DESENVOLVIMENTO DE UMA UNIDADE DE CLASSIFICAÇÃO ROBOTIZADA – RECONHECIMENTO DE FORMA DE OBJETOS

DEVELOPMENT OF A ROBOTIC SORTING NODE – RECOGNITION OF THE SHAPE OF OBJECTS

РАЗРАБОТКА РОБОТИЗИРОВАННОГО СОРТИРОВОЧНОГО УЗЛА – РАСПОЗНАВАНИЕ ФОРМЫ ОБЪЕКТОВ

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RESUMO

O objetivo deste trabalho é desenvolver um algoritmo para reconhecer a forma de objetos que é resistente a várias interferências: rotação, deformação, sobreposição e conectividade de objetos. Com base no algoritmo apresentado, o software será desenvolvido para um sistema de visão automatizada projetado para funcionar como parte de uma unidade de classificação robotizada. A estrutura do algoritmo e os resultados da modelagem de seu trabalho em objetos que são típicos para a composição de resíduos domésticos sólidos são mostrados. Para melhorar a qualidade do reconhecimento, nas próximas etapas do trabalho, planeja-se combinar dados de câmeras de vídeo e sensor NIR. Direções para mais pesquisas são descritas, ou seja, o uso de um scanner tridimensional e a combinação de fluxo de dados.

Palavras-chave: *processamento de imagens, seleção de contornos, correspondência de contorno, detecção de objetos, reconhecimento de objetos, classificação de resíduos.*

ABSTRACT

The purpose of this work is to develop an algorithm for recognizing the shape of objects that are resistant to various interferences: rotation, deformation, overlapping and connectedness of objects. Based on the presented algorithm, the software will be developed for a computer vision system designed to work as part of a robotic sorting complex. The structure of the algorithm and the results of modeling its work on objects that are typical for the composition of solid household waste are shown. To improve the quality of recognition, at the next stages of work, it is planned to combine data from video cameras and NIR-sensor. Outlined directions for further research, namely, the use of a three-dimensional scanner and the combination of data flow.

Keywords: *image processing, contour selecting, contour matching, object detection, object recognition, waste sorting.*

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АННОТАЦИЯ

Целью данной работы является разработка алгоритма распознавания формы объектов, устойчивого к различным помехам: вращение, деформация, перекрытие и связанность объектов. На основе представленного алгоритма будет разработано программное обеспечение для системы машинного зрения, предназначенной для работы в составе робототехнического сортировочного комплекса. Показана структура алгоритма и результаты моделирования его работы на объектах, являющихся типичными для состава твёрдых бытовых отходов. Для повышения качества распознавания, на следующих этапах работ планируется совмещение данных видеокамер и NIR-сенсора.Намечены направления дальнейших исследований, а именно использование трехмерного сканера и совмещение потока данных.

Ключевые слова:*обработка изображений, подбор контура, соответствие контура, обнаружение объекта, распознавание объекта, сортировка мусора.*

INTRODUCTION

The technological operation of sorting objects is widely used in various industrial processes: recycling household waste, processing agricultural products, preparing raw materials, or vice versa, finished products for further operations, etc. When sorting objects of complex shape, such as elements of solid household waste, often the process is performed manually. The monotony and fatigue of workers do not allow to achieve high performance, and the ambiguity and recognition errors reduce the quality of the sorted material.

One of the possible ways to automate the process is the use of robotic systems that completely replace a person. At its core, sorting is a pick-and-place task, where a robot captures objects moving on a conveyor belt and moves them into separate containers. Along with a robotic manipulator and a conveyor belt, one of the main elements of a robotic assembly is the machine vision system, which provides information about sorting objects: composition, shape, orientation, contact points (Antonucci *et al.*, 2017; Teo *et al.*, 2015; Horbert *et al.*, 2015; Gómez *et al.*, 2015; Tsarouchi *et al.*, 2016).

In an automatic sorting complex, the robot must completely replace a person, that is, perform all its functions, including the perception of the sorted objects. The main task of the machine vision system, which is part of the complex, is the selection of individual objects and the recognition of their forms. The shape of the object, along with the texture, is an important aspect of its perception and recognition by man (Formalev *et al.*, 2016; Formalev *et al.*, 2015). Even without texture and color, a person is able to recognize an object by its silhouette. Due to this, the problem of recognition of forms is still relevant and attracts the attention of many researchers and developers (Kittler and Illingworth, 1986; Sjöström*et al.*, 1986). The main problem is the distortion of the forms caused by the deformation of the object, its coherence, and overlap with other objects.

The machine vision system as part of the sorting complex also controls the robotic manipulator, calculating the coordinates of the captured objects (Menesatti*et al.*, 2012). Since the objects move on the conveyor, the robot, for reliable capture, it is necessary to know their exact position taking into account the positioning time of the manipulator. To do this, it is necessary to determine the speed and direction of movement of objects, as well as to predict its trajectory. Thus, the task of this work is to develop an algorithm for recognizing the shapes of objects that are resistant to various deformations of objects, determine their speed and predict the trajectory.

