An adaptive radial object recognition algorithm for lightweight drones in different environments

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Abstract

The paper proposes a group of radial shape object recognition methods capable of finding many different-sized circular objects in an image with high accuracy in minimum time and conditions of uneven brightness of frame areas. The methods are not computationally demanding, making them suitable for use in computer vision systems of light unmanned vehicles, which cannot carry powerful computing devices on board. The methods are also suitable for unmanned vehicles traveling at high speed, where image processing must be performed in real-time. The proposed algorithms are robust to noise. When combined into a single group, the developed algorithms constitute a customizable set capable of adapting to different imaging conditions and computing power. This property allows the method to be used for detecting objects of interest in different environments: from the air, from the ground, underwater, and when moving the vehicle between these environments. We proposed three methods: a hybrid FRODAS method combines the FRST and Hough methods to increase accuracy and reduce the time to search for circles in the image; a PaRCIS method based on sequential image compression and reconstruction to increase the speed of searching for multiple circles of different radii and removing noise; an additional modification of LIPIS is used with any of the primary or developed methods to reduce the sensitivity to sharp variations in the frame's brightness. The paper presents comparative experiments demonstrating the advantages of the developed methods over classical circle recognition methods regarding accuracy and speed. It shows the advantage of recognizing circles of different brightness. Experiments on recognizing multiple real-world objects in photographs taken on the ground, in the air, and underwater, with complex scenes under distortion and blurring with different degrees of illumination, demonstrate the effectiveness of the set of methods.

Keywords: computer vision, multiple object recognition, image compression, recognition within a sliding window, non-uniform image brightness, changing shooting conditions.

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Introduction

Currently, unmanned vehicles can perform various tasks on the ground, in the air, and underwater [1 – 4]. Their autonomous operation usually requires a computer vision (CV) system. CV systems are used both for detecting target objects, tracking manipulations, and positioning the vehicle. In particular, the tasks of position determination of unmanned vehicles based on computer vision are widely covered in the literature: automatic landing of unmanned aerial vehicles based on the recognition of optical landing marks on the ground [5 – 7], navigation of unmanned vehicles based on the detection of highway dividing lanes [8 – 10], orientation of unmanned submarines using the detection of docking station markers [11 – 13], and others. The tasks of image capture as monitoring objects are considered, for example, in the works on recognition of road signs by the onboard camera of unmanned vehicles [14 – 15], buildings of various structures from UAVs [16 – 17], underwater artifacts from unmanned submarines [18], and others.

As a rule, the methods used in each of the tasks described above are developed, taking into account the specifics of the corresponding task. For example, for the automatic landing of UAVs, special attention is paid to the possibility of recognizing a single object (mark), most often black and white, in different lighting conditions and at different viewing angles [19]. For unmanned vehicle CV systems, color recognition of the object of interest is significant [20 – 23]. On the contrary, for recognition tasks from underwater vehicles, color is usually not taken into account, and the focus is on the problems of blurriness and noise, which is typical for images of objects in turbid water or natural bodies of water [24]. Such specialization of algorithms, on the one hand, is their advantage, as it allows them to take into account all the features and extract all the advantages from the specifics of the drone's environment.

On the other hand, it is also their disadvantage if the drone has to operate in mixed conditions. For example, in the air with high humidity, where condensation or splashes form on the lens lenses [25], in surface-submarine surveillance, for example, using a periscope, where part of the image is above water, and the other part is underwater. Or for dual-medium vehicles like a "diving airplane" [26] or an octoquadrocopter [27], which can both fly and dive and perform tasks underwater and must be able to navigate both environments.

