Data and Metadata. 2025; 4:872
doi: 10.56294/dm2025872

ORIGINAL

Increasing the operating efficiency of sorting robotic complexes based on multi-projection processing

Aumento de la eficacia operativa de los complejos robotizados de clasificación basados en el procesamiento multiproyección

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Cite as: Alzoubi S. Increasing the operating efficiency of sorting robotic complexes based on multi-projection processing. Data and Metadata. 2025; 4:872. https://doi.org/10.56294/dm2025872

Submitted: 10-06-2024 **Revised:** 07-10-2024 **Accepted:** 05-05-2025 **Published:** 06-05-2025

Editor: Dr. Adrián Alejandro Vitón Castillo

ABSTRACT

Introduction: this paper explores computer vision techniques for automated sorting of objects based on their geometric shape, color, and brightness. The research addresses two primary scenarios: objects moving along a conveyor belt and objects placed unordered in a common container.
Method: the sorting system utilizes computer vision algorithms that incorporate edge pixel extraction, cellular automata, and the Radon transform. Edge detection is achieved using the Prewitt operator to extract object contours. Cellular automata are employed to generate object backgrounds and define polygonal regions, improving shape recognition. The Radon transform is applied with a hexagonal image grid to produce six projections, aiding in noise reduction and accurate shape and orientation detection.
Results: the combined use of six Radon projections and cellular automata enables the system to distinguish individual objects even when they are placed together in a single container. The approach effectively detects and sorts distorted or variably shaped objects with high precision, regardless of their arrangement—either random or orderly.
Conclusions: the proposed computer vision-based sorting method is robust and versatile, capable of handling complex object configurations. It offers a reliable solution for sorting objects by shape, color, and brightness in diverse industrial or logistical settings.

Keywords: Robot Robotic Manipulator; Sorting Complex; Prewitt Operator; Radon Transform; Hexagonal Mosaic; Raster Image; Computer Vision.

RESUMEN

Introducción: este artículo explora técnicas de visión por ordenador para la clasificación automatizada de objetos en función de su forma geométrica, color y brillo. La investigación aborda dos escenarios principales: objetos que se mueven a lo largo de una cinta transportadora y objetos colocados sin ordenar en un contenedor común.
Método: el sistema de clasificación utiliza algoritmos de visión por ordenador que incorporan la extracción de píxeles de borde, autómatas celulares y la transformada de Radon. La detección de bordes se realiza mediante el operador Prewitt para extraer los contornos de los objetos. Los autómatas celulares se emplean para generar fondos de objetos y definir regiones poligonales, lo que mejora el reconocimiento de formas. La transformada de Radon se aplica con una rejilla de imagen hexagonal para producir seis proyecciones, lo que ayuda a reducir el ruido y a detectar con precisión la forma y la orientación.
Resultados: el uso combinado de seis proyecciones de Radon y autómatas celulares permite al sistema distinguir objetos individuales incluso cuando están colocados juntos en un mismo contenedor. El método detecta y clasifica con gran precisión objetos distorsionados o de formas variables, independientemente de su disposición, ya sea aleatoria u ordenada.

Conclusiones: el método de clasificación por visión artificial propuesto es robusto y versátil, capaz de manejar configuraciones complejas de objetos. Ofrece una solución fiable para clasificar objetos por forma, color y brillo en diversos entornos industriales o logísticos.

Palabras clave: Robot Manipulador Robótico; Clasificación Compleja; Operador de Prewitt; Transformada de Radon; Mosaico Hexagonal; Imagen Raster; Visión por Computador.

INTRODUCTION

In the modern world, population growth on the planet entails an increase in the amount of waste that requires effective processing for further use in the manufacture of various useful products. Modern scientific and technological progress causes the emergence of new and diverse human consumption items. This is especially true for food storage items, which after eating food become waste in places where they are concentrated. The area of waste concentration is constantly increasing and, if waste is not processed by sorting and distributing it for further use, then contaminated areas will cover ever larger areas. Most waste items can be either reused or further used to create new items needed in human life. This is especially true for various packaging items and containers for storing liquids, bulk materials, food for people and animals, etc. Containers can be made of various materials (glass, paper, plastic, etc.). After using the contents of the containers, empty containers end up in a landfill without prior sorting.

To effectively sort waste in places where it accumulates, various robotic systems based on computer vision are used. Automated sorting complexes can also be used for sorting and placing cargo in warehouses, sorting fruits and vegetables and other objects.(1,2,3,4,5) In such tasks, the geometric shapes, color and brightness properties of sorting objects are known in advance, which simplifies the process of classifying objects and their distribution. In waste sorting systems, the classification process aims to identify not only whole, but also deformed objects that have the same purpose. For example, sorting can be done by items that are shaped like bottles, cardboard boxes, and other objects. Moreover, both bottles and boxes can have different geometric shapes and sizes, and also consist of different materials. Basically, sorting units on such robotic complexes are located on a conveyor belt or in a special container of a certain size. Issues of increasing the efficiency of sorting objects in these two types of sorting are considered and studied in this paper.

Literature review

There are four main categories of modern robot navigation systems:

- Inertial navigation systems (INS).(1)
- Global positioning system (GPS).(2,3,4,5,6)
- Local positioning system (LPS).(7,8)
- Simulated navigation systems.(9,10,11,12)

Each of these systems possess unique characteristics and serves to address specific situational challenges. Each of these systems find widespread application across various industries, particularly where their effectiveness is most pronounced.

Inertial navigation systems (INS) are based on the use of inertial sensors and measuring instruments.(13,14) Accelerometers and gyroscopes can be used as inertial sensors, using which, the robot can autonomously determine its location without relying on other navigation systems. However, autonomous use of INS is most effective for short distances with minimal obstacles. Combining INS with other navigation systems enhances overall effectiveness. In addition, the operation of such systems is significantly influenced by the topography of the surface on which the robot moves.

GPS uses satellite systems for navigation.(2) Robots exchange signals with satellites, enabling the satellite system to determine their location. The satellite signals provide the robots with necessary information about the next direction of movement. GPS based robot navigation systems excel in open areas with high navigation accuracy. However, it often fails in closed spaces, such as indoor rooms. In addition, expensive equipment is required to implement such GPS based system. In terms of security, unauthorised access may compromise the robot's navigation.

LPS are implemented based on the placement of local sensors, as well as various pointers in the form of signal beacons, which allow the robot to navigate in the local space.(7) These systems are typically used in enclosed spaces, such as automated warehouses, conveyors and restaurants. However, LPS based robot navigation systems have their own limitations: they make the robots dependent on the placement of various sensors and beacons, without which the robot cannot navigate effectively. In addition, LPS does not perform optimally in dynamically changing environments.