THEORETICAL OVERVIEW

1.1. Recognition of the shape of objects

One of the main methods of recognition of the shape of an object is the recognition of the shape of the contour of this object. The contour defined by a sequence of coordinates is insensitive to affine transformations. The authors of the article (Antonucci *et al.*, 2017) proposed an algorithm for optical image analysis and recognition of the shape of rice grains of various varieties, moving on a conveyor belt. As a result of image processing, data is obtained on the shape, size, and color of grains. The proposed method can be used for sorting various fruit and vegetable products. Figure 1 shows the selected features of the contours of recognizable objects.

The authors of the paper (Teo *et al.*, 2015) derived a mathematical operator that groups angles and faces into a connected contour. The data obtained after applying the operator, form a special contour descriptor that is used to recognize the object. The algorithm is resistant to deformations, ruptures and partial overlap of contours. Images of objects and their depth maps are used as input data, allowing to select contours with high accuracy. Figure 2 shows the object recognition process.

In (Horbert *et al.*, 2015), the authors presented a method for selecting and recognizing objects based on data obtained from a single video camera. The algorithm also allows you to track the movement of selected objects. Object shape recognition is widely used in robotics. The articles (Gómez *et al.*, 2015; Tsarouchi *et al.*, 2016; Lin *et al.*, 2016; Kennard and Stone, 1969) present methods for recognizing moving objects and integrating the vision system with a robotic manipulator. Figure 3 shows an example of using object shape recognition and its orientation to be captured by an industrial manipulator.

Excellent results of object recognition were achieved by the authors of the article (Shen *et al.*, 2016), who applied a special approach to the formation of the input data of the algorithm. In the presented method, the integration of the external contour and the internal skeleton of the recognizable object associated with it is implemented. Figure 4 shows the associated contour and skeleton of the object. This approach allowed us to use the advantages of both methods – the insensitivity of the circuit to affine transformations and the stability of the skeleton to deformations.

1.2. Recognition of the shape of three-dimensional objects

A promising direction is the recognition of the shapes of three-dimensional objects. For the formation of point clouds and the creation of three-dimensional models, various sensors are used: stereo cameras, laser scanners, etc. Working with three-dimensional objects can significantly improve the quality of recognition, but significantly increases the performance requirements of computational modules due to the complexity of the algorithms and a large amount of data processed.

Excellent results of recognition of three-dimensional objects demonstrate artificial neural networks. In the articles (Tsarouchi *et al.*, 2016; Lin *et al.*, 2016; Shen *et al.*, 2016), the authors present algorithms for recognition of three-dimensional objects based on convolutional neural networks. Two-dimensional images of objects and their reconstructed depth maps are fed to the input of the neural network. At the same time, for training the neural network, a corrected depth map is used, from which reconstruction errors are removed. Figure 5 shows the structure of the neural network and the input data. The output of the neural network is a set of key features of a recognizable object.

The actual problem is the recognition of moving objects for further interaction with the robotic manipulator. The authors of (Eitel *et al.*, 2015) presented a tree-like algorithm based on artificial neural networks for recognizing the shape of an object. After recognition of the form, the algorithm allows determining the contact points on the object, for its capture by a robotic manipulator. Figure 6 shows samples of recognized objects.

In (Maturana and Scherer, 2015), a method for recognizing the shape of an object, the data on which was obtained using tactile scanning, was presented. As a scanner, a matrix of movable pins is used, which, when applied to an object, take its shape. Thus, the tactile scanner allows you to get an approximated three-dimensional surface. Figure 7 shows the appearance of a tactile scanner.

A combined (Schwarz *et al.*, 2015; Asif *et al.*, 2017; Martins*et al.*, 2018) vision system of the visible spectrum and data on the depth of the scene are used to assess the trajectory of grasp. The authors of (Luo *et al.*, 2016; Guo *et al.*, 2014) proposed a method for recognizing 3D objects based on identifying local features of the object and determining the characteristic points.

MATERIALS AND METHODS

In the task of developing a sorting node, especially in relation to the sorting of solid household waste, the stability of recognition algorithms is particularly relevant. Elements of solid waste fall on the sorting conveyor after mixing, pressing and breaking. After transportation by a garbage truck, even initially simple objects acquire a complex, arbitrary shape.

The arbitrariness of the shape of the object is a separate complex task for the robotic complex. For reliable capture, retention, and movement of the sorted objects, it is necessary to correctly determine the contact points on the objects. Disruption of capture during movement will lead to the fact that the robot drops the captured object, which can fall as if back onto the conveyor, blocking other elements lying on it. Also, the dropped object can fall into the capacity for objects of other types, which significantly reduces the quality of sorting. For example, when sorting polymeric materials, it is unacceptable for polyvinyl chloride products to enter other polymers. This leads to a significant reduction in the quality and cost of secondary raw materials.