Recognizing several objects in one image at a time is rarely considered. For example, [28] solves the problem of locating and classifying a group of objects in a UAV image. In [29], an approach to tracking multiple objects from a UAV is proposed to solve small target detection problems. In [30], the authors propose methods for detecting and identifying "low, slow, and small" UAVs to counter their unauthorized flights, including group flights. Group recognition of underwater objects is even rarer in the literature. One example of such work is the article [31], where the authors, among other things, propose a method for recognizing schools of fish. The problem when recognizing several objects in one image is the different characteristics of individual parts of the image: the desired objects may be visible and have high definition in some areas and be poorly visible in others. In this case, known methods, as a rule, detect only the brightest objects, referring less clear objects to noise [32 – 33].

Among image recognition technologies, convolutional neural networks of various modifications are the absolute leader [34]. The main advantage of the neural network approach is relatively high recognition accuracy without the need for a mathematical description of the detected object; the main disadvantage is the high requirements for computational resources and the availability of a relevant training dataset balanced by statistical characteristics [35]. The learning algorithm can train the network for quite a long time to achieve high recognition accuracy, from several minutes to several hours [36]. The need for complex long computations on powerful onboard computers can be a challenge when applying neural network-based recognition methods on lightweight drones that can carry little weight. In addition, fast recognition methods are required for fast-moving UAVs. These two requirements - low processor requirements and high algorithm speed - are crucial to developing methods for recognizing images from lightweight UAVs and flying underwater hybrid vehicles.

For a model based on a neural network, the geometric characteristics of the object of interest do not matter - the network will spend the same resources to recognize a complex object, such as a human face, and the simplest geometric shapes, such as a square or a circle. At the same time, many practical recognition tasks involve searching for simple objects of a given geometric shape in an image. In particular, several tasks are based on the recognition of circles: recognition of round-shaped landing markers for automatic UAV landing [37], recognition of traffic light signals [38], round-shaped road signs [39], eye pupils [40], round docking markers underwater [13], etc. Based on the above, it is an urgent task to develop fast, not computationally demanding methods capable of recognizing multiple objects of interest of different sizes of simple geometric shapes of varying degrees of visibility in images with varying degrees and types of noise.

1. Background

Let's consider the problem of recognizing a symmetrical geometric object from an unmanned vehicle under different external conditions and computing power in the example of detecting circles. Since the geometric shape of a circle is an essential condition for correct recognition, methods of shape feature analysis are used.

Many approaches used in practice to analyze the shape of objects in images are based on contour analysis methods [41 – 45].

In neural network methods, neural networks are trained to detect objects of given shapes in images [46].

In the context of the formulated problem, recognition methods' parameters, such as robustness to noise, high speed of operation, and low requirements for computational resources, are essential. Table 1 summarizes the advantages and disadvantages of each approach.

Tab. 1. Advantages and disadvantages of contour analysis methods for detecting objects of a given shape

Group of methods	Implementation examples	Noise resistance	Recognition speed	Computing Requirements	Shape of objects	Note
Methods based on derivative operators	Marr–Hildreth algorithm, Canny Boundary Detector	low	high	low	any	Difficulty in selecting parameters
Methods based on model fitting	RANSAC, J-Linkage	low	average	high	Defined Shapes	Ease of implementation
Methods based on the Hough transform	Generalized Hough Transform, Probabilistic Hough Transform	high	low	average	Defined geometric shapes	Difficulty in selecting parameters
Neural network methods	YOLO, AlexNET	average	average	very high	any	The need to form a large relevant training dataset

Table 1 shows that only some of the approaches simultaneously satisfy all the requirements of the problem of fast object recognition in various noisy environments on low-power computers. Therefore, we decided to create a new hybrid method that combines the advantages of several approaches and minimizes their disadvantages.

The most excellent prospects have methods based on derivative operators, such as the fastest and least resource-consuming, and methods based on the Hough transform, which is relatively resistant to noise and explicitly designed to search for objects of specified shapes, particularly circles. In addition, it is reasonable to use the geometric properties of the object being searched - a circle. The use of this method is potentially effective if it is possible to solve the problem of sensitivity to changes in parameter values, as noted in the article [47]. Since circles are images possessing radial symmetric shapes, methods based on analyzing radial symmetry properties can be applied for their detection and localization [48].

