Multiple robots (robotic centers) and systems. Remote sensing and non-destructive testing

Роботизированные комплексы и системы.
Технологии дистанционного зондирования неразрушающего контроля

UDC 004.89; 004.93
https://doi.org/10.32362/2500-316X-2023-11-4-26-35

RESEARCH ARTICLE

Algorithms for the visual analysis of an environment by an autonomous mobile robot for area cleanup

Maksim E. Beliakov @**,**
Sekou Abdel Kader Diane

MIREA – Russian Technological University, Moscow, 119454 Russia
@ *Corresponding author, e-mail: beliakow.m@gmail.com*

Abstract
Objectives. At present, increasing rates of pollution of vast areas by various types of household waste are becoming an increasingly serious problem. In this connection, the creation of a robotic complex capable of performing autonomous litter collection functions becomes an urgent need. One of the key components of such a complex comprises a vision system for detecting and interacting with target objects. The purpose of this work is to develop the underlying algorithmics for the vision system of robots executing area cleaning functions.
Methods. Within the framework of the proposed structure of the system for visual analysis of the external environment, algorithms for detecting and classifying objects of various appearance have been developed using convolutional neural networks. The neural network detector was set up by gradient descent on the open dataset of TACO training samples. To determine the geometric parameters of a surface in the field of view of the robot and estimate the coordinates of objects on the ground, a homography matrix was formed to take into account information about the characteristics and location of the video camera.
Results. The developed software and algorithms for a mobile robot equipped with a monocular video camera are capable of implementing the functions of neural network detection and classification of litter objects in the frame, as well as projection of found objects on a terrain map for their subsequent collection.
Conclusions. Experimental studies have shown that the developed system of visual analysis of the external environment of an autonomous mobile robot has sufficient efficiency to solve the tasks of detecting litter in the field of view of an autonomous mobile robot.

Keywords: neural detection, computer vision, homography, mobile robots, territory cleaning

• **Submitted:** 10.03.2022 • **Revised:** 28.02.2023 • **Accepted:** 02.05.2023

For citation: Beliakov M.E., Diane S.A.K. Algorithms for the visual analysis of an environment by an autonomous mobile robot for area cleanup. *Russ. Technol. J*. 2023;11(4):26–35. https://doi.org/10.32362/2500-316X-2023-11-4-26-35

Financial disclosure: The authors have no a financial or property interest in any material or method mentioned.

The authors declare no conflicts of interest.

НАУЧНАЯ СТАТЬЯ

Алгоритмы визуального анализа внешней среды автономным мобильным роботом в задаче уборки территории

М.Э. Беляков @,
С.А.К. Диане

МИРЭА – Российский технологический университет, Москва, 119454 Россия
@ Автор для переписки, e-mail: beliakow.m@gmail.com

Резюме

Цели. В настоящее время опасной глобальной тенденцией становятся нарастающие темпы загрязнения огромных по площади территорий различными типами бытовых отходов. В связи с этим актуальной потребностью является создание робототехнических комплексов, способных в автономном режиме осуществлять сбор такого мусора. Одной из ключевых составляющих подобных комплексов должна стать система технического зрения для детекции и взаимодействия с целевыми объектами. Цель работы – разработка алгоритмического обеспечения системы технического зрения робототехнических комплексов в задаче уборки территории.

Методы. В рамках предложенной структуры системы визуального анализа внешней среды были оптимизированы под задачу распознавания мусора алгоритмы детекции и классификации объектов различного внешнего вида с применением технологии сверточных нейронных сетей. Настройка нейросетевого детектора производилась методом градиентного спуска на открытой базе обучающих примеров TACO. Для определения геометрических параметров плоского пространства в поле зрения робота и оценки координат объектов на местности использована матрица гомографии, формируемая с учетом информации о характеристиках и расположении видеокамеры в пространстве.

Результаты. Разработанное программно-алгоритмическое обеспечение системы технического зрения для мобильного робота, оснащаемого монокулярной видеокамерой, реализует функции нейросетевой детекции и классификации объектов в кадре, а также проекции найденных объектов на карту местности для их последующего сбора.

Выводы. Проведенные экспериментальные исследования показали, что разработанная система визуального анализа внешней среды автономного мобильного робота обладает достаточной эффективностью для решения поставленных задач, в т.ч. для обнаружения мусора в поле зрения автономного мобильного робота.