The aim of the work is the development of the object shape recognition algorithms. Object detection is divided into several subtasks:

1. Select the contour of the object.

2. Approximation of the contour by a polynomial.

3. Finding the center of the object.

4. Getting the volume of the object.

To select the contours of the object and find the center of the object, consider the following algorithm for obtaining a mask:

1. Getting a frame from a video stream.

2. Convert the frame color palette to grayscale.

3. Remove static background.

4. Search for groups of pixels not belonging to the background.

5. Noise filtering.

6. Filling Contour Breaks.

7. Filtering by threshold size of contour.

8. Combining contours into static objects.

RESULTS AND DISCUSSION:

3.1. Object selection and form definition

The process of selecting the boundaries of an object is based on the sequential convolution of the area around each pixel of the original image with the filter mask at each point of the image (x, y). The filter response is given by the matrix product of the filter coefficients and the pixel neighborhood. For a 3x3 mask of the element shown in Figure 1, the result (response) **R** of the linear filtering at the point **(x, y)** of the image will be as in Equation 1.

When detecting differences in brightness, discrete analogs of first and second order derivatives are used. For simplicity, one-dimensional derivatives will be considered. The first derivative of the one-dimensional function f (x) is defined as the difference of the values of neighboring elements (Equation 2).

Here, the record is used in the form of a partial derivative in order to preserve the same notation in the case of two variables f (x, y), where you have to deal with partial derivatives along two spatial axes. The use of the partial derivative does not change the substance of the consideration. Similarly, the second derivative is defined as the difference of the neighboring values of the first derivative (Equation 3).The calculation of the first derivative of a digital image is based on various discrete approximations of a two-dimensional gradient. By definition, the gradient of the image ***f*** **(x, y)** at the point **(x, y)** is the vector in Equation 4.

As is known from the course of mathematical analysis, the direction of the gradient vector coincides with the direction of the maximum rate of change of the function ***f***at the point***(x,y)***. An important role in the detection of contours is played by the module of this vector, which is denoted $\nabla f$and equal (Equation 5).

This value is equal to the maximum rate of change of the function. ***F***at the point ***(x,y)***, moreover, the maximum is achieved in the direction of the vector ∇f. The magnitude ∇falso often called gradient. The direction of the gradient vector is also an important characteristic. Denote***α(x,y)***angle between vector direction ∇fat the point ***(x,y)***and axis ***x***(Equation 6).From here it is easy to find the direction of the contour at the point ***(x,y)***, which is perpendicular to the direction of the gradient vector at this point. Andyou can calculate the image gradient by calculating the values of partial derivatives$\partial f/\partial x$and$\partial f/\partial y$for each point.

3.1.1. Roberts operator

Let the 3x3 area shown in Figure 8 be luminance values in the neighborhood of some image element. One of the easiest ways to find the first partial derivatives at z_5 consists of applying the following Roberts cross gradient operator (Equations 7, 8). These derivatives can be implemented by processing the entire image using the operator described by the masks from Figure 9, using the filtering procedure described earlier.

The implementation of masks with dimensions of 2x2 is not very convenient since they do not have a clearly defined central element, which significantly affects the result of filtering. But this "minus" generates a very useful feature of this algorithm –high-speed image processing.

3.1.2. Operator Prewitt

The Prewitt operator, like the Roberts operator, operates on the 3x3 image area shown in Figure 2, only the use of such a mask is given by other expressions (Equations 9, 10)

In these formulas, the difference between the sums in the upper and lower rows of a 3x3 neighborhood is an approximate value of the derivative along the x-axis, and the difference between the sums along the first and last columns of this neighborhood is the derivative along the y-axis. To implement these formulas, use the operator described by the masks in Figure 10, which is called the Prewitt operator.

3.1.3. Sobel operator

The Sobel operator also uses the 3x3 image area shown in Figure 2. It is similar to the Prewitt operator, and the modification is to use weighting factor 2 for the middle elements (Equations 11, 12).This increased value is used to reduce the smoothing effect by adding more weight to the midpoints.The masks used by the Sobel operator are shown in Figure 11.

The above masks are used to obtain the components of the gradient G_x and G_y. To calculate the magnitude of the gradient, these components must be used together (Equations 13 or 14).

3.2. Search facility center

After detecting an object on the frame, we get the image (mask) shown in Figure 12.Next, we find three groups of white pixels. For each of these three groups, we take each white pixel as a unit mass. Then to find the center of the object, we use the formula for finding the center of mass of the object (Equation 15), where, R–pixel coordinate, m – unit mass; r_c – object center coordinates.