For example, such an approach was realized in [49], where the authors used the symmetry property of the circle relative to the center to detect opposite brightness gradients. The FCD (Fast Circle Detection) algorithm proposed in the paper, which replaced the three-dimensional accumulating array by clustering candidate circles, showed high performance. However, as the authors note, the method is effective only for circles that differ significantly in brightness from the background. In addition, authors achieved better results when prior information, such as the number of circles in the image, is available. Similar studies have also been conducted for ellipses [50]. The authors also emphasize the method's speed, recommending it for embedded systems on mobile platforms.

However, the problem of searching for an unknown number of multi-sized objects in an image under conditions of variable frame brightness still needs to be solved.

2. Approaches and methods

2.1. Solving the problem of speed and computing resources

To recognize circular objects of interest at a high speed while consuming a small amount of computational resources, we propose a hybrid method consisting of sequentially applying the Fast Radial Symmetry Transform (FRST) to quickly find the potential centers of the desired circles, detecting the contours, and calculating the radii of the circles in a given neighborhood of the potential centers using the Hough transform. We called this hybrid method FRODAS: Fast Radial Object Detection Algorithm with Small number of computations.

Thus, the hybrid method for recognizing circles includes the following stages:

Stage 1. Preparatory.

1.1. Determine the set of possible circle radii $\tilde{N} = \{n_i\}, i = \overline{1, N}$;

1.2. Set the radial stiffness parameter α;

1.3. Determine the type of noise reduction filter G;

1.4. Convert the image into halftone form.

Stage 2. Determine the centers of circles using FRST method.

2.1. For each image pixel (i, j), starting from the lower left corner:

2.1.1. calculate the gradient of the luminance function in the horizontal direction $g_x(i, j)$;

2.1.2 calculate the gradient of the luminance function in the vertical direction $g_v(i, j)$;

2.1.3 calculate the total gradient of the luminance function $|g_x(i, j)|$.

2.2. For each possible value of the circle radius n from the set $\tilde{N}$:

2.2.1. For each image pixel (i, j):

a) compute the coordinate of the positively-affected pixel in the gradient direction $(i, j)^+$;

b) calculate the coordinate of the negatively affected pixel in the anti-gradient direction $(i, j)^-$;

c) calculate the values of the orientation projection matrix elements $O_n((i, j)^+)$, $O_n((i, j)^-)$;

d) calculate the values of the magnitude projection matrix elements $M^n((i, j)^+)$, $M^n((i, j)^-)$;

2.2.2. Normalize the elements of the orientation projection matrix $O^n(i, j)$;

2.2.3. Normalize the elements of the magnitude projection matrix $M^n(i, j)$;

2.2.4. Compute the elements of the matrix of generalized weights $F^n(i, j)$ with radial stiffness parameter α;

2.2.5. Calculate the elements of the matrix S^n, by applying the noise suppressing filter G^n to the matrix $F^n(i, j)$.

2.3. Calculate the values of the elements of the averaged weights matrix $\boldsymbol{S}$;

2.4. Generate a set of potential centers of circles $\boldsymbol{B} = \{(i_k, j_k)\}$, or which the elements of the averaged weights matrix $S(i_k, j_k)$ are greater than a given threshold η.

Stage 3: Determination of the radii of circles using the Hough method.

3.1 Define a simplified three-dimensional accumulator array $A(i_k, j_k, n)$, where (i_k, j_k) are the potential centers of the circles defined in Step 2, n is the possible radius of the desired circle;

3.2 For each image pixel (i, j), starting from the lower left corner:

3.2.1. Recalculate elements of the accumulative array $A(i_k, j_k, n)$;

3.3. Voting: Determine the elements of the accumulator array with the maximum value of $A(i_l^*, j_l^*, n^*)$, corresponding to the elements of the set of recognized circles $\tilde{A}\{(i_l, j_l, r_l)\}$ with center at the point $(i_l, j_l) = (i_l^*, j_l^*)$ and radius $r_l = n^*$.