Ключевые слова: нейросетевая детекция, техническое зрение, гомография, мобильные роботы, уборка территории

• **Поступила:** 10.03.2022 • **Доработана:** 28.02.2023 • **Принята к опубликованию:** 02.05.2023

Для цитирования: Беляков М.Э., Диане С.А.К. Алгоритмы визуального анализа внешней среды автономным мобильным роботом в задаче уборки территории. *Russ. Technol. J.* 2023;11(4):26–35. https://doi.org/10.32362/2500-316X-2023-11-4-26-35

Прозрачность финансовой деятельности: Авторы не имеют финансовой заинтересованности в представленных материалах или методах.

Авторы заявляют об отсутствии конфликта интересов.

INTRODUCTION

In most countries of the world, including Russia, waste produced in the course of daily human activity is generally disposed of in one of two ways: incinerated in waste incinerators or buried in landfills. Both methods of disposal have a negative impact on the environment. The incineration of waste is accompanied by the release of toxic gases and dust into the atmosphere, contributing to global warming and the pollution of water bodies, forests and cities far from the location of their release into the atmosphere. While incinerators used in post-industrial countries dispose of the toxic and polluting part of the waste in such a way as to reduce the impact of air pollution, the majority of waste continues to be buried in landfill sites, which also involves negative impacts in terms of emissions, contamination of ground water, etc.

These factors determine the importance of sorting waste into categories in order to reduce the amount of hazardous pollution as a result of waste disposal. The wastes produced by human activities can be divided into hazardous and safe [1]. Safe wastes include food residues, cardboard and paper, cellophane, and other organic wastes. Since such wastes when decomposed do not poison the soil or water sources, their negative impact on the environment is minimal; moreover, such materials can be easily recycled into new products. Hazardous wastes such as electric batteries, paint and varnish products, polyethylene, etc., can poison the soil and water bodies within a radius of several kilometers. Thus, waste sorting helps to reduce the amount of pollution by decreasing the amount of hazardous waste being sent to landfill sites instead of proper disposal sites, as well as increasing the quantity of recycled wastes and reducing associated waste removal costs.

An equally noteworthy problem involves the unintentional or intentional littering of public places such as streets, parks, picnic areas and beaches. According to Report Park Litter2020[1], the most common objects of litter in public spaces are cigarette butts, food wrappers, and plastic bottles. Given the diversity and vastness of the areas exposed to pollution and the general trend towards automation, a need arises to create automated robotic systems capable of autonomously picking up litter.

This present work considers a visual environmental analysis system for an autonomous mobile robot to search for and recognize different categories of waste, and localize the litter in a given area for subsequent collection. For such purposes, it is sufficient for the robot to have a single on-board camera.

[1] https://www.legambienteverona.it/wp-content/uploads/2021/01/Report-Park-Litter_English-final.pdf. Accessed January 25, 2022.

ANALYSIS OF DEVELOPMENTS IN THE FIELD OF ROBOTIC TERRITORY CLEANING

A number of R&D and production organizations around the world are working on the issue of automating litter pickup. Thus, in [2], a robotic system (RS) for the recognition of litter objects and their further collection, equipped with a gripper, a camera, and a visual sensing system, is described. This RS comprises an easy-to-implement hardware and software complex, forming the basis for creating an autonomous mobile robot for performing area cleaning tasks.

Since the visual analysis system of this RS uses the MobileNet pre-trained machine learning model [3], the system is only able to recognize bottles as litter. The work uses a simplified system of pointing and estimating the distance to the object. After detecting an object on the camera frame, the difference between the center of the frame and the center of the object's dimensional frame obtained from the MobileNet detector output is used to rotate the robot and point it at the object.

A PID (Proportional-Integral-Differential) controller can be used to control the motion of the robot [4]. The distance to the object is calculated using the parameters of the camera location on the base of the robot, taking tilt angle, height from the floor, and camera opening angle into account. The disadvantage of this approach is that, when recognizing multiple objects, there is no possibility of building an optimal route for their collection. Moreover, the system offers no litter sorting function.

In [5], a robotic system for litter processing is also described. However, in this case, the described system is not a mobile robot, but a conveyor system equipped with a mechanical manipulator, as well as a camera for visual classification and subsequent segregation assembly of waste arriving on the conveyor belt. The visual analysis system is capable of classifying waste into four classes: paper, metal, glass, plastic. Instead of using neural network algorithms, this system is based on the classical image processing algorithms, consisting of the following steps: recognition of object boundaries on the basis of the corresponding Canny algorithm [6]; threshold detection to separate objects from the background and remove noise; Gaussian filtering to blur object details; photo conversion into black-and-white format in order to use the brightness channel for edge detection; object contour recognition on the binary image. Further processing steps are the use of Hu Moments [7] and Fourier [8] descriptors to describe the shape of objects, along with the Hyperplane K-Nearest Neighbors method [9] for classification by object descriptors.