Simulation of navigation systems are very popular[9,10,11,12] and play a crucial role in testing and refining navigation algorithms and strategies without relying on physical robots. Such simulations can be implemented purely through software. For instance, a combined framework utilising CoppeliaSim and robot operating system (ROS) has gained popularity amongst the robot developers and researchers.[9,15] Additionally, the robot virtual navigation (RVN) framework, based on OpenGL[10] serves as one of the effective tools for simulating robot navigation. Another approach is to integrate the physical models with the software-based ones. For instance, the interactive robotics modelling & simulation System (IRMSS),[11] which consists of two subsystems: a physical model for robots and a 3D robotics modelling subsystem.

While virtual models dominate these systems, they often overlook the real-world unpredictability and the changes in the environment of the movement platform. Therefore, robotic experts are focusing on the autonomous navigation and path planning. One of highly researched algorithms in autonomous robot navigation is the use of graph theory, which plays a key role in finding optimal paths and determining efficient movement.[16,17,18,19,20] However, it requires pre-assessing the environment along the entire path, which can be challenging due to dynamic changes.

Heuristic path-finding algorithms using A* and D* also require preliminary terrain assessment and substantial computing resources.[21,22,23,24,25,26,27] A comprehensive overview of various methods and tools used for robot path planning is provided by Sánchez-Ibáñez at al.[28]. This paper[28] examines different types of cell shapes that define the robot movement spaces and discusses various interaction methods between robots and surfaces. Algorithms, such as local and global planning, reactive computing local optimisation, etc. were also evaluated, emphasising on their advantages and disadvantages. These algorithms use cell decompositions and roadmaps that are defined in advance. These algorithms require significant computing resources, and local optimisation may lead to local minima.[29,30,31,32] Researchers continue to explore graph-based algorithms, which despite being time-consuming to construct, offer promising solutions.

There are numerous works that leverage cellular automata (CA) technologies for developing robot path planning algorithms.[33,34,35] The paper [33] presents a model, namely Genetic Shared Tabu Inverted Ant Cellular Automata (GSTIACA), for observing a group of robots by combining cellular automation technologies, genetic algorithms, ant algorithms and insights from the social behaviour of the pedestrians. The model initially implements a genetic algorithm, followed by CA technologies applied during specific navigation steps across diverse environments. The results demonstrate effective swarm behaviour of the robots. However, this model requires substantial computing resources and exhibits inertial since the individual robot behaviour model consumes time in analysing pheromones and queues, determining positions and also preliminary room identification. Additionally, the robot's analysis is confined to neighbouring cells within the Moore neighbourhood, without considering the broader environmental context of the movement platforms.

Syed et al.[36] propose a robot path planning algorithm based on CA. The algorithm pre- processes the environmental contexts of the workspace employing image processing techniques using Minkowski sums. The CA generates a set of waypoints by analysing the activated parent and daughter cells within Moore neighbourhood. This algorithm is effective for short robot path distances. While the scale of the resulting image has a significant influence, it may not always be commensurate with the actual size of the robot. It's important to note that the algorithm pre-determines the optimal path, which, in real conditions, may not always be possible to implement. Furthermore, at each step of the movement, the robot estimates the path a single cell distance.

To address the potential existing issues, combining path planning with internal robot navigation allows the robot to adapt to unforeseen situations, minimising delays as well as avoiding unwanted trajectories. This combination allows the robot to function autonomously, continuously adjusting its movement trajectory even when deviations from the planned path occur, all while progressing toward its intended goal.

Relative works

The problem of identifying objects in an image is an important task. This is especially true for the tasks of identifying objects in images of the earth's surface,[6] images used for efficient organization of vehicle traffic,[7] for warehouse complexes,[8] for sorting complexes[2,9] etc. Specialists pay a lot of attention to systems that use autonomous mobile robots, which select the necessary units from a collection of things and transport them to a collection point.[3,4,10,11]

There are many object sorting problems that can be divided into two directions:

- Sorting objects arranged in an orderly manner on a conveyor belt.[12]
- Sorting of objects located in one container or in a limited area.[13,14]

For items located on a conveyor belt, various methods and means are used, which depend on the specific tasks assigned and parameters that affect the distribution of objects among placement points. The main influencing factors in such systems are: the speed of operation of the technical vision system, the accuracy of determining the main characteristics and the orientation of objects. The greatest problems arise if the object located on the conveyor belt has distortions in its geometric shape, color and brightness characteristics.

There are systems that sort similar objects by color and size.[5,15] To solve the assigned problems in such systems, complex image processing algorithms are not required. However, they often use complex architectures built on artificial neural networks. Limited sorting options limit the use of such systems in systems that are more complex.

An important parameter at sorting complexes is the geometric shape and size of objects present in the recorded image. There are many solutions to such problems,[11,12,13,14] which are based on various technical solutions. For example, computer vision systems based on Mask R-CNN[4] are used to predict the material of objects and on this basis object classification is carried out. Such a system requires a long process of forming a training sample, as well as complex calculations, which complicates the computer vision system. Also, the pollution present at the facilities is not taken into account.

Papers [13,14] consider the problem of determining the geometric shapes of objects highlighted in different colors, as well as their orientation in the image. Such a system is limited by the fact that classical geometric shapes are considered without taking into account the distortion of geometric shapes and the noise present in the image.

In work [16], sorting is carried out according to the properties of color, shape, based on the centroid and edge selection algorithm, and the coordinates of the object's location were determined. However, non-matching identification results based on shape and color properties can sometimes lead to errors in sorting, which is not always acceptable in some systems.

Many works are devoted to the use of artificial neural networks to solve such a problem. The most popular are systems built on the basis of deep learning based on YOLO of various modifications.[11,21,22,23,24] Such systems require the use of a database with predefined object shapes. However, they are not able to detect objects of uncertain shape, and also require a large number of calculations. If items are damaged, false identification may occur in such systems, which can lead to system failures.[33,34,35,36]

Currently, an urgent task is the sorting of waste, the objects of which can have various unpredictable shapes, which complicates the formation of a database for training and testing samples. Therefore, it is necessary to search for new, most effective approaches to solve the problem of waste sorting based on computer vision.

This paper describes a method for sorting waste using cellular automata technologies and Radon transformation[6,37,38,39] which allows you to determine the internal area of objects, as well as construct Radon projections, the analysis of which provides high accuracy of geometric identification of objects both on the conveyor belt and in a common container.

