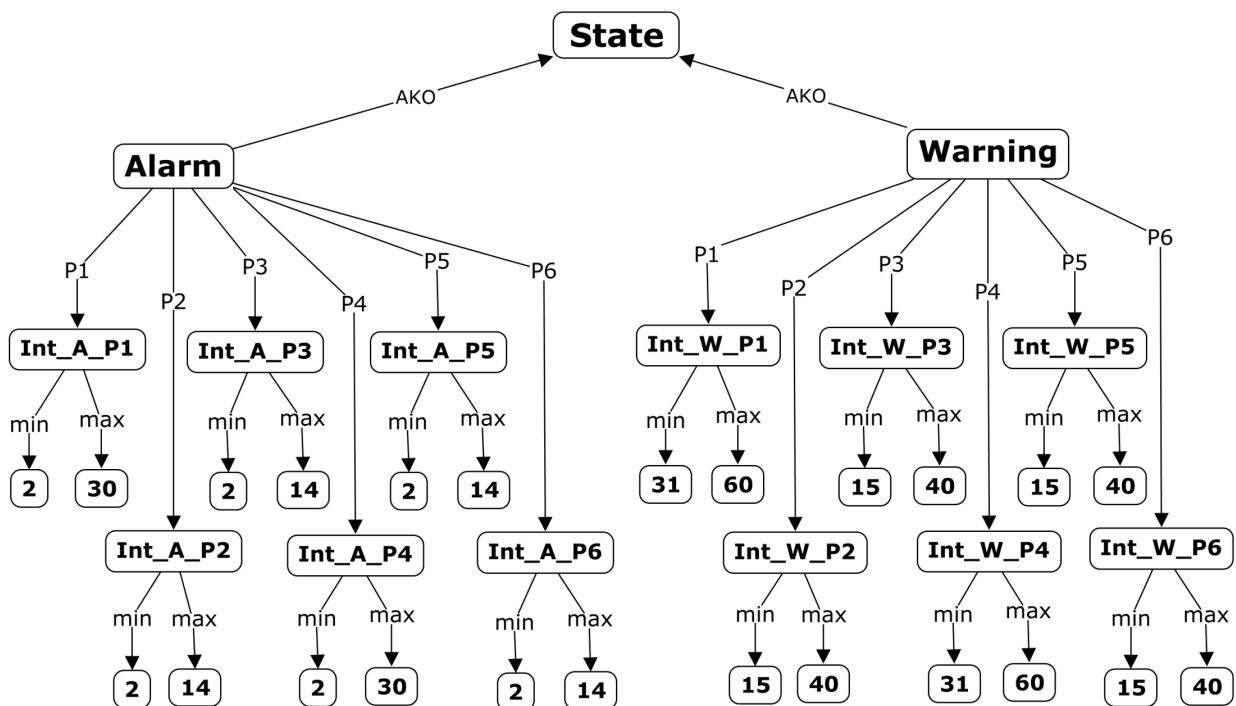


Fig. 2. Flowchart of Knowledge Base by Concept Map

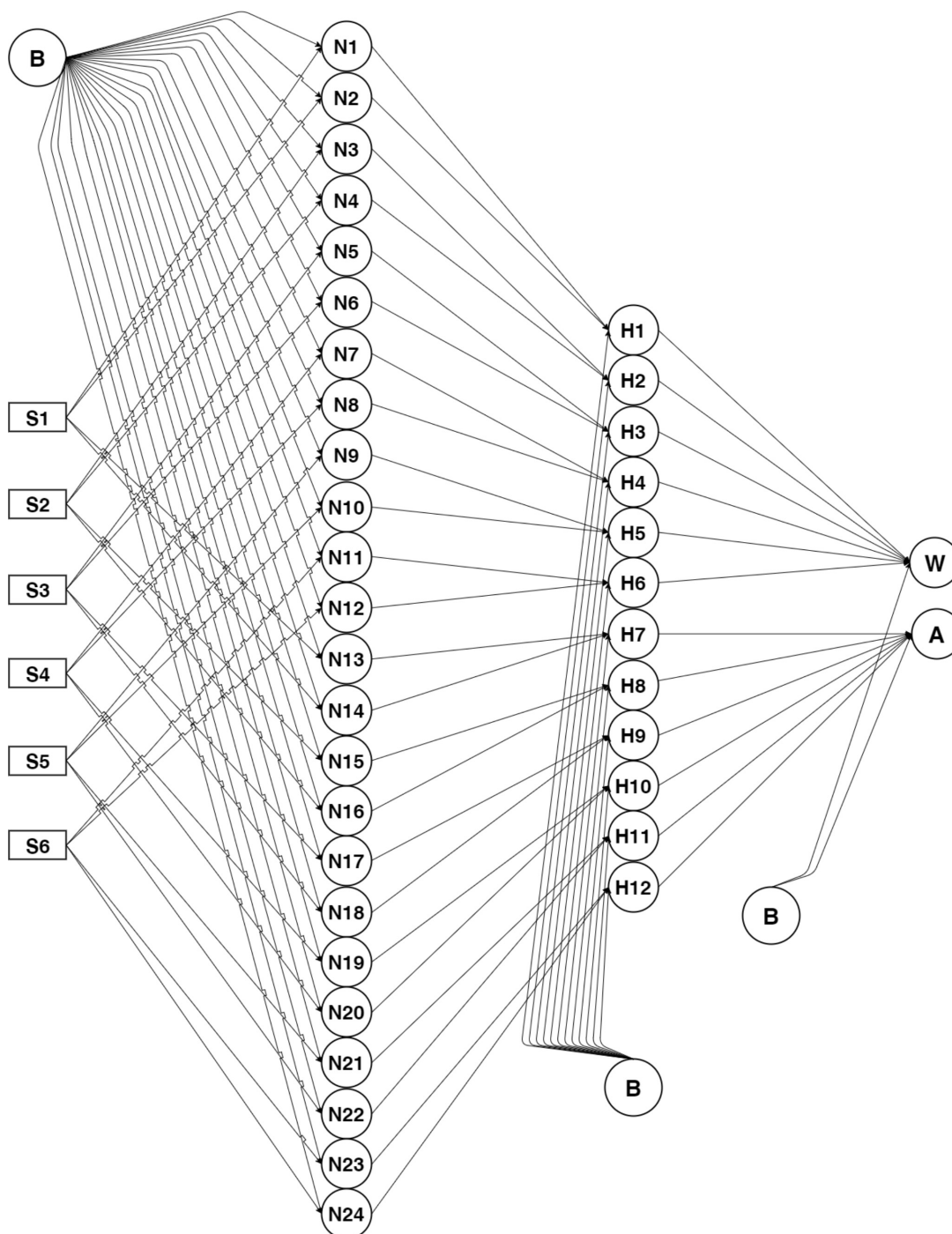


Fig. 3. Neural Network Knowledge Base

number of neurons in the first layer and the added hidden layer are needed because of the complexity of the conditions for calculating and finding out one from two statements for each sensor, Alarm or Warning. The output layer activates one of two neurons if at least

one sensor was in the critical interval. Each layer has an extra neuron called «bias» and it is marked as letter B on the scheme. The bias is an artificial threshold with its specific value for each connection and it plays the role of a kind of «helper» to adjust weights giving more

or less significance to the appropriate neuron. Bias is always activated. To provide comparison analysis for querying time with the Symbolic Knowledge Base, the output layer was improved to show the results for each sensor separately.

The main specific characteristic of the Knowledge-Based Neural Network is that the knowledge is put inside in advance by adjusting the appropriate weights and there is no need to train the Neural Network and it can be used straight away. This can be done if the conditions are known from the very beginning.

The character of relationships in the developed Neural Network is a feed forward. It means that all communication is directed strictly from input neurons to output ones [8–13].

### Algorithm of the system operation

The primary task in constructing the algorithms for overcoming obstacles for the mobile robot is intellectualization and automation of the control processes themselves. The mobile robot has to perform the task of navigation in an unknown environment. The goal is to explore the unknown environment, collect data about the distances from the ultrasonic sensors, send them to the central computer and come back to the initial point.