For each pixel of the object, we obtain its distance from the camera. Then the height of the pixel above the pipeline will be as follows in Equation 16, where,h_{ob} – height of the object pixel above the pipeline; H_{cam}-camera height above the conveyor;r_{cam}-camera measurement result.Then we get the profile of the visible part of the object. Next, each object is broken by x lines (Figure 13). On each of these lines, we get a cut of the object in height. Next, we find the area of each slice and summarize all the cuts (Equations 17 or 18). Then the resulting volume will be equal to Equation 19, where: n – the number of slices; t – the number of points in the slice

After receiving the coordinates of the centers of objects on the original image in accordance with the result of the selection mask, impose a depth map obtained from the depth sensor. As a result, for each point of the object, its height from the surface of the conveyor is known. At the end of the algorithm, we obtain the coordinates of the center for each object, its volume, and color at each of its points.

3.3. Determining the orientation of an object on a conveyor belt

The orientation of an object in an image can be determined by calculating a minimum-sized rectangle bounding an object. In the general case, the contour of an object consists of a set of points; to reduce the computational load, it is necessary to approximate the contour with the help of the so-called convex hull (convex hull). Which is a set of n points that form a closed polyhedral chain of external points of a given set that completely covers all the original points of the set (Figure 14).

In general, the computational complexity is estimated as $O(n \log n)$. The algorithm for computing an oriented bounding box is an iterative process called "rotating shtarentsikuly", originally designed to calculate the diameters of convex polygons. In (Freeman and Shapira, 1975), the theorem was proved that the described rectangle around a polygon has the smallest area only in the case when one of the sides is collinear to one of the sides of the convex hull. Using this condition can significantly reduce the computational complexity of the search algorithm.

Algorithm steps:

1. Calculate convex hull for the contour;

2. Search for extrema of the resulting shell (Equations 20, 21).

3. Construction of two vertical lines passing through points $x_{\min}$ and $x_{\max}$;

4. Construction of two vertical lines passing through points $y_{\min}$ and $y_{\max}$;

5. Rotation of the obtained lines until one of them coincides with the face of the shell. Calculatetheareaoftheresultingrectangle;

6. Repeat step 5 for the remaining faces of the shell.

As a result of the algorithm's operation, the geometric parameters of the bounding rectangle — the coordinates of the vertices and the angle of rotation around the axis — will be determined (Figure 15).The calculated parameters of the bounding box are used further for the correct orientation of the gripping head around the object.

3.4. Determination of the velocity of the object

To calculate the speed of moving an object, we use the algorithm for matching special points (descriptors) of the same objects at different points in time, i.e. for adjacent frames of video system images. When comparing descriptors of two images containing identical objects, the quality metric is parallel lines connecting the pairs of corresponding characteristic points and components of the so-called optical flow (Figure 16). Optical flow is a set of directional vectors that characterize the movement of elements and areas of the image in time and are used to solve a number of video processing tasks:

1. Compression of images as a private subtask – approximation of the trajectory of the frame elements with the preservation of the structure of the movement instead of direct use of data on the intensity of pixels.

2. Video stabilization.

3. Extract the structure of the surrounding space. An alternative way to extract the depth of the image.

The main laws in the optical flow:

1. The intensity of the pixels does not change between adjacent frames;

2. Adjacent pixels have a similar motion law.

Those, fair Equation 22, where, $f(x, y, t)$ –pixel intensity with coordinates (x, y) at the moment of time *t;*Δx, Δy –object displacement over time Δt .

Equation 23 transform the expression like this in Equation 24. As a result, we get Equation 25, where, υ_x and υ_y –the projections of the speed of the optical flux on the x and y-axes, respectively; $f_x = \frac{df}{dx}$ –axis intensity gradient *x;* $f_y = \frac{df}{dy}$ –axis intensity gradient *y.*Thus, gradients are related by Equation 26.

To calculate the speed of the optical flow, we use the method of Lukas-Canada. The method uses the assumption that neighboring pixels of optical motion have similar movements. Use the neighborhood of the point, then all the matrix points of the neighboring 3x3 pixels have the same movement. Thus, solving a system of equations for all 9 points, we can find the desired velocities (Equation 27). To calculate the speed of movement (pixels/sec) of the conveyor belt, the components of the optical flow vectors are averaged.

3.5. The forecast of the trajectory of the object

The speed of the conveyor belt is a controllable value, but at each moment of time, it is a constant value. As a result, the coordinates of the motion of objects on the conveyor belt are described by linear transformations (Equations 28, 29).

Thus, the geometric center of the object (x_0, y_0), found at the stage of recognition of objects, at any time can be calculated as in Equation 30. Subject to compliance with the camera orientation parallel to the direction of movement of the conveyor belt will be Equation 31.Thus, it is necessary to transfer the velocity vectors of the optical flow and the coordinates of the geometric center of the object to the planning system of the trajectory of the capture motion of the manipulator.

3.6. Analysis of the developed algorithm

In the process of working on the project, an algorithm for recognizing the shape of objects was developed. Table 1 presents examples of the operation of the algorithm. For testing the algorithm, elements typical for the composition of solid household waste were used. The software of the machine vision system of the robotic sorting complex has the following functions:

• construction of a spatial image containing information about the material of the object, the intensity of color at a point and the distance to the vision system;

• determination of the speed of movement of the conveyor belt based on the visual analysis of the optical flow;

• automatic synchronization of the spatial image and the position of the conveyor belt;

• selection of individual objects on the conveyor belt;

• recognition of the class of the object based on data from the technical vision system;

• prediction of the trajectory of the object on the conveyor belt.