According to the above procedure, we develop a Fast Radial Object Detection Algorithm with Small number of computations (FRODAS).

2.2. Solving the problem of searching for multi-size objects in noisy images

In natural images, there can be many circles of different radii simultaneously. The developed Algorithm FRODAS can recognize all such multi-sized circles, and the search for potential centers of circles is performed for all n_i from the set of possible radius values $\tilde{N}$. Suppose the researchers have no prior information about the potential parameters of the searched circles. If researchers do not have prior information about the potential parameters of the searched circles, they must search for all radius values from 1 pixel to the size of the image. However, the information about the radius value is auxiliary for detecting the center of the circle. Therefore, we can significantly reduce the number of computations if we can transform the image to a scale where the spread of radius values is minimized. In this case, we preserve the positions of potential centers, and the recognition accuracy will not change. The application of image compression with its subsequent restoration will also allow the simultaneous removal of noise from the image.

We developed a parallel circle center recognition method based on image scaling with a reduced radius range, which we named PaRCIS - Parallel Recognition of Circle centers based on Image Scaling, including the following steps:

Stage 1. Preparatory.

1.1. Determine the set of possible circle radii $\tilde{N} = \{n_i\}, i = \overline{1, N}$;

1.2. Set the number of ranges L of circle radii;

1.3. Sort the radius values of the set $\tilde{N}$ in ascending order: $n1 \le n2 \le \ldots \le n_N$. The bubble method is selected for sorting;

1.4. Partition the set of desired radii $\tilde{N}$ into L subsets $\tilde{N}^l$, $l = \overline{1, L}$ of reduced ranges, with the smaller subset number corresponding to smaller values of the desired radii;

1.5. Convert the original image **P** to grayscale.

Stage 2. Scaling-compression.

2.1. For each subset $\tilde{N}^l$ perform compression of the original image, with the subset number proportional to the compression ratio;

2.2. Get L images P^l, $l = \overline{1, L}$ with decreasing size.

Stage 3. Parallel computation of weight matrices.

3.1. For all images P^l, $l = \overline{1, L}$ form the matrices of averaged weights of reduced ranges S^l for radii from the subset $\tilde{N}^l$ according to Algorithm FRODAS, paragraphs 2-8. For multiprocessor systems the calculation can be performed in parallel.

Stage 4. Scaling-Recovery.

4.1. For each averaged weight matrix S^l, $l = \overline{1, L}$ perform the inverse of step 2.1 to restore the original image size for all S^l matrices.

Stage 5. Determining the centers of the circles.

5.1. Calculate the integral matrix of averaged weights $\boldsymbol{S}$ as a composite of the reduced range weight matrices;

5.2. Form a set of potential circle centers similarly to Algorithm FRODAS.

According to the above procedure, we develop an Algorithm for Parallel Recognition of Circle centers based on Image Scaling (PaRCIS). To recognize circles as their centers and radii, Algorithm 2 should be used together with Algorithm 1.

Applying the Algorithm PaRCIS increases the number of images in which the centers of circles are searched. Still, the total number and computation time is reduced due to three advantages:

1. Each image is searched for a smaller set of possible radii;
2. The search is performed on images that are halved in size;
3. The search is performed on multiple images simultaneously if a multiprocessor system is available.

In addition, the PaRCIS method is less sensitive to noise. Moderate compression is applied to search for circles of small radii, which prevents the loss of fine details during scaling. Stronger compression is applied to find circles of relatively large radius, which helps to remove noise, distortion, and blurring while the circle remains clearly visible in the image.

2.3. Solving the problem of searching for objects of different brightness

When recognizing several objects in a single image, it is often the case that they have different brightnesses. Depending on the background, the result is that some objects are visible in the image, while others are less visible. Standard algorithms, in particular the FRST algorithm, are luminance sensitive. As a result, objects of high brightness on a light background (or less bright objects on a dark background) may not be recognized if there are simultaneously objects of interest with lower or higher brightness in the image. This situation is typical, for example, for images under variable frame illumination conditions, night images, images at the fog or cloud boundary, images from a periscope under incomplete immersion in water, etc. Since we use FRST as an essential component of the hybrid FRODAS algorithm, it can also not recognize objects of different brightness in a single image.