MODELS AND ALGORITHMS FOR RECOGNIZING THE TYPICAL OBJECTS IN THE ROBOT'S FIELD OF VIEW

Recognition and localization of objects is typically performed by the processing of raster images by methods of computer vision. However, there are different approaches and methods of computer vision. Classical methods include algorithms for finding key points, selecting object boundaries, and geometric transformations. Such algorithms are well suited for simpler and more deterministic tasks in terms of external factors, e.g., lighting and distance to the subject, as well as slight variations in the shape of objects. Alternatively, recognition algorithms based on deep learning are more robust to false positives when the illumination, size or foreshortening of the object changes. Such algorithms, which are usually built using convolutional neural networks, allow the creation of more advanced and fault-tolerant computer vision systems.

The convolutional network architecture is so named due to the convolution operation, whose essence is that each image fragment is multiplied element-by-element by the convolution matrix (kernel), with the result being summed and written in the similar position of the output image. The best results in the generalizability of the network and its computational efficiency are achieved when the convolutional layers and sub-sampling layers are alternated. Since this leads to a consistent reduction in the dimensionality of the input data, it makes the network robust to minor transformations of the analyzed image.

Among the computer vision problems solved by convolutional neural network methods, we can single out the problem of detecting objects in an image [10] as most suitable for the problem discussed in the present work. The detection problem consists in the need to determine the class and coordinates of target objects in order to permit processing of the image algorithm.

Since the neural network can be represented as a multidimensional function, the learning process consists in the optimization of the numerous internal parameters by the method of gradient descent [11].

To train a neural network model for the task of litter detection in the robot's field of view an open dataset TACO[2] [12] was chosen, comprising 1500 images with 4784 labeled objects sorted into 28 classes, which are globally divided into paper, glass, plastic, and metal (Fig. 1).

[2] TACO is a growing image dataset of waste in the wild. It contains images of litter taken under diverse environments: woods, roads and beaches.

As the architecture of the neural network detector, the YOLOv4 algorithm was selected [13]. This architecture offers a compromise between accuracy of object detection and speed (up to several hundreds frames per second when running on a graphics gas pedal). As a result of training, the model was optimized to 0.13 mAP (mean average precision) by 4 classes.

Fig. 1. Examples of marked images in the TACO training examples database

The complex and comprehensive mAP metric [14] takes into account both classification errors (FP, FN) and errors in localization of objects in the frame. Therefore, the obtained value of accuracy according to mAP metric is sufficient for practical application. The result of the detector operation is shown in Fig. 2.

Fig. 2. Result of the YOLOv4 detector operation

MODELS AND ALGORITHMS FOR LOCALIZATION OF TYPICAL OBJECTS ON THE TERRAIN MAP

Since it is assumed that the coordinates of the robot on a given territory are known, their coordinates can be calculated relative to the robot in order to determine the coordinates of litter objects (Fig. 3). This can be done by using the homography matrix. However, this transformation is valid only for objects on a flat surface. Thus, the proposed model of coordinate determination is valid only for objects lying on a flat surface.

Perspective distortion can be eliminated by converting the previously determined coordinates of litter objects on the frame from the mobile robot's onboard camera into coordinates in the top view of the space in front of the robot on the basis of the tilt angle, height above the surface and focal length of the camera.

The coordinates on the shot plane and spatial plane are defined by the following relation:

$$\begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix} = \mathbf{H}_0 \times \begin{bmatrix} x_{\mathrm{w}} \\ y_{\mathrm{w}} \\ 1 \end{bmatrix}. \qquad (1)$$

According to the geometrical explanation in Fig. 4, the homography matrix $\mathbf{H}_0$ can be described as follows [15]:

$$\mathbf{H}_0 = \begin{bmatrix} f & x_0 \cos\alpha & x_0 h \cos\alpha \\ 0 & f \sin\alpha + y_0 \cos\alpha & y_0 h \cos\alpha - fh \sin\alpha \\ 0 & \cos\alpha & h \cos\alpha \end{bmatrix}. \qquad (2)$$

where f is the focal length of camera; h is the camera height; α is the camera tilt angle; (x_0, y_0) are coordinates of intersection point of image axes.