The mobile robot is equipped with ultrasonic sensors that will be used for the decision-making process. At the same time, the operator will be able to control the mobile robot at a distance by remote control if some urgent situation happens [14, 16]. The sensors will read

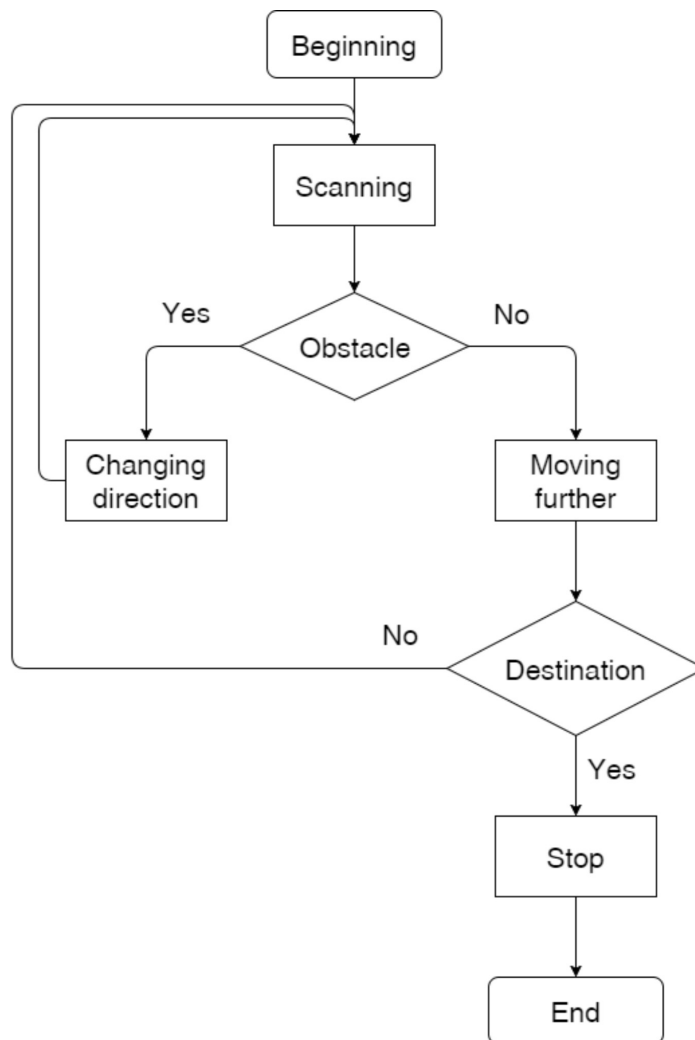


Fig. 4. Flowchart of the algorithm for overcoming an obstacle

the data from the environment and record the distance to the objects around the mobile robot. If there is a probability of a collision or the current situation may cause an accident, the system slows down the mobile robot and runs the obstacle-overcoming algorithm.

Fig. 4 shows a simplified algorithm for the movement of the mobile robot.

### Equipment

A six-wheel base, namely, 6WD Smart Carwas chosen as the mobile robot for the implementation of the hardware part of the project. It has active suspension that helps to go in rough terrain. Also, the advantage of this mobile robot is in its ability to carry heavy equipment. The own weight of the mobile robot is about 2 kg and it can carry about 3 kg, which is enough for all needed sensors, microcontrollers, batteries, wires, etc. Other parameters:

- size: 28x21x11.5 cm;
- weight: 2 kg;
- maximum load: 3 kg;
- number of DC motors: 6;
- working voltage: 12 v.

Ultrasonic sensors HC-SR04 were chosen

as sensors for scanning the environment around the mobile robot. Selection of this type of ultrasonic sensors is due to their low cost and quite good quality for the purposes of scientific experiments. They have a good accuracy, which is 1 cm, and the distance of measurement up to 4 m. All these features and six sensors together make it possible to carry out scanning of the environment around in 360 degrees and recognize necessary objects and detect obstacles. The main disadvantage of this type of ultrasonic sensors is that if the environment is too dusty, it can cover the sensors and make it difficult for them to work properly.

To collect data received from the sensors, a single-board microcontroller Arduino Mega is used. All data are sent to the central computer which processes information. Exchange of information is provided via a Bluetooth module. Also, Arduino Mega controls the six motors by sending commands to move and directions to go.