RESULTS

Object sorting modes

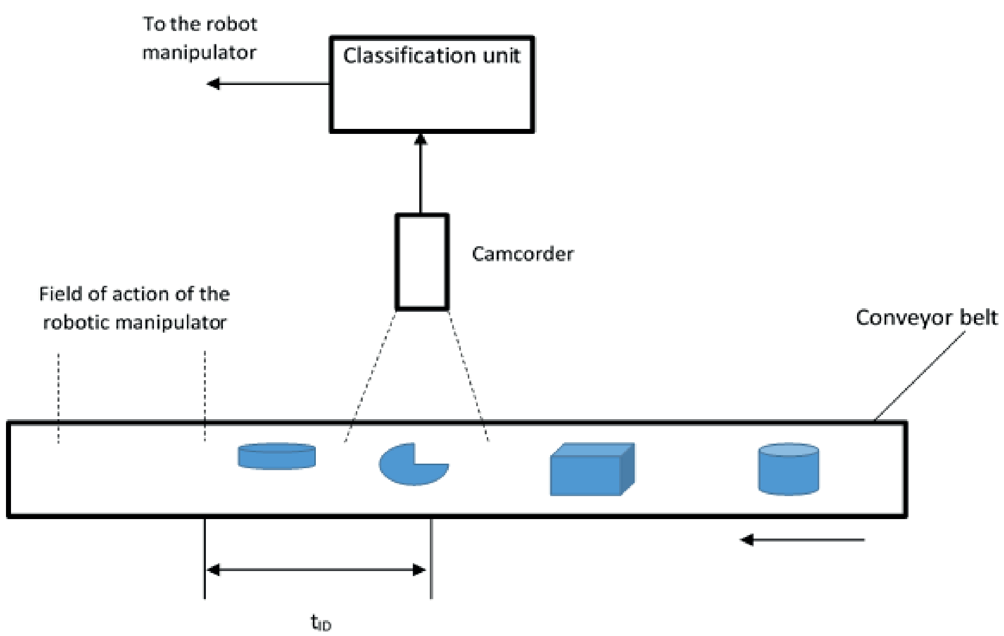

Figure 1. Sorting objects on a conveyor belt

Objects located on a conveyor belt are usually sequentially distributed throughout the entire belt and, during movement, enter the field of view of the video camera one or more. Sorting of objects recorded by a video camera is carried out after the time spent on their identification figure 1.

Sorting items are distributed on a conveyor belt that moves towards the sorting station. When an object enters the field of view of the video camera, an image is formed at the output of the video camera, which is sent to the object classification unit on the tape. During the time (tID) required to recognize an object on the conveyor belt, the object moves towards the sorting unit. The classification unit, within a time tID, recognizes an object captured in the image and transmits a description of the recognized object to the robotic manipulator located in the sorting unit. The classification unit also transmits the number of the container into which the recognized object must be moved. The dimensions and possible points of grip of the object by the robot are also transmitted. Other mechanical components for transferring an item into a given container may be used. For example, an object can be pushed into the desired container at the moment they are combined during the movement of the conveyor belt.

If a common special container is used in which many sorting items are placed, then special methods and algorithms for selecting and recognizing objects in the image are used. In this mode, objects located in a special container are not discarded as a result of sorting. Robots are used that, with the help of a special mechanized arm, grab a recognized object from a common special container and transfer it to a given container in which objects of the same class are collected.

Solving the problem of sorting many objects located in one container using robotic manipulators requires the use of modern methods and tools for image processing and recognition, in which one of the main operations is the selection of objects in an image containing many objects of different geometric shapes with different brightness and colors characteristics. In this case, objects can have different locations and orientations in space. The most problematic situation is when objects touch each other, which requires additional solutions for separating these objects with subsequent recognition. An automated robotic complex of objects with one common container in figure 2 is shown.

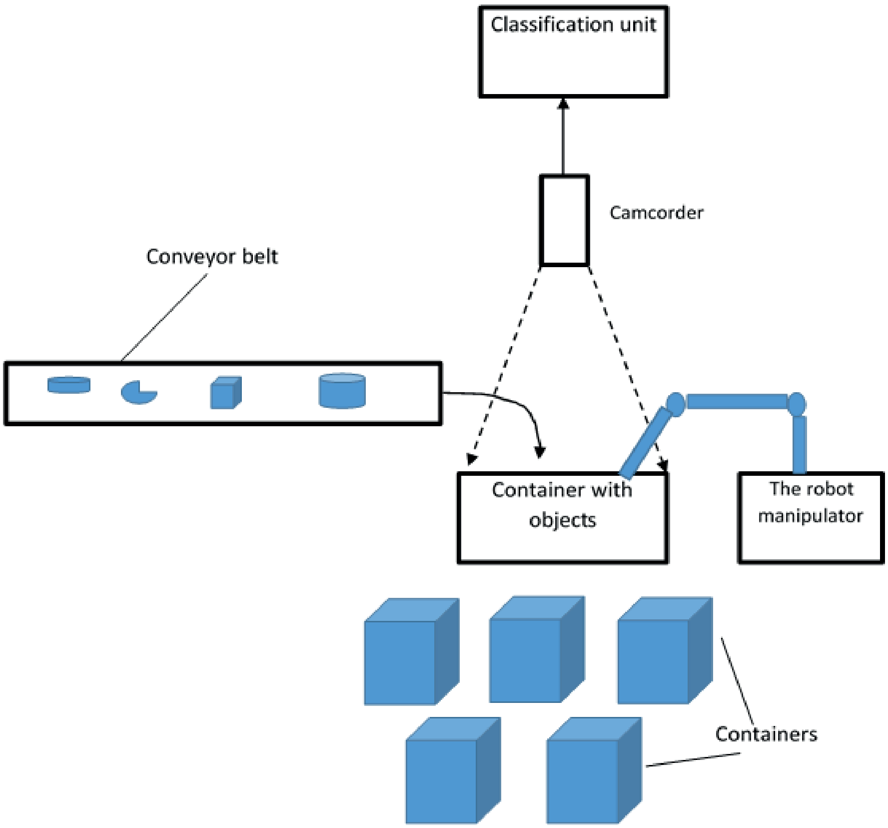

Figure 2. Structure of a robotic complex for sorting various objects

Waste items are moved along a conveyor belt and placed in a common container. The video camera forms an image of the contents of the common container and transmits it to the recognition unit. The recognition unit selects objects, alternates them and transmits to the robotic manipulator information about the selected objects, their order, as well as the containers into which they need to be moved.