To reduce the sensitivity to brightness, we developed a modification based on Local Image Processing Inside a Sliding window (LIPIS). In comparison with FRODAS, the modification's main feature is calculating the elements of the magnitude projection matrix $M_n(i, j)$ at the normalization stage. In contrast to the standard formula:

$$\bar{\boldsymbol{M}}^n(i,j)=\frac{\boldsymbol{M}^n(i,j)}{\max\limits_{(k,l)}\left\{\left|\boldsymbol{M}^n(k,l)\right|\right\}}$$

we proposed the following formula:

$$\bar{\boldsymbol{M}}^n(i,j)=\begin{cases} 0, & \left|\boldsymbol{O}^n(i,j)\right|<\Delta; \\ \dfrac{\boldsymbol{M}^n(i,j)}{\max\limits_{(k,l)\in U(k,l)}\left|\boldsymbol{M}^n(k,l)\right|}, & \left|\boldsymbol{O}^n(i,j)\right|\geq\Delta, \end{cases}$$

where: Δ – acceptance threshold; $U(i, j)$– pixel neighborhood (i, j) – window of a given dimension $(N_x^U \times N_y^U)$.

In this case, only luminance values corresponding to pixels within the sliding window are considered in the calculation. Secondly, pixels for which the orientation projection matrix elements $O^n(i, j)$ value is less than a given threshold are suppressed. The size of the sliding window and the threshold Δ are variable parameters that can be adjusted to maximize the effect.

3. Computational experiments. Comparative analysis of methods

The study of the comparative effectiveness of the proposed methods over existing methods of circle recognition was conducted on test-drawn images, as well as on selected relevant images of publicly available datasets from the Internet.

3.1. Testing the FRODAS algorithm

The advantage of the hybrid FRODAS algorithm is that it reduces the search area of circles using the Hough method due to the preliminary fast search of potential centers. In this case, the Hough algorithm is used to search only in the neighborhood of the found potential centers.

To demonstrate the effectiveness of the proposed approach, we conducted experiments on the recognition of circles on 20 images, each of which contained from 6 to 8 circles of different radii with different minimum distances between their centers. The radius of the circles was increased sequentially on ten images and randomly on ten images.

Experiments were conducted on the classical Hough method and the proposed hybrid algorithm. The results for recognizing images with sequential radius changes are shown in Fig. 1.

The proposed FRODAS method's recognition accuracy increases, primarily due to a significant reduction in false recognitions.

Fig. 3, 4 illustrate one of the experiments, which involved imaging eight differently sized circles with random radii and a maximum center-to-center distance of 45 pixels. Fig. 3 represents the image under test.

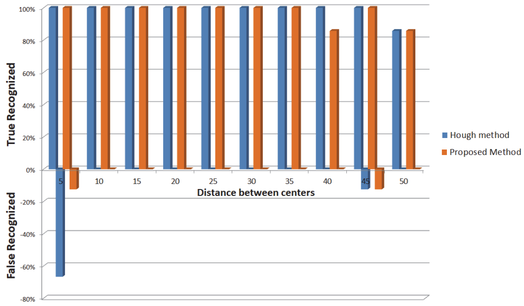


Fig. 1. Correctly and falsely recognized images for the compared methods for successive changes of radii

The results for recognizing images with random radius variation are shown in Fig. 2.