### Implementation results

For the implementation of the theoretical part of the system, the C Sharp Windows Form application was developed. As a result,

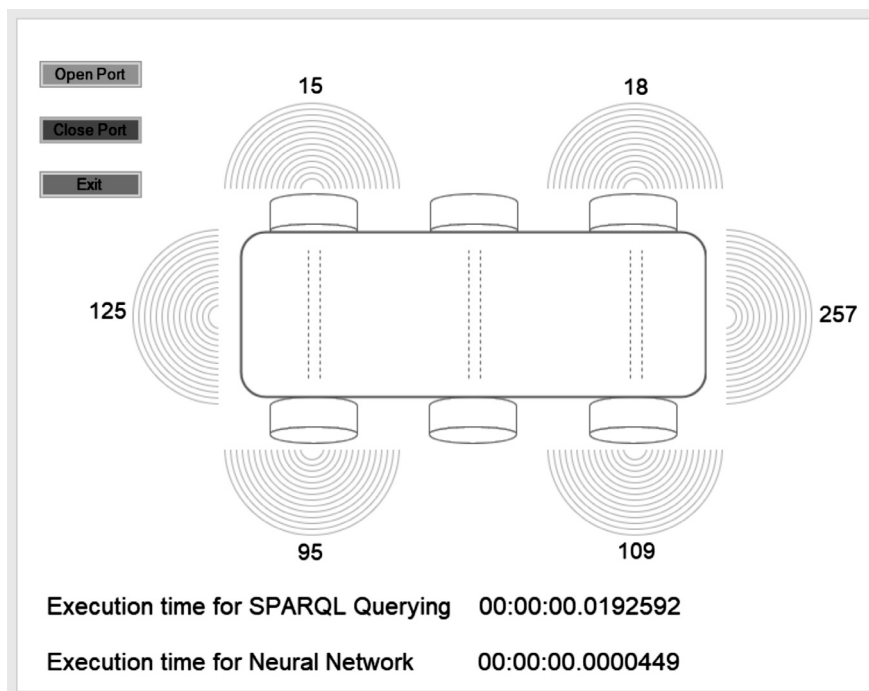


Fig. 5. C Sharp Windows Form application for representing the results



the application shows the system working in real time with an interface that is intuitively understandable for the operator. The application is directly connected with the mobile robot via a Bluetooth connection providing transmission of data in both ways. Fig. 5 shows the main window of the application.

As shown in the main window, the operator can see and control the zones around the mobile robot in six different directions. If the area is clear and there is no Warning or Alarm statements, the system allows the mobile robot to enter and pass through the checked area. The values from all ultrasonic sensors are being checked continuously 5 times a second. This feature provides enough data for the algorithm of the system and based on the results it makes a decision which allows to avoid any collision.

All data received from the sensors are being processed in two different threads in parallel. One thread is developed for querying the Symbolic Knowledge Base and another one is developed for querying the Neural Network Knowledge Base. This approach allows to check and compare the execution time for each thread. In the program, the Symbolic Knowledge Base is loaded as a graph and querying is done by SPARQL language through this graph. The Neural Network Knowledge Base is represented by matrices in the program and results are being obtained by sending data to the input layer.

As seen in the main window in Fig. 5, the processing time is shown for both threads in

real time. Comparison analysis was provided by collecting information about execution times from two threads for two different types of Knowledge Bases. The results were evaluated through a variety of tests in different conditions for the mobile robot. Table 2 shows the execution time in ten experiments.

These experiments were done in different situations. Experiment number 1 was done with no obstacle detected in the Warning zone, and the result shows that the execution time is minimum for both types of Knowledge Bases. Experiment number 2 was done when all sensors detected an obstacle in the Warning zone. Although the situation when the mobile robot is completely surrounded with obstacles was not possible for current research, it was important to understand how fast the system will react on this condition. Other experiments were done by different combinations with the number of obstacles in different zones, and these conditions are described below.

Experiment 3: side sensors number 3 and 6 detected obstacles in Warning zone, back sensor number 4 detected obstacle in Alarm zone; other sensors did not detect obstacles in Alarm and Warning zones.

Experiment 4: side sensors number 2 and 6 detected obstacles in Alarm zone, front sensor number 1 detected an obstacle in Warning zone; other sensors did not detect obstacles in Alarm and Warning zones.

Experiment 5: side sensors number 5 and 6 detected obstacles in Warning zone in

Table 2

Testing results for the execution time for two different Knowledge Bases

| Experiment | Symbolic Knowledge Base | Neural Network Knowledge Base |
|------------|-------------------------|-------------------------------|
| 1          | 0.0125929               | 0.0000458                     |
| 2          | 0.9172391               | 0.0009884                     |
| 3          | 0.1740155               | 0.0005356                     |
| 4          | 0.2929742               | 0.0000854                     |
| 5          | 0.5692983               | 0.0000973                     |
| 6          | 0.0926548               | 0.0003466                     |
| 7          | 0.8287374               | 0.0009266                     |
| 8          | 0.0284718               | 0.0000774                     |
| 9          | 0.0413314               | 0.0005626                     |
| 10         | 0.0155394               | 0.0003917                     |



the border close to Alarm zone, back sensor number 4 detected an obstacle in Alarm zone; other sensors did not detect obstacles in Alarm and Warning zones.

Experiment 6: front and back sensors number 1 and 4 detected obstacles in Alarm zone; other sensors did not detect obstacles in Alarm and Warning zones.

Experiment 7: side sensors number 2, 3, 5 and 6 detected obstacles in the Alarm zone; other sensors did not detect obstacles in Alarm and Warning zones.

Experiment 8: side sensors number 3 and 5 detected obstacles in Warning zone; other sensors did not detect obstacles in Alarm and Warning zones.

Experiment 9: side sensors number 2 and 3, front sensor number 1 detected obstacles in the Warning zone; other sensors did not detect obstacles in Alarm and Warning zones.

Experiment 10: only one side sensor number 6 detected an obstacle in Alarm zone; other sensors did not detect obstacles in Alarm and Warning zones.

Experiments number 1 and 2 showed a strong dependence between detecting the obstacles and the execution time for both two types of Knowledge Bases. When no obstacle was detected in experiment number 1, the execution time was one order less for both threads than it was in experiment number 2, when all sensors detected obstacles in Warning zone. Experiment number 2 showed the maximum execution time over all 10 experiments.

Experiments from 3 to 10 showed that a different number of obstacles detected by the sensors has a different effect on the execution time for both threads, and can vary due to the zone in which the obstacle was detected. These experiments revealed that it takes more time to process data for an obstacle detected in Warning zone in the border with Alarm zone than for an obstacle detected in Alarm zone. This situation occurs because requests are sent first to check if the obstacle was detected in Warning zone close to Alarm zone, and if it was, then requests are sent further to check if the obstacle was detected in Alarm zone also. That is why execution time is longer for cases when the obstacle is in the border between Warning and Alarm zones.

Execution time is longer when more obstacles are detected because each sensor that detects obstacles in Warning or Alarm zones starts to send data to be processed. A minimum difference of around 500 times between the execution time for two different approaches was recorded. A maximum difference of around 11,000 times was recorded. Absolutely in all cases the thread with the Neural Network Knowledge Base was much faster, which is a big advantage for using this approach in real time systems with the ability for fast decision-making.

### Conclusions

In this paper, the system that controls the statements around the mobile robot was developed. The system has six sensors that control the environment around the mobile robot creating a “bubble” and if there is any penetration inside this “bubble”, then system reacts immediately. The system automatically takes control of the mobile robot if there is a probability of collision.

The main research was put into two different types of Knowledge Bases that are implemented in the system. Each of them have advantages and disadvantages. The main advantage of the Symbolic Knowledge Base is in the ease of creating, adding and changing data inside it. However, the comparison analysis made on a series of experiments showed that the Neural Network Knowledge Base was always much faster and the difference was in the range from 500 to 11,000 times. The main advantage of the Neural Network Knowledge Base is in the speed of processing data. The main disadvantage of this type of Knowledge Base is in the necessity to adjust the weights inside the Neural Network each time it is needed to be correct and it also makes it more complicated to add and update data.

For the systems where data is stable and there is no need to update it too often, the Neural Network Knowledge Base is more suitable. For the systems where data has to be updated very often, the Symbolic Knowledge Base is more suitable as it can be done easier. Also, the processing time has to be considered, as the Neural Network Knowledge Base gives the results much faster.



## REFERENCES / СПИСОК ЛИТЕРАТУРЫ

1. Rao A., Elara M.R., Elangovan K. Constrained VPH+: a local path planning algorithm for a bio-inspired crawling robot with customized ultrasonic scanning sensor. *Robotics and Biomimetics*, 2016, Vol. 3, Pp. 1–13. DOI: 10.1186/s40638-016-0043-1
2. Yakoubi M., Laskri M. The path planning of cleaner robot for coverage region using Genetic Algorithms. *Journal of Innovation in Digital Ecosystems*, 2016, Vol. 3, Issue 1, Pp. 37–43. DOI: 10.1016/j.jides.2016.05.004
3. Feilmayr C., Wolfram W. An analysis of ontologies and their success factors for application to business. *Data & Knowledge Engineering*, 2016, Vol. 101, Pp. 1–23. DOI: 10.1016/j.datak.2015.11.003
4. Labra Gayo J.E., Jeuring J., Alvarez Rodriguez J.M. Inductive triple graphs: A purely functional approach to represent RDF. *Graph Structures for Knowledge Representation and Reasoning*, 2014, Vol. 8323, Pp. 92–110. DOI: 10.1007/978-3-319-04534-4\_7
5. Yuan P., Xie C., Jin H. Dynamic and fast processing of queries on large-scale RDF data. *Knowledge and Information Systems*, 2014, Vol. 41, Issue 2, Pp. 311–334. DOI: 10.1007/s10115-013-0726-7
6. McCarthy L., Vandervalk B., Wilkinson M. SPARQL Assist language-neutral query composer. *BMC Bioinformatics*, 2012, Vol. 13, Pp. 1–9. DOI: 10.1186/1471-2105-13-S1-S2
7. The theory underlying concept maps and how to construct and use them. Available: <https://cmap.ihmc.us/docs/theory-of-concept-maps> (Accessed: 23.01.2017).
8. Sailamul P., Jang J., Paik S.B. Synaptic convergence regulates synchronization-dependent spike transfer in feedforward neural networks. *Journal of Computational Neuroscience*, 2017, Vol. 43, Issue 3, Pp 189–202. DOI: 10.1007/s10827-017-0657-5
9. Arulmozhi V., Reghunadhan R. Predicting the protein localization sites using artificial neural networks. *Journal of Cheminformatics*, 2013, Vol. 5, Issue 1, P. 46. DOI: 10.1186/1758-2946-5-S1-P46
10. Zhang W., Cao J., Wu R. Projective synchronization of fractional-order delayed neural networks based on the comparison principle. *Advances in Difference Equations*, 2018, Vol. 73, Pp. 1–16. DOI: 10.1186/s13662-018-1530-1
11. Gunther F., Pigeot I., Bammann K. Artificial neural networks modeling gene-environment interaction. *BMC Genetics*, 2012, Vol. 13, Pp. 1–18. DOI: 10.1186/1471-2156-13-37
12. Zhang Y., Yamaguchi R., Imoto S. Sequence-specific bias correction for RNA-seq data using recurrent neural networks. *BMC Genomics*, 2017, Vol. 17, Issue 11, Pp. 1–6. DOI: 10.1186/s12864-016-3262-5
13. Al Machot F., Ali M., Haj Mosa A. Real-time raindrop detection based on cellular neural networks for ADAS. *Journal of Real-Time Image Processing*, 2016, Vol. 1, Pp. 1–13. DOI: 10.1007/s11554-016-0569-z
14. Kobayashi Y., Hosoe S. Cooperative enclosing and grasping of an object by decentralized mobile robots using local observation. *International Journal of Social Robotics*, 2012, Vol. 4, Issue 1, Pp. 19–32. DOI: 10.1007/s12369-011-0118-7
15. Dennis L.A., Fisher M., Lincoln N.K. Practical verification of decision-making in agent-based autonomous systems. *Automated Software Engineering*, 2016, Vol. 23, Issue 3, Pp. 305–359. DOI: 10.1007/s10515-014-0168-9
16. Lunenburg J., Molengraaf R., Steinbuch M. A representation method based on the probability of collision for safe robot navigation in domestic environments. *Autonomous Robots*, 2018, Vol. 42, Issue 3, Pp 601–614. DOI: 10.1007/s10514-017-9653-x

Received 19.03.2018. / Статья поступила в редакцию 19.03.2018.

## THE AUTHORS / СВЕДЕНИЯ ОБ АВТОРАХ

SICHKAR Valentin N.  
СИЧКАР Валентин Николаевич  
E-mail: valenty.n.s2014@yandex.ru