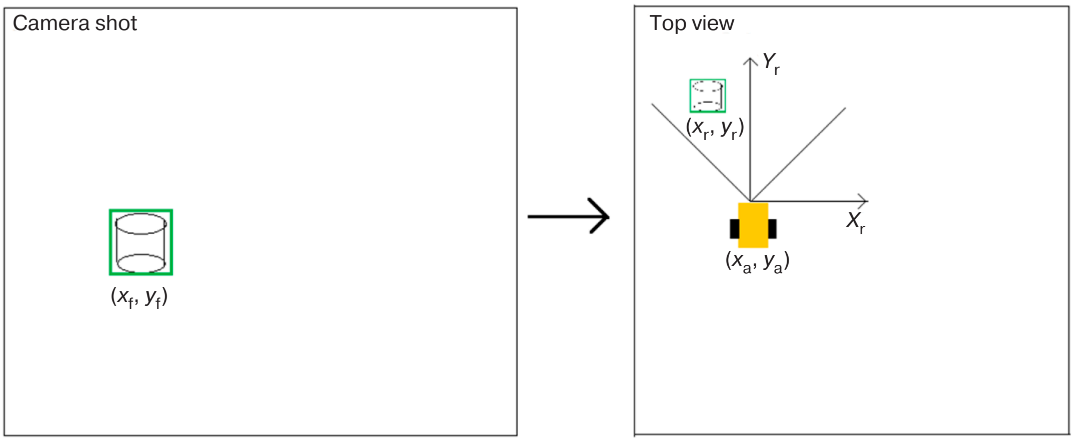


Fig. 3. Calculating the coordinates of the object relative to the robot: (x_r, y_r) – object coordinates in the coordinate system relative to the robot; (X_r, Y_r) – coordinate system relative to the robot; (x_a, y_a) – robot coordinates in the global coordinate system; (x_f, y_f) – coordinates of the object on the shot

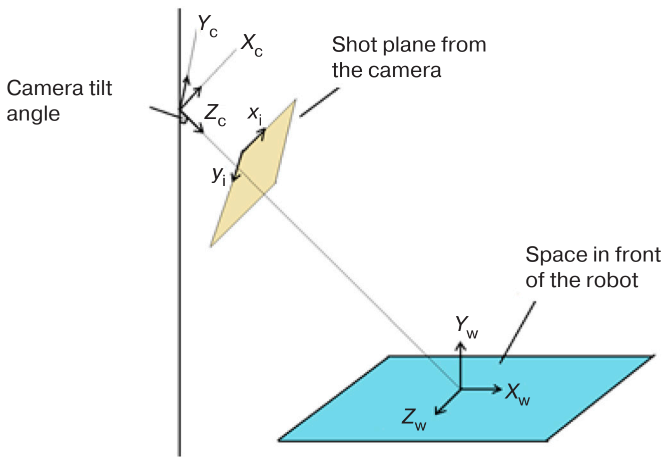


Fig. 4. Geometric representation of the homography matrix: (X_c, Y_c, Z_c) – coordinate system relative to camera; (X_w, Y_w, Z_w) – coordinate system in the plane of space in front of the robot; (x_i, y_i) – coordinates of points of rectangle framing object

Provided the camera angle is different from 0° and 90°, there is an inverse to this transformation, which can be used to obtain the top view from an image with a distorted perspective and vice versa.

Figure 5 shows a distorted perspective image taken at a tilt angle of $\alpha = 45°$, at height $h = 0.7$ m, as well as its corresponding transformation to the top view.

The frame from the robot's camera is analyzed by the neural network algorithm YOLOv4, which determines the pixel coordinates of the object on the frame as four coordinates of points $p_i = (x_i, y_i)$ of the framing rectangle (Fig. 2); thus, the center of the rectangle is taken as a single-valued coordinate of this object $p_c = \left\{\frac{x_1 + x_2}{2}, \frac{y_1 + y_2}{2}\right\}$.