The contents of the container are imaged using special lighting to clearly separate the background pixels from the objects. There should be no shadows or reflections of light from the background surface. An example of such an image in figure 3 is shown.

Figure 3. An example of a generated image of the contents of a common container

The container is covered with a material so that it does not reflect light, and the video camera and lighting are positioned to reduce the formation of shadows and create a clear contrast between objects and the background.

Sorting objects located on a conveyor belt

On the conveyor belt, objects are placed one at a time and move along with the conveyor belt towards the sorting unit, where containers for different groups of objects are located (figure 1). All sorting in this mode is based on the use of highly efficient technical vision, capable of determining the geometric shapes of objects and indicating the points at which an object can be grabbed by a robotic arm for transferring them to the appropriate container in the sorting unit. Sorting of objects on a conveyor belt is carried out mainly according to geometric shapes, since there are difficulties in determining the material from which they are composed. For example, bottles on a conveyor belt can be made of light or dark glass, and can also be made of plastic in a variety of colors. Therefore, initially sorting is carried out for all types of bottles, and later, using special image processing methods, they are classified according to the materials from which they are composed.

In conveyor belt mode, a separate object located on the conveyor belt and located in the visual field of the vision system is identified. After this, the object with the tape is moved to the sorting unit and, if the technical vision system has identified the geometric shape of the object, it is moved to the appropriate container. To facilitate the work of the technical vision system, the material of the conveyor belt is selected so that it forms the background in the image and does not form glare and shadows. Examples of the obtained images in figure 4 are presented.

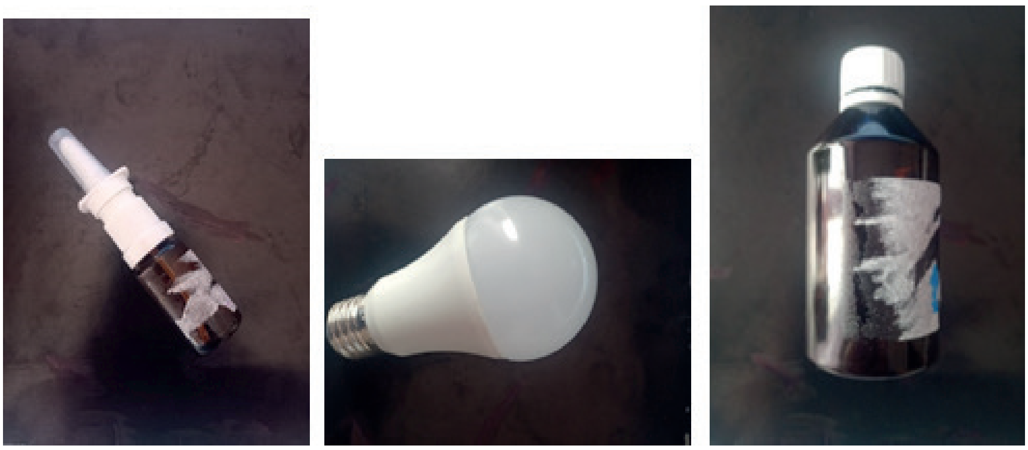

Figure 4. Examples of images of objects placed on a conveyor belt

The presented examples (figure 4) show images that contain minor light reflections, to remove which it is necessary to use additional algorithms. Also, the methods must take into account the orientation of the object on the conveyor belt.

To identify the geometric shape of an object located on a conveyor belt, the following algorithm is used.

1. An image of an object located on the conveyor belt in the viewing area of the video camera is

formed.

2. The smallest pixel code that does not occur in any pixel are determined. If the image pixels contain all the codes (the image has more than 16777215 pixels), then the code that belongs to the smallest number of image pixels is determined. To eliminate this situation, the image is reduced in size so that the number of pixels is less than 16777215.

3. Pixels that border the background pixels (are adjacent) are assigned the code determined in step 2. Background pixels are determined by thresholding.

4. From each selected edge pixel to which the selected code is assigned, neighboring pixels that do not have a background code go into a state encoding the edge pixel code. Thus, pixels belonging to the inner region of an object in the image encode a number equal to the code number of the edge pixels.

5. The pixels that received the code of the edge pixels to code 1 are converted, and the background pixels are coded to 0. Thus, a binary image is formed.

6. Six Radon projections are generated for the resulting binary image.

7. The resulting projections are analyzed and the geometric shape of the image of the object on the conveyor belt, recorded and formed at a certain point in time using a video camera, is determined.

At stage 2, edge pixels are selected and assigned a code that is not present in one pixel of the resulting image.[22] To select edge pixels, the Prewitt operator is used, which practically does not create contour breaks in the image, unlike other operators figure 5.

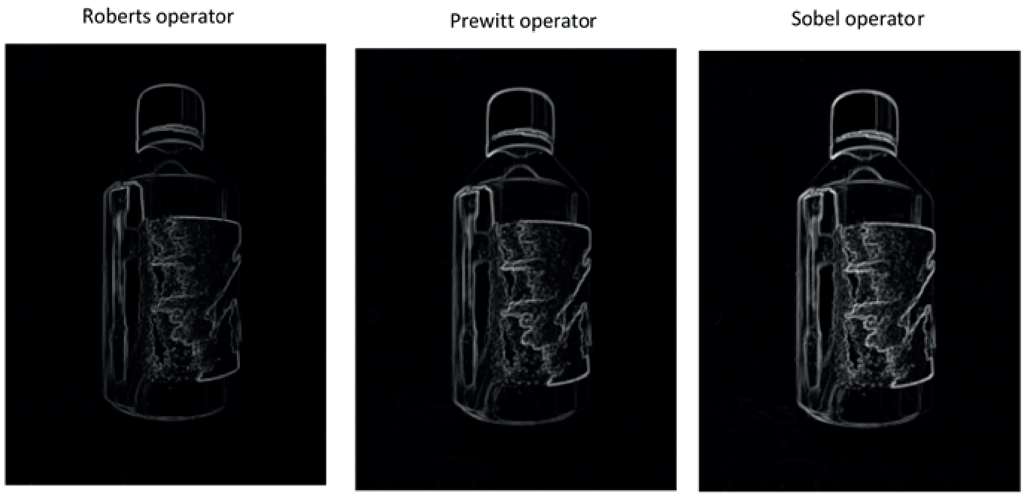

Figure 5. Examples of edge pixel selection for the Roberts, Prewitt and Sobel operators

By using thresholding, pixels belonging to the background are determined. As a rule, background pixels are assigned a white color code. Situations often arise when pixels inside an area take on the properties of background pixels, since they have the same color characteristics. Thus, preparation is made for image processing to form a background outside the polygonal area.