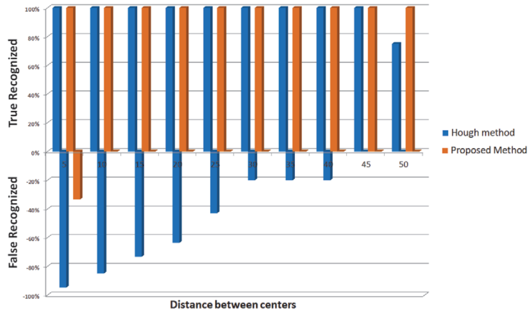


Fig. 2. Correctly and falsely recognized images for the compared methods when the radii are randomly changed

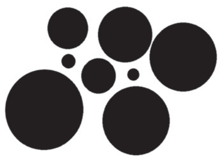
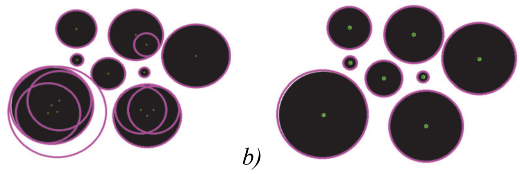


Fig. 3. Test drawn image with random values of radii

The recognition results are shown in Fig. 4.



a) b)

Fig. 4. Result of recognizing objects of different sizes: (a) Hough method (b)hybrid FRODAS method

3.2. Testing the PaRCIS algorithm

The main advantage of the PaRCIS method is the reduction of time for processing images containing many objects with an extensive range of potential radius values. Therefore, the comparative analysis of the efficiency of this method was carried out based on the determination of the time required to process the same image with the described properties by the classical method and PaRCIS method. The experiments were conducted for images containing 10, 20, 30, and 50 possible radii values of the desired circles. One of the fastest methods for searching circles - FRST - was chosen as a primary comparison method.

We culled the images from the datasets:

- Kaggle: LISA Traffic Light Dataset (100 images);
- Kaggle: Bosch Small Traffic Lights Dataset (200 images);
- Photographs obtained by the authors of the paper using a camera (50 images);
- Artificially synthesized images using special software developed by the authors (50 images);
- Images from open sources on the Internet.

Fig. 5. shows examples of the images used.

Recognition time was evaluated when running on an Intel Core i5-3230M 2.60GHz processor. Fig. 6 presents the comparative performance results.

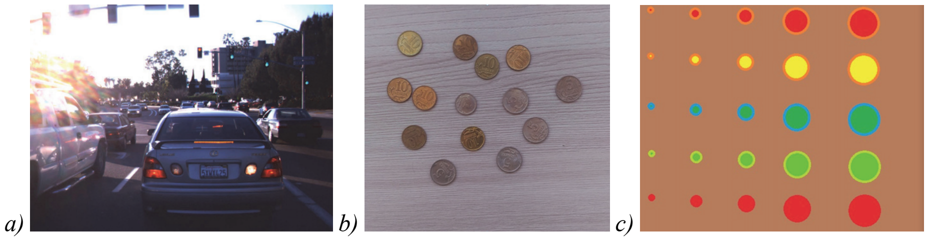


Fig. 5. Examples of images used in the test: (a) LISA Traffic Light Dataset; (b) author's photo; (c) artificially synthesized

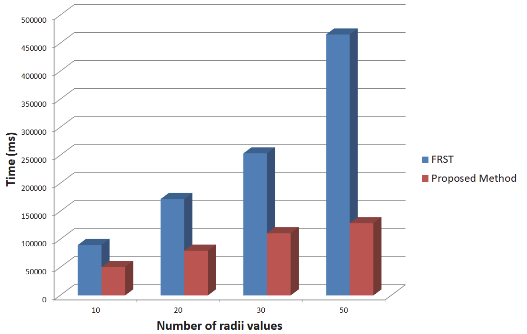


Fig. 6. Time to recognize multy-sized objects by the basic FRST method and the PaRCIS method

You can see that as the range of searched circles increases, the relative speed of the proposed PaRCIS method increases compared to the baseline method.

3.3. Testing of LIPIS modification

The LIPIS modification can be applied to hybrid algorithms of FRODAS and PaRCIS and classical algorithms. In this paper, we have applied it to the classical FRST method for determining the centers of circles to demonstrate its effectiveness.