This coordinate undergoes the transformation (3) to determe the relative pixel coordinates of the object within the visible space in front of the robot:

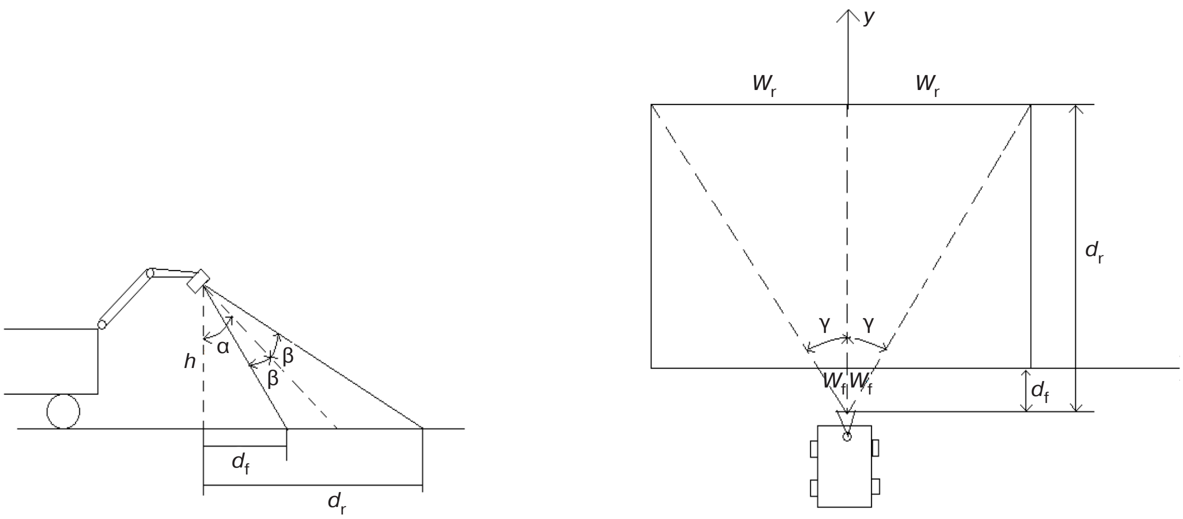
$$\begin{bmatrix} x_m \\ y_m \\ 1 \end{bmatrix} = \mathbf{H}_0^{-1} \times \begin{bmatrix} x_f \\ y_f \\ 1 \end{bmatrix}, \quad (3)$$

where x_m, y_m are coordinates of the object on the space in front of the robot.

To convert the pixel coordinates of objects in the visible space in front of the robot into meter coordinates relative to the robot, it is necessary to calculate the dimensions of the visible space. According to the explanations in Fig. 6, the geometric parameters of the space in front of the robot are unambiguously specified

(a) (b)

Fig. 5. Top view: (a) image taken with the camera; (b) image after correction of perspective distortion



(a) (b)

Fig. 6. Geometry of the observed space in front of the robot: (a) camera field of view in the vertical projection; (b) camera field of view in the horizontal projection

by the horizontal opening angle, vertical opening angle, height and camera tilt angle.

The distance from the camera to the near edge of the visible space d_f, the distance from the camera to the far edge of the visible space d_r, and the length of the visible space Y are determined by the following relations:

$$d_f = h \cdot \mathrm{tg}(\alpha - \beta), \quad (4)$$

$$d_r = h \cdot \mathrm{tg}(\alpha + \beta), \quad (5)$$

$$\mathrm{Y} = d_r - d_f. \quad (6)$$

The half-width of the near edge of the visible space w_f, the half-width of the far edge of the visible space w_r, and the width of the visible space X are determined by the following relations:-

$$w_f = \mathrm{tg}\gamma\sqrt{d_f^2 + h^2}, \quad (7)$$

$$w_r = \mathrm{tg}\gamma\sqrt{d_r^2 + h^2}, \quad (8)$$

$$X = 2w_r. \quad (9)$$

According to the aforesaid, the coordinates of objects relative to the robot are defined by the following ratios:-

$$x_0 = \frac{X \cdot x_{\mathrm{pxl}}}{w_{\mathrm{pxl}}} - w_r, \quad (10)$$

$$y_0 = Y\left(1 - \frac{X \cdot x_{\mathrm{pxl}}}{h_{\mathrm{pxl}}}\right) + d_f, \quad (11)$$

where x_{pxl}, y_{pxl} are the screen coordinates of the object in the visible space; w_{pxl}, h_{pxl} are the screen width and height of the visible space, respectively.

SOFTWARE STRUCTURE

The structure of the software and algorithmic support is determined by the previously established problems and tasks (Fig. 7). The software includes a subsystem of the user interface, libraries of image acquisition and preprocessing, as well as modules of target object recognition and calculation of its coordinates relative to the mobilebot.

The object recognition module includes not only the procedures directly responsible for the detection and classification process, but also a file with the preconfigured neural network architecture and its preconfigured weighting coefficients.

The Python programming language provides a convenient means for integrating different computer vision technologies and reducing debugging time.