According to the method described in [21], the background signal is propagated from the outermost pixels of the image, taking into account the selected shape of the neighborhood in accordance with cellular automata technologies. It starts by assigning a specific background code to the pixels of the outermost rows and columns. For a binary image this can be code zero or for white color code 16777215 (if the image must be represented in black and white colors). At the next time step, neighboring pixels take on the state of the pixels of the outermost rows and columns of the image matrix if the following conditions are met.

$$b_{ij}(t+1) = \begin{cases} 0, if\, b_{ij}(t) < T \text{ and } B \\ b(t), \text{in other cases} \end{cases}$$

$$B = (b_{i-1,j-1}(t) < T \text{ or } b_{i,j-1}(t) < T \text{ or } b_{i+1,j-1}(t) < T \text{ or } b_{i-1,j}(t) < \\ < T \text{ or } b_{i+1,j}(t) < T \text{ or } b_{i-1,j+1}(t) < T \text{ or } b_{i,j+1}(t) < T \text{ or } b_{i+1,j+1}(t) < T)$$

Where:

$b_{ij}(t)$:code of the pixel located at the intersection of the i-th row and the j-th column at time t.

T – threshold value of the pixel code that determines whether the pixel belongs to the code.

Based on these conditions, the background state of the pixels is distributed across the image pixels, starting from the outer pixels to the center of the image. For this, it is better to use the Moore neighborhood, which reduces the propagation time of the background signal.(37) Simplifying calculations allows preliminary conversion of the image to binary. Then simple logical expressions are used with the signals of the pixels that form the Moore neighborhood. An example of the formation of a background outside the polygonal area in figure 6 is shown.

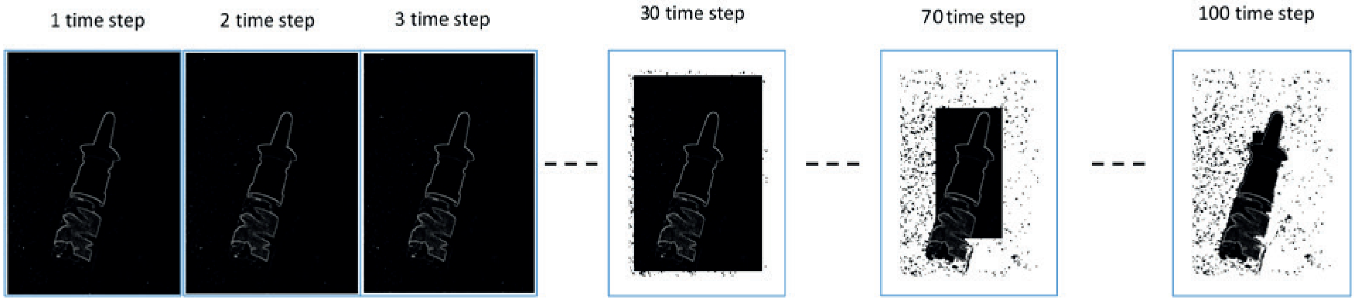

Figure 6. Example of background formation outside the polygonal area

An example figure 6 shows that pixels located inside the selected polygonal area do not form a background. These pixels subsequently become part of the polygonal area, which is filled with unit codes. Thus, the image contains two types of pixels: black (belonging to the geometric figure and noise) and white (belonging to the background). An example of such an image on figure 7 is shown.

Figure 7. An example of a binary image obtained as a result of transformations

After a binary image obten, the geometric shape of the figure and the points of capture of the object by the robotic manipulator are determined to transfer it to the appropriate container. Determination of the geometric shape of the selected area is carried out based on the methods presented in (6,20,23). These works use the Radon transform and the hexagonal shape of pixels to represent the image and form six Radon projections, which determine the geometric shape of the selected area and the point of capture of the object by the robotic manipulator. The use of orthogonal mosaics allows the formation of only three Radon projections, which does not always give an accurate idea of the geometric shape of the figure.

As a result of the generated binary image, there are noise pixels outside the selected area, which are also displayed on Radon projections outside the selected area. Figure 8 shows an example of six generated projections for a selected object. Based on the resulting projections, pixels are determined that are not located in the selected area and are the result of a poorly formed image. In this example figure 8 these are parts of the projections that have small values. They are present in every projection and indicate the presence of noise pixels.

After analyzing all six projections, noise pixels are clipped and removed, and in the binary image, the clipped pixels become background pixels. As a result, the images shown in Fig. 9 are obtained, in which pixels that do not belong to the background and the selected polygonal area are transferred to background pixels.