The developed algorithm showed resistance to deformations of objects and blurring as a result of movement on a conveyor belt. The simplicity of the algorithm and low demands on computing resources provide high performance.

CONCLUSIONS:

During the work on the project, an analysis of the algorithms and techniques described by the researchers was carried out. An algorithm was developed for recognizing the shape of objects, calculating their speed and predicting the trajectory of motion, which showed high resistance to interference and deformation of objects and ensured a high quality of recognition. The use of the algorithm in the robotic sorting complex will allow you to calculate the contact points and ensure reliable capture, retention, and movement of objects.

To improve the quality of recognition, at the next stages of work, it is planned to combine data from video cameras and NIR-sensor. The combination of the spectrum of the material and the visual image will significantly improve the quality of recognition of objects and materials from which they are made. Analysis of the articles showed that excellent results are obtained when using three-dimensional scanners and performing object recognition in three-dimensional space. Thus, further, it is necessary to use a three-dimensional scanner and to combine data streams. Such a measure will allow recognizing objects that are heavily damaged during transportation and pressing.

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$$R = w(-1,-1)f(x-1,y-1) + w(-1,0)f(x-1,y) + \cdots + w(0,0)f(x,y) + \cdots + w(1,0)f(x+1,y) + w(1,1)f(x+1,y+1) \quad (1)$$

$$\frac{\partial f}{\partial x} = f(x+1) - f(x) \quad (2)$$

$$\frac{\partial^2 f}{\partial x^2} = f(x+1) + f(x-1) - 2f(x) \quad (3)$$

$$\nabla f = \begin{bmatrix} Gx \\ Gy \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \quad (4)$$

$$\nabla f = |\nabla f| = \sqrt{G_x^2 + G_y^2} \quad (5)$$

$$\alpha(x,y) = arctg\left(\frac{Gy}{Gx}\right) \quad (6)$$

$$G_x = (z_9 - z_5) \quad (7)$$

$$G_y = (z_8 - z_6) \quad (8)$$

$$G_x = (z_7 + z_8 + z_9) - (z_1 + z_2 + z_3) \quad (9)$$

$$G_y = (z_3 + z_6 + z_9) - (z_1 + z_4 + z_7) \quad (10)$$

$$G_x = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3) \quad (11)$$

$$G_y = (z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7) \quad (12)$$

$$\nabla f \approx |G_x| + |G_y| \quad (13)$$

$$f = \sqrt{G_x^2 + G_y^2} \quad (14)$$

$$\vec{r}_C = \frac{m_1 r_1 + m_2 r_2 + \ldots + m_n r_n}{m_1 + m_2 + \ldots + m_n} \quad (15)$$

$$h_{ob} = H_{cam} - r_{cam} \quad (16)$$

$$y(t) = \int_0^t x(\tau)\, d\tau \quad (17)$$

$$y(n) = y(n-1) + \frac{T}{2} \cdot [x(n-1) + x(n)] \tag{18}$$

$$V = \sum_{i=1}^{n} \int_0^t x(t)dt \tag{19}$$

$$c_{\min} = (x_{\min}, y_{\min}) \tag{20}$$

$$c_{\max} = (x_{\max}, y_{\max}) \tag{21}$$

$$f(x, y, t) = f(x + \Delta x, y + \Delta y, t + \Delta t) \tag{22}$$

$$\frac{df}{dx}\Delta x + \frac{df}{dy}\Delta y + \frac{df}{dt}\Delta t = 0 \tag{23}$$

$$\frac{df}{dx}\frac{\Delta x}{\Delta t} + \frac{df}{dy}\frac{\Delta y}{\Delta t} + \frac{df}{dt}\frac{\Delta t}{\Delta t} = 0 \tag{24}$$

$$\frac{df}{dx}\upsilon_x + \frac{df}{dy}\upsilon_y + \frac{df}{dt} = 0 \tag{25}$$

$$f_x\upsilon_x + f_y\upsilon_y = -f_t \tag{26}$$

$$\begin{bmatrix} \upsilon_x \\ \upsilon_y \end{bmatrix} = \begin{bmatrix} \sum_i f_{x_i}{}^2 & \sum_i f_{x_i} f_{y_i} \\ \sum_i f_{x_i} f_{y_i} & \sum_i f_{y_i}{}^2 \end{bmatrix}^{-1} \begin{bmatrix} -\sum_i f_{x_i} f_{t_i} \\ \sum_i f_{y_i} f_{t_i} \end{bmatrix} \tag{27}$$

$$x(t + \Delta t) = x(t) + \upsilon_x t \tag{28}$$

$$y(t + \Delta t) = y(t) + \upsilon_x t \tag{29}$$

$$\begin{aligned} x(t) &= x_0 + \upsilon_x t \\ y(t) &= y_0 + \upsilon_y t \end{aligned} \tag{30}$$

$$\begin{aligned} x(t) &= x_0 + \upsilon_x t \\ y(t) &= y_0 \end{aligned} \tag{31}$$