EXPERIMENTAL RESEARCH

The conducted experiments confirmed the performance of the software and algorithmic software. Thus, Fig. 8 demonstrates procedures for recognizing and localizing several litter objects in the robot's field of view, removing perspective distortion, and calculating the coordinates of objects relative to the robot according to a camera of height $h = 0.5$ m, tilt angle $\alpha = 45°$, vertical camera opening angle $\beta = 23.75°$, and horizontal camera opening angle $\gamma = 30.41°$.

In the following experimental study (Fig. 9), the camera is in a position described by height $h = 0.5$ m, tilt angle $\alpha = 45°$, operating against a different background and identifying objects of different categories

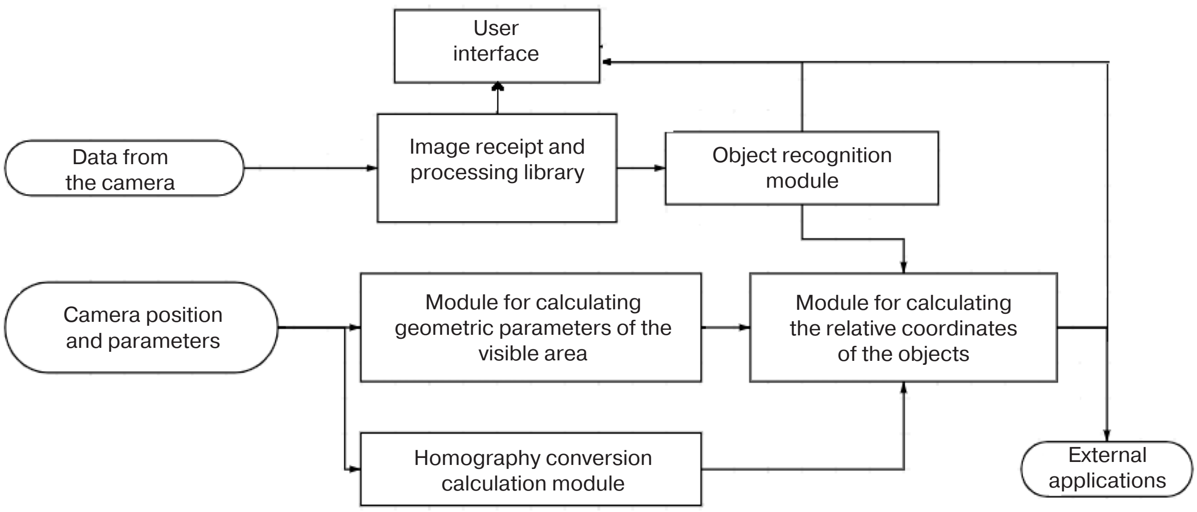


Fig. 7. Structure of software and algorithms for visual analysis of the mobile robot environment

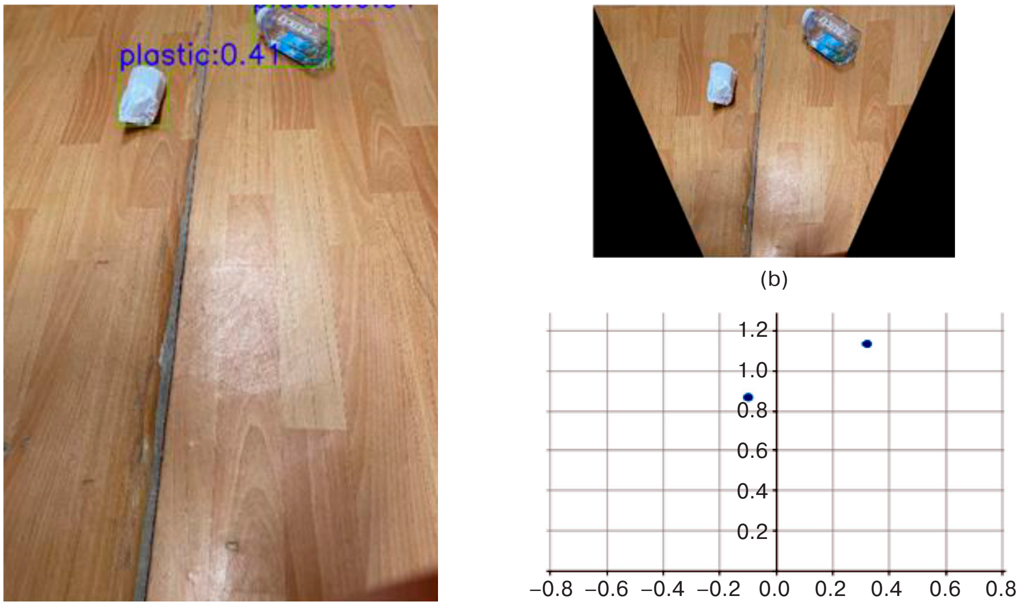


Fig. 8. Object recognition: (a) camera view; (b) top view;
(c) map of objects in the robot's field of view with coordinates in the metric system