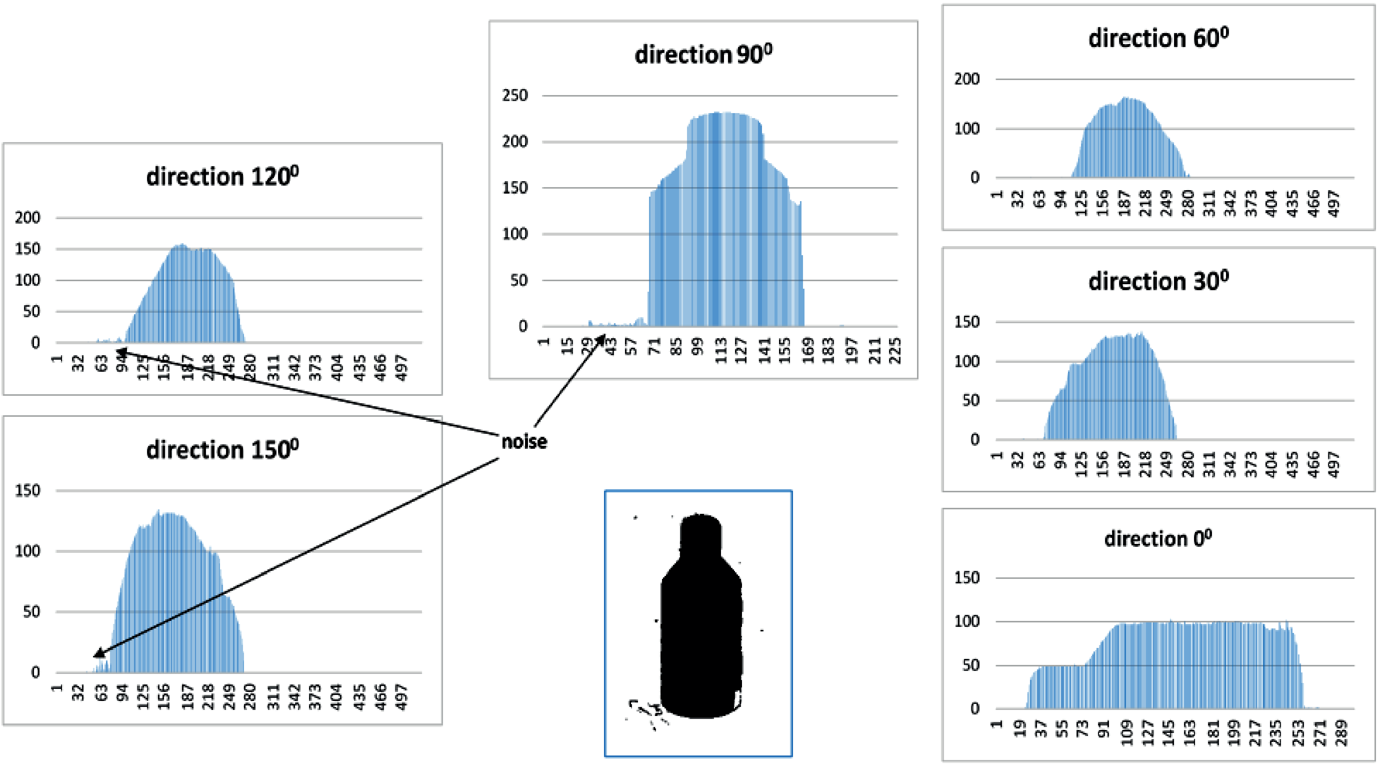

Figure 8. Example of six generated projections for the original binary image

Figure 9. Example of a binary image without noise pixels

As can be seen from figure 9, on the Radon projections there are no parts that reflect the presence of noise pixels, and in these directions the noise pixels have taken on the states of background pixels.

Based on the obtained Radon projections figure 8, the geometric shape of the selected figure in the image and its orientation are also determined. From the obtained projections, the largest values of the projections are determined. These values are determined on projections obtained at angles of 0^0 and 90^0. Horizontal projection determines the largest value on the horizontal axis, and vertical projections indicate the maximum value on the vertical axis. According to these projections, the width of the figure is determined, which is relatively flat.

Since such shapes (the shape of a bottle) have already been used during training of the system and the formation of reference vectors, the system defines the geometric shape as a bottle located along the direction corresponding to the direction at an angle of 900 from the horizontal of the video camera lens. In connection with determining the orientation and width of the bottle, gripping points in the image are determined, the coordinates of which are transmitted to the robotic manipulator.

If the orientation of the object on the conveyor belt is different, then it is determined by other projections figure 10 or the image is sequentially rotated by a given discrete angle and all six Radon projections are analyzed at each rotation step.

The largest values on the projections determine the orientation of the bottle. For this example, the highest value was obtained for direction 60^0.

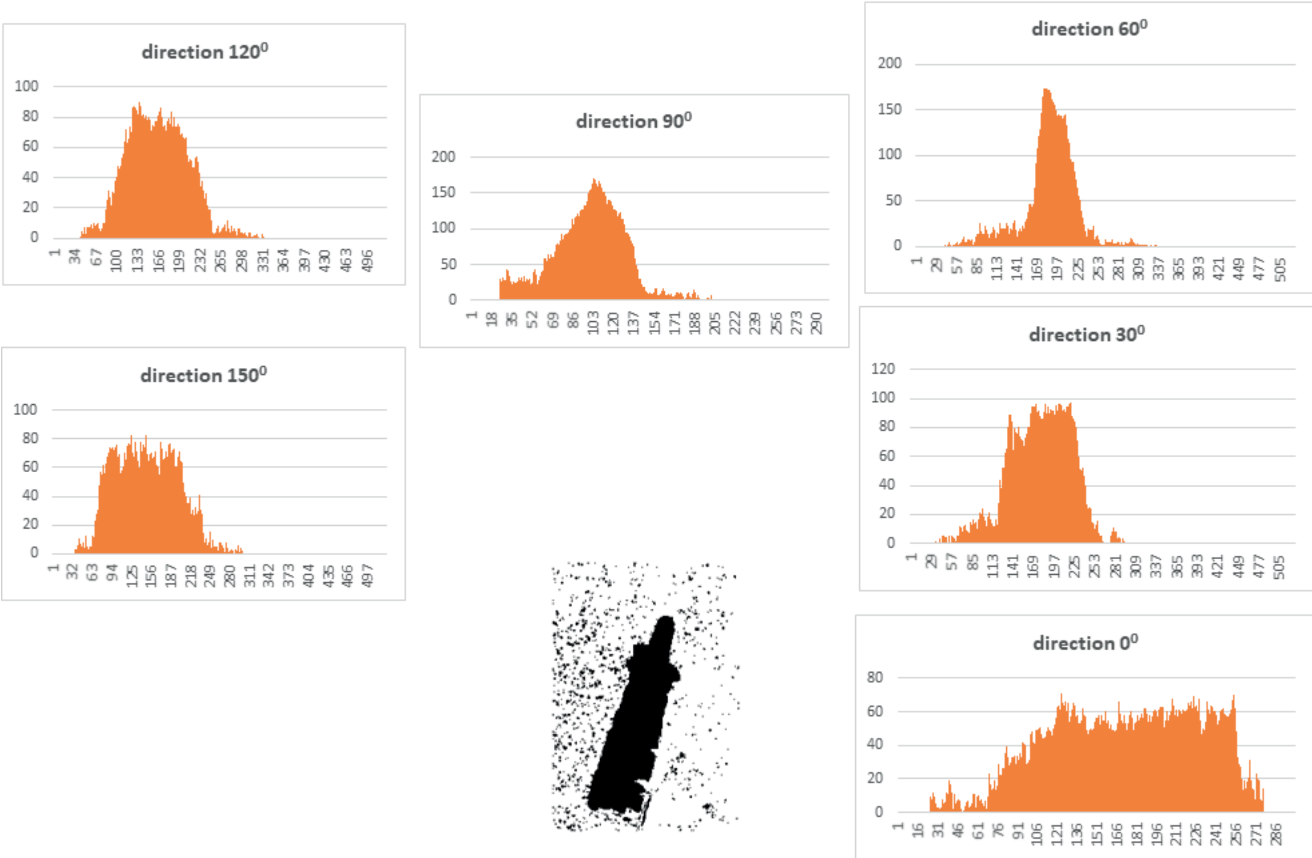

Figure 10. Example of Radon projections for a bottle with arbitrary orientation

Sorting objects placed in one container

Therefore, the problem of determining the geometric shape of an object and its orientation is solved. If a technology is used where objects are placed in one container, then the problem of selecting the object among all others located in the same container is initially solved, and then identifying it and determining its orientation. An example of placing objects of different geometric shapes and orientations on figure 11 is shown.

Figure 11. Examples of placing objects of various shapes in one container

To facilitate the operation of the vision system, the container is made of a material that does not reflect light or create shadows. Also, the lighting is positioned so that there are no shadows or reflections from the surface of the container or the objects themselves. There is also a need for objects inside the container to be in a static state. The ideal situation is when the objects in the container do not touch each other. Otherwise, additional difficulties arise when selecting objects in the image. Additional methods are used to solve this problem.

The first step in solving this problem is the step described in identifying an object on a conveyor belt. Edge pixels in the resulting image are highlighted. Filling is carried out inside closed areas described by closed contours. A binary image is formed figure 12.

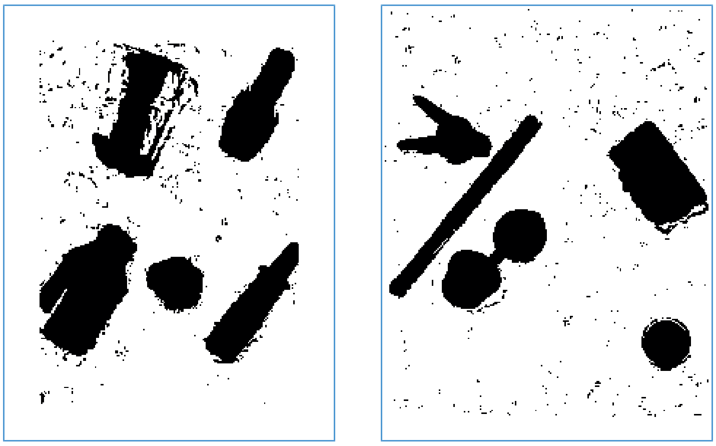

Figure 12. Examples of binary images in accordance with figure 11 with filled areas

To identify objects in a binary image, six Radon projections are formed and the projections obtained in the 0^0 and 90^0 directions are analyzed. The places on these projections where they contain zero values or values less than a specified threshold value T are determined. Areas with the largest values are selected on the projections and the original binary image is divided into areas that contain objects that form areas on the projections with the largest values. Projections are also formed on the resulting individual areas and analyzed. Then also are divided into separate images. An example of the formation of two Radon projections on figure 13 is shown. The process of such image separation is shown in the examples presented in figure 14.

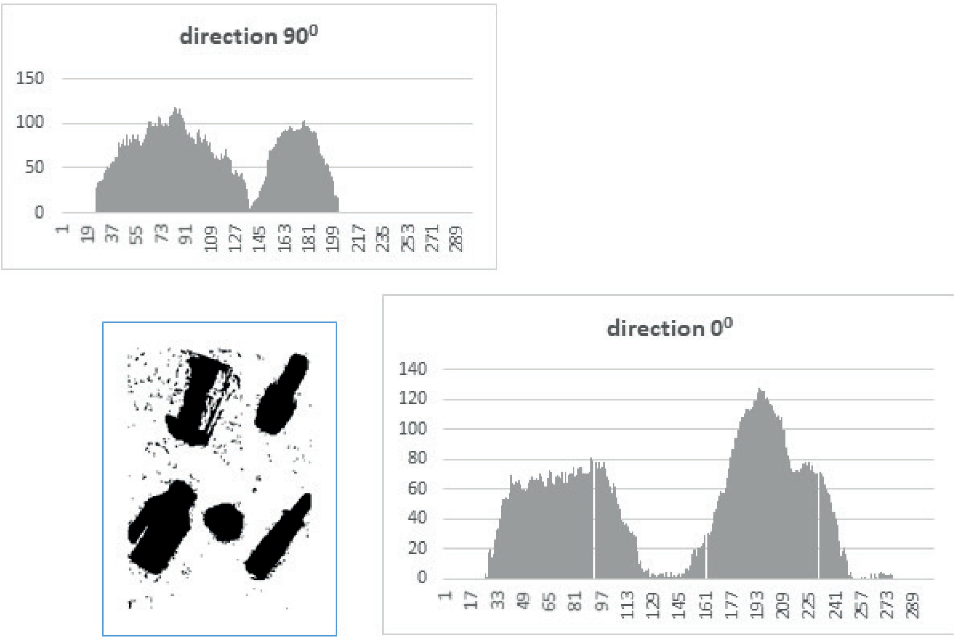

Figure 13. Examples of the formation of two Radon projections

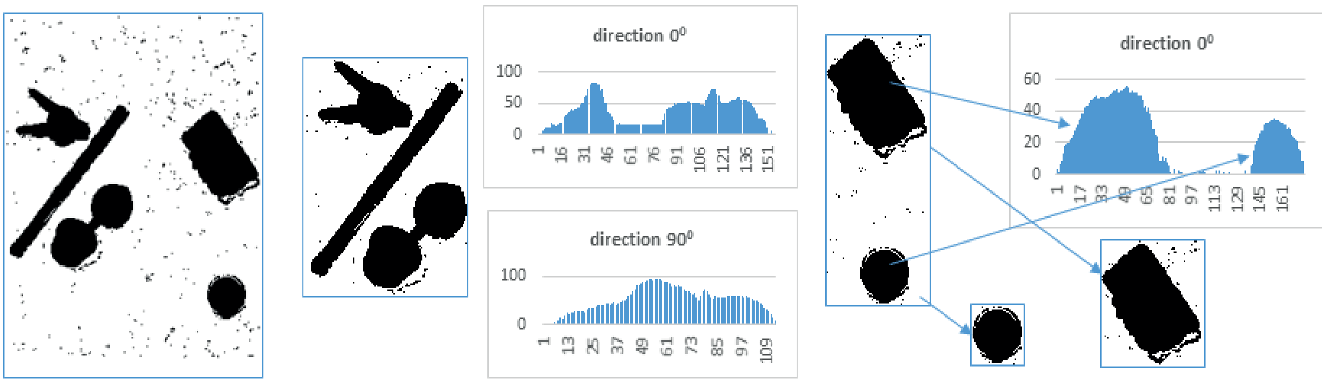

Figure 14. Examples of dividing an image into smaller images containing one object

https://doi.org/10.56294/dm2025872

The examples figure 14 show an image that can be divided into rectangular areas with vertical and horizontal sides. However, the first (located on the left in the image) image contains objects with different orientations, and their location on the container pallet is such that it does not allow separating the original binary image by analyzing only horizontal and vertical projections. To determine such objects, the remaining four projections are analyzed, which by their structure make it possible to separate objects from other objects. Projections show the location of objects. To determine their orientation, images with unseparated objects are rotated until maximum values are obtained on horizontal or vertical projections, as well as gaps between them with zero values or values less than a given threshold value T. An example of the rotation procedure in figure 15 is shown.

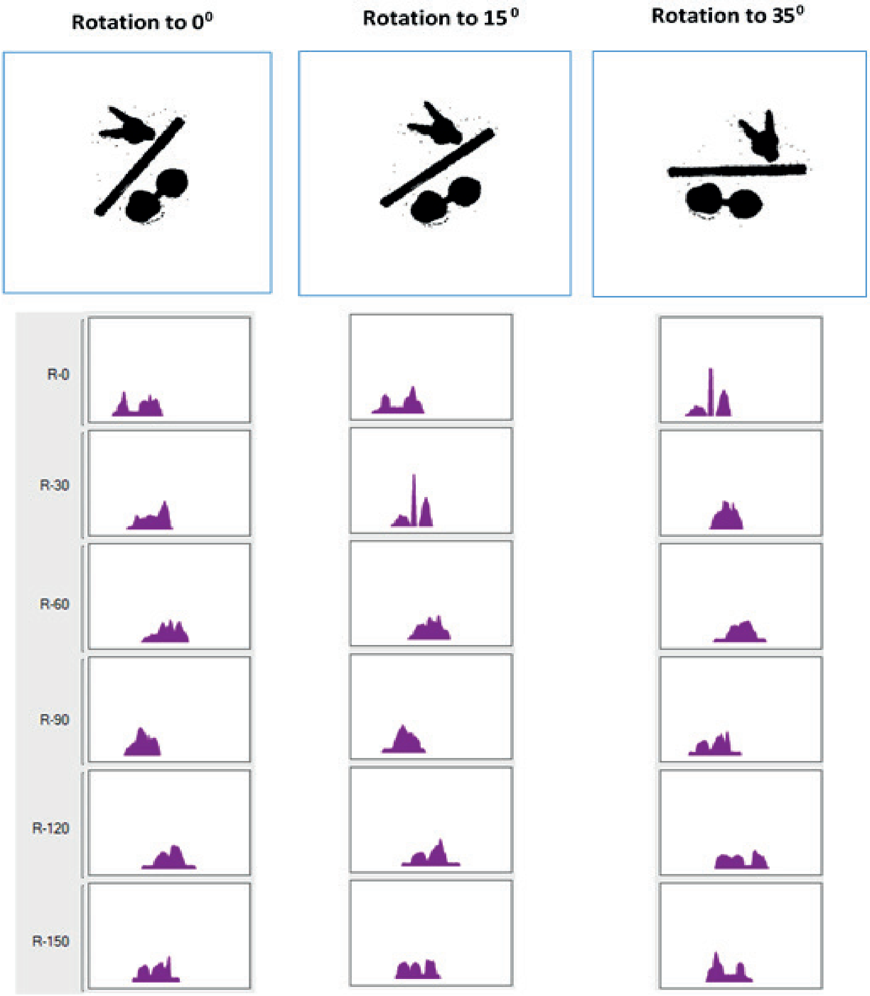

Figure 15. An example of rotation of a binary image and the resulting projections at each rotation angle

The resulting rotation angle is taken into account and, after determining the geometric shape, is used to determine the orientation of objects. The projection in direction 0^0 determines the rotation angle (in figure 15 this is an angle of 35^0) necessary to separate objects. This angle is also involved in determining the orientation of objects. The longest length of the objects determines the orientation of objects. Geometric dimensions are determined by analyzing Radon projections for each object, and the points of capture of the object by the robotic manipulator are also determined. Size and coordinates that determine its location characterize each selected rectangular field of the original image of the container's contents. For example, two vectors $<X_1, Y_1>$ and $<X_2, Y_2>$ indicate that the top left pixel of a rectangular box is specified by coordinates $<X_1, Y_1>$, and the bottom right pixel is specified by coordinates $<X_2, Y_2>$.

The technical vision system determines the geometric shape of the object, according to which the location of the container into which the object needs to be moved is transmitted to the robot. Knowing the coordinates of the object's location, its size and orientation, the robot grabs the object and transfers it to the specified container.

In such a system, the robotic complex does not determine the material of which the object located in the container consists. Also, objects can be deformed with distorted color characteristics of the surface, and not have a clear geometric shape. Therefore, the vision system determines the overall geometric shape of the object to determine the container into which the object will be transferred. If a robotic complex sorts predetermined objects without deformation and distortion, then the methods for their identification are significantly simplified, since the number of geometric shapes is limited and there are no distortions of geometric shapes and color characteristics.

CONCLUSIONS

The paper presented the principles of robot navigation from the starting point to a designated target. The principles combine insights from analysis of the internal characteristics as well as the environment of the movement surface. Leveraging cellular technologies based on cellular automata with active cells has significantly enhanced robot navigation. Notably, this method is especially effective when the movement map is formed in advance and all obstacles are already located within the cellular navigation environment. Remarkably, in such scenarios there is no need to use sensors.

The paper explores a methodology for increasing the efficiency of functioning of sorting robotic complexes that use modern methods of processing and recognition of patterns in images based on the Radon transform. The use of methods for identifying edge pixels, which form a closed contour of a figure in a two-dimensional image, made it possible to effectively separate background pixels and pixels of the internal region, even if their brightness and color parameters coincide. Research has shown that the most effective is the Prewitt operator, which gives a continuous contour of the selected polygonal area. Effective selection and separation of objects located in the same container allows the analysis of Radon projections formed after converting the original image into a binary one with selected objects. In addition, the use of Radon transform based on hexagonal coverage allows you to effectively remove noise pixels that do not belong to the selected areas. Also, the hexagonal coating makes it possible to form six Radon projections, with the help of which the orientation of objects is determined, and objects are easily separated, the location of which is such that on an orthogonal mosaic the addition can be divided with high accuracy. This approach is highly effective in sorting objects without distortion of the geometric shape and different coating materials. The proposed method allows you to sort items both in a random order of selecting items, and in a strictly defined sorting order.

In further research, the author plans to develop and explore the principles of sorting overlapping objects placed in the same container.

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FINANCING
None.

CONFLICT OF INTEREST
Authors declare that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION

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