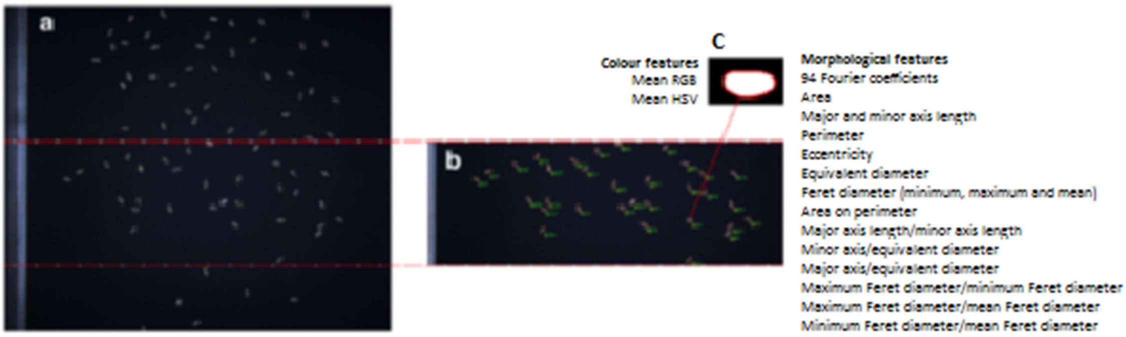

***Figure 1**. Select features of objects*

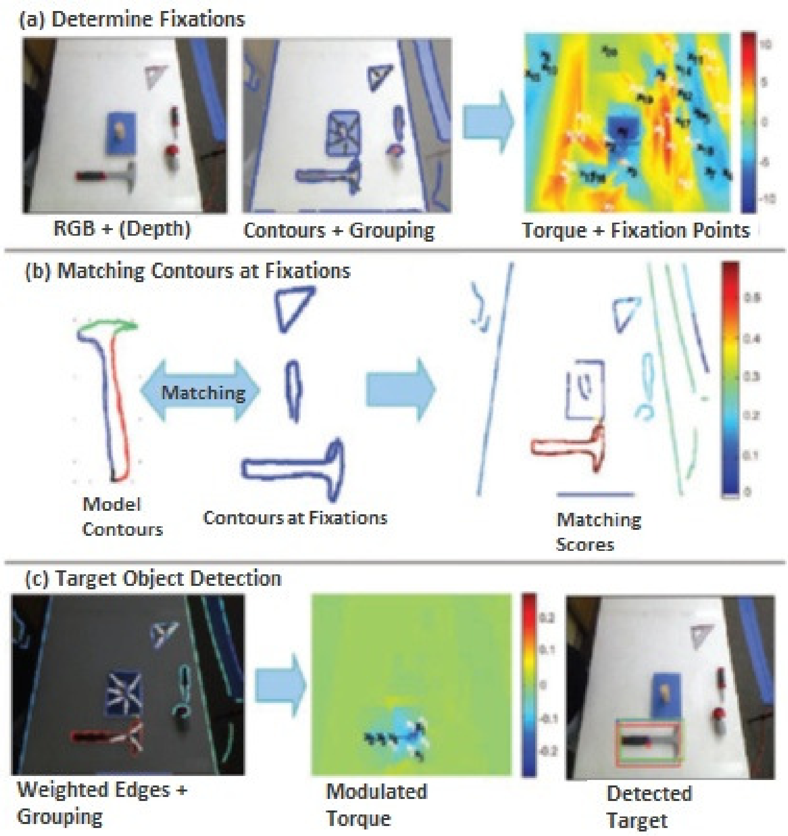

***Figure 2**. Object recognition process*

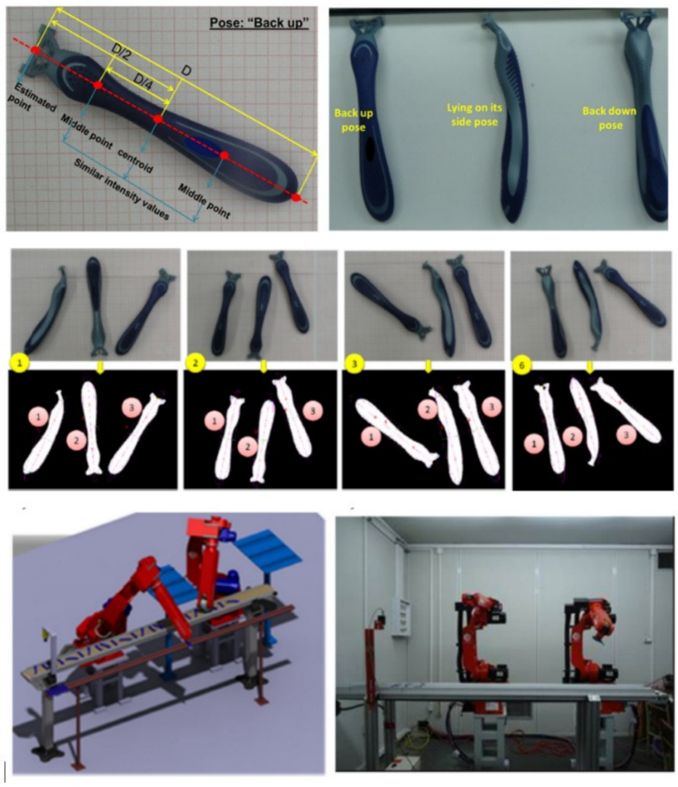

***Figure 3**. Application of object shape recognition in robotics*

***Figure 4.**Contour and skeleton of the object*

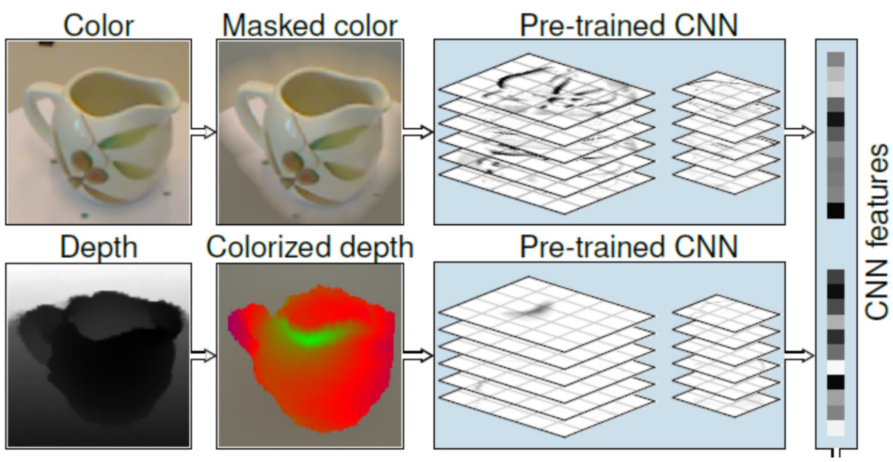

***Figure 5**.Neural network structure and input*

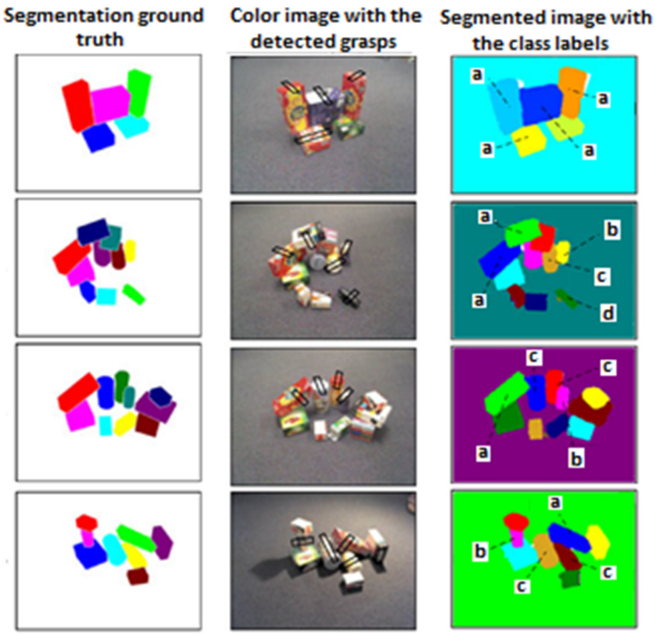

Figure 6.*Recognized objects: a – food box; b – soda can; c – food can; d – stapler*

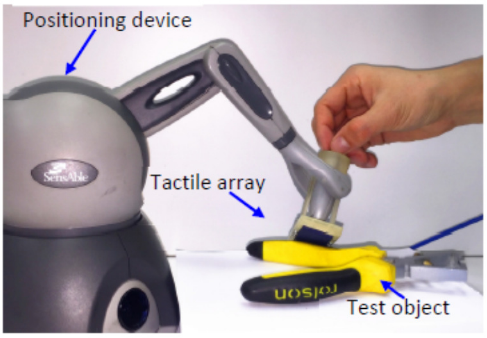

Figure 7.*Tactile Scanner Manipulator*

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

Figure 8..*3x3 surroundings inside the image*

-1	0
0	1

0	-1
1	0

Figure 9. *Masks of Roberts operator*

-1	-1	-1
0	0	0
1	1	1

-1	0	1
-1	0	1
-1	0	1

Figure 10. *Prewitt operator masks*

-1	-2	-1
0	0	0
1	2	1

-1	0	1
-2	0	2
-1	0	1

Figure 11. *Masks operator Sobel*

Figure 12. *Contours of objects*

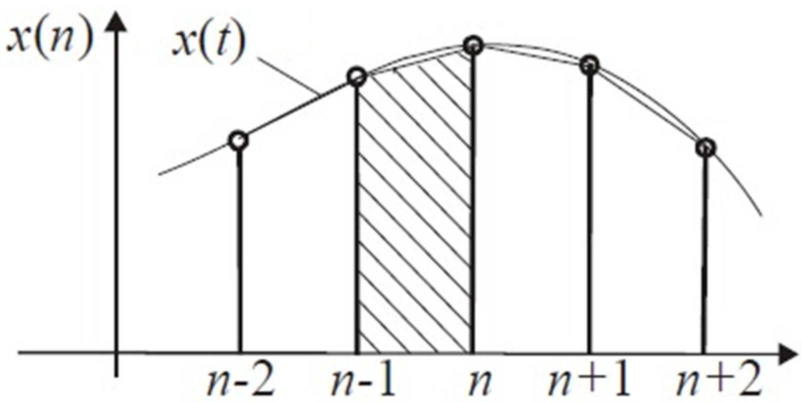

Figure 13.*Profile of the visible part of the object*

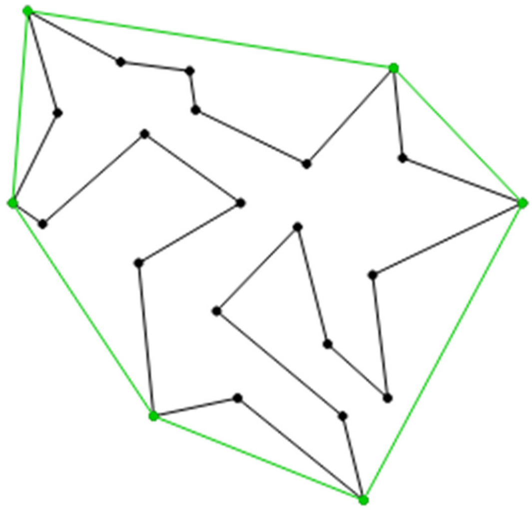

Figure 14.*Convex hull*

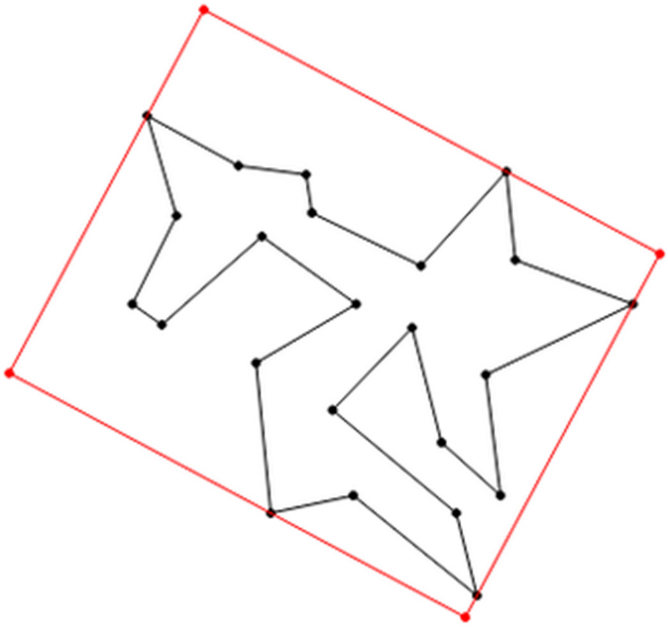

Figure 15.*OrientedBoundingBox*

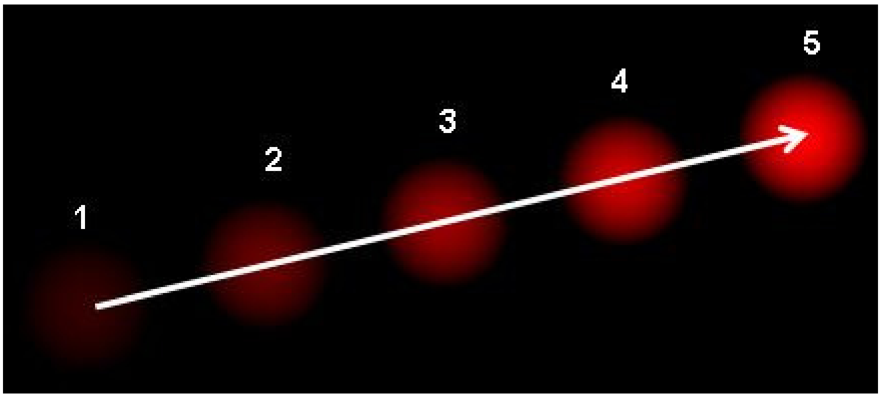

Figure 16.*Optical flow for moving objects*

Table 1.*ItemSet*

No.	Blurradius, pixel	Originalimage	Outlineselectionresult
1	0		
2	1		
3	3		
4	5		
5	7		
6	9		
7	11