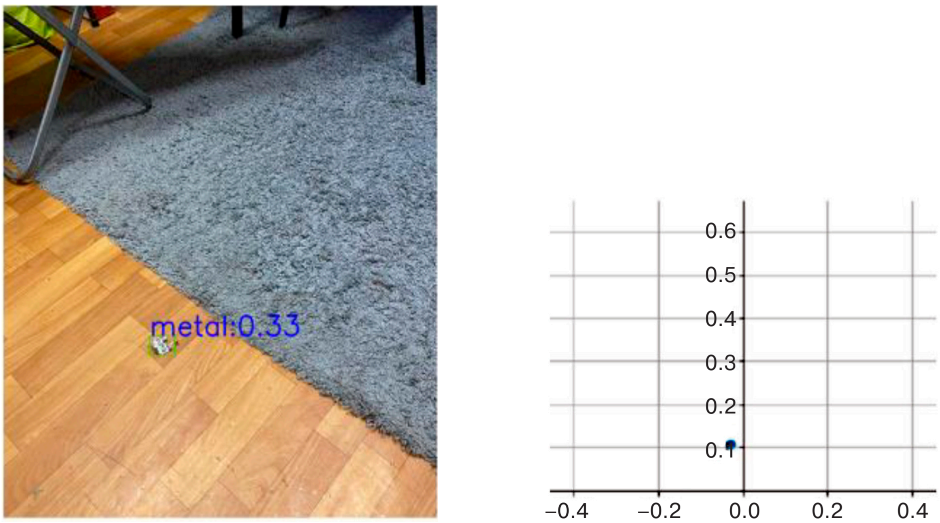


Fig. 9. Object recognition: (a) camera view;
(b) map of objects in the robot's field of view with coordinates in the metric system

of household waste. This case demonstrates that the software-algorithmic software is invariant both to the background, the number and categories of objects, as well as their spatial positions relative to the camera.

CONCLUSIONS

Unlike existing studies and approaches in this field, which do not combine the mobility of the platform and intelligent separate waste collection, the present study demonstrates the relevance and feasibility of automating these separate functions. The possibility of separate waste collection consists in the flexible intelligent collection with autonomous search for objects in a given area. In the framework of the study, the following results were achieved.

1. Proposed structure (Fig. 7) of software and algorithms for visual analysis of the mobile robot environment in the task of area cleaning with integrated waste sorting function.
2. Optimized algorithms for recognizing objects of different appearance and different waste categories on robot camera images using neural network algorithms.

3. Developed model for determining the geometric parameters of planar space in the field of view of the robot.
4. Developed model for determining the coordinates of objects in the field of view relative to the robot according to the position of the camera in space.

The experimental studies confirmed the performance and universality of the developed algorithms. Correct data were obtained for the recognition of various objects and further determination of their relative coordinates. In addition, the system demonstrated its performance when detecting objects of different categories and different spatial camera positions, taking into account uncertainties in the background of the underlying surface and the number of searched objects.

Further prospects for the development of the research presented consist in the development of algorithms for path planning on the ground and motion control of the mobile robot in the process of collecting and transporting the detected objects of litter.

Authors' contribution. All authors equally contributed to the research work.

REFERENCES

1. Chernyaeva T.K. Actual problems of the impact of production and consumption waste on environment and public health (review of literature). *Gigiena i sanitariya = Hygiene and Sanitation*. 2013;3:32–35 (in Russ.).
2. Bansal S., Patel S., Shah I., Patel A., Makwana J., Thakker R. *AGDC: Automatic Garbage Detection and Collection*. arXiv preprint arXiv:1908.05849. 2019. https://doi.org/10.48550/arXiv.1908.05849
3. Howard A.G., Zhu M., Chen B., Kalenichenko D., Wang W., Weyand T., Andreetto M., Adam H. *MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications*. arXiv preprint arXiv:1704.04861. 2017. https://doi.org/10.48550/arXiv.1704.04861
4. Karpov V.E. *PID-upravlenie v nestrogom izlozhenii* (*PID-Control in a Loose Presentation*). Moscow; 2012. 34 p. (in Russ.). Available from URL: http://radioservice.at.ua/_fr/0/Karpov_mobline1.pdf
5. Salmador A., Cid J.P., Novelle I.R. Intelligent Garbage Classifier. *Int. J. Interact. Multimedia Artif. Intell.* 2008;1(1):31–36.
6. Xu Z., Ji X., Wang M., Sun X. Edge detection algorithm of medical image based on Canny operator. *J. Phys.: Conf. Ser*. 2021;1955(1):012080. https://doi.org/10.1088/1742-6596/1955/1/012080
7. Ming-Kuei Hu. Visual pattern recognition by moment invariants. *IRE Transactions on Inform. Theory*. 1962;8(2): 179–187. https://doi.org/10.1109/TIT.1962.1057692
8. El-ghazal A., Basir O., Belkasim S. A novel curvature-based shape Fourier Descriptor. *2008 15th IEEE International Conference on Image Processing* (*ICIP*). 2008. P. 953–956. https://doi.org/10.1109/ICIP.2008.4711914
9. Pascal V., Yoshua B. K-Local Hyperplane and Convex Distance Nearest Neighbor Algorithms. In: Dietterich T.G., Becker S., Ghahramani Z. (Eds.). *Advances in Neural Information Processing Systems*. The MIT Press; 2001. V. 14. P. 985–992.
10. Deng J., Xuan X., Wang W., Li Z., Yao H., Wang Z. A review of research on object detection based on deep learning. *J. Phys.: Conf. Ser.* 2020;1684(1):012028. https://doi.org/10.1088/1742-6596/1684/1/012028
11. Bredikhin A.I. Training algorithms for convolutional neural networks. *Vestnik Yugorskogo gosudarstvennogo universiteta = Yugra State University Bulletin*. 2019;1(52):41–54 (in Russ.). https://doi.org/10.17816/byusu20190141-54
12. Proença P.F., Simões P. *TACO: Trash Annotations in Context for Litter Detection*. arXiv preprint arXiv: 2003.06975. 2020. https://doi.org/10.48550/arXiv.2003.06975
13. Bochkovskiy A., Wang C.Y., Liao H.Y.M. *YOLOv4: Optimal Speed and Accuracy of Object Detection*. arXiv preprint arXiv: 2004.10934. 2020. https://doi.org/10.48550/arXiv.2004.10934
14. Liu L., Özsu M.T. (Eds.). *Encyclopedia of Database Systems*. New York, NY, USA: Springer; 2009. V. 6. https://doi.org/10.1007/978-0-387-39940-9
15. Yasuda T. (Ed.) *Multi-Robot Systems, Trends and Development*. London, United Kingdom: IntechOpen; 2011. 598 p. https://doi.org/10.5772/544

About the authors

Maksim E. Beliakov, Bachelor, Department of Control Problems, Institute of Artificial Intelligence, MIREA – Russian Technological University (78, Vernadskogo pr., Moscow, 119454 Russia). beliakow.m@gmail.com. https://orcid.org/0000-0001-7193-049X

Sekou Abdel Kader Diane, Cand. Sci. (Eng.), Associate Professor, Department of Control Problems, Institute of Artificial Intelligence, MIREA – Russian Technological University (78, Vernadskogo pr., Moscow, 119454 Russia). E-mail: sekoudiane1990@gmail.com. ResearcherID T-5560-2017, Scopus Author ID 57188548666, RSCI SPIN-code 8691-0290, https://orcid.org/0000-0002-8690-6422

Об авторах

Беляков Максим Эдуардович, бакалавр, кафедра проблем управления Института искусственного интеллекта ФГБОУ ВО «МИРЭА – Российский технологический университет» (119454, Россия, Москва, пр-т Вернадского, д. 78). E-mail: beliakow.m@gmail.com. https://orcid.org/0000-0001-7193-049X

Диане Секу Абдель Кадер, к.т.н., доцент, кафедра проблем управления Института искусственного интеллекта ФГБОУ ВО «МИРЭА – Российский технологический университет» (119454, Россия, Москва, пр-т Вернадского, д. 78). E-mail: sekoudiane1990@gmail.com. ResearcherID T-5560-2017, Scopus Author ID 57188548666, SPIN-код РИНЦ 8691-0290, https://orcid.org/0000-0002-8690-6422

Translated from Russian into English by Lyudmila O. Bychkova
Edited for English language and spelling by Thomas A. Beavitt