We considered an artificially drawn image of nine circles with different brightnesses on the same white background and the same radius equal to 50 pixels (Fig. 7). In Fig. 7, the top row contains circles with brightnesses 0, 30, 60, the middle row contains circles with brightnesses 90, 120, and 150, and the bottom row contains circles with brightnesses 180, 210, and 240.

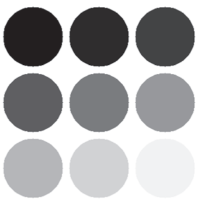


Fig. 7. Test image of circles of different brightness on a homogeneous background

First, the classical FRST algorithm without modification with parameters was applied for recognition:

- Radial stiffness $\alpha = 3$;
- The set of potential radii $\tilde{N} = [40; 60]$;
- Noise reduction filter type: Gaussian low-pass filter;
- Filter kernel size G^r: $(0.5r \times 0.5r)$, $r \in \tilde{N}$;
- The kernel elements are calculated according to the standard deviation value $\sigma_r = 0.5r$.

The result of the algorithm is demonstrated by Fig. 8.

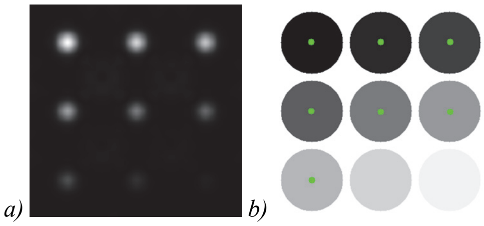


Fig. 8. Result of recognition of objects of different brightness by FRST method: (a) visualization of the integral matrix of averaged weights S(i,j), (b) found coordinates of the centers of circles

You can see that the primary method is sensitive to the ratio between the highest and lowest brightnesses of radially symmetric objects in the image. This is illustrated by Fig. 9, which shows the detection of the centers of circles of the same radius and on the same background as in Fig. 7 but of the same brightness, equal to 210 (the second circle in the bottom row in Fig. 7 – not previously recognized). In Fig. 9, you can see that the method localizes the corresponding regions to detect the centers of the circles.

We then augmented the basic method with the developed LIPIS modification with parameters:

- Sliding window size $(N_x^U \times N_y^U) = (7 \times 7)$;
- Threshold $\Delta = 2$.

Fig. 10 shows the result of recognizing the image given in Fig. 7.

You can see that when applying the developed LIPIS modification, the ratio between the highest and lowest brightnesses of radially symmetric objects does not affect the detection of their centers.

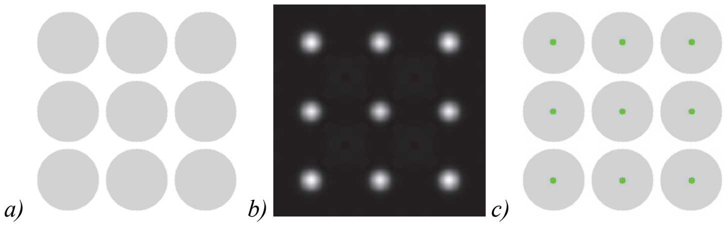


Fig. 9. Recognizing objects of the same low brightness FRST: (a) original image; (b) visualization of the integral matrix of averaged weights S(i,j), (c) found circle centers

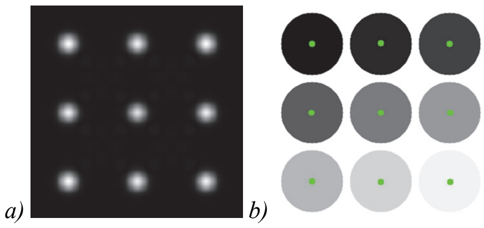


Fig. 10. Circles recognition with different brightness using LIPIS modification: (a) visualization of the integral matrix of averaged weights S(i,j), (b) found centers of circles

Further experiments demonstrated that the proposed modification is quite robust to distortions. For example, let us consider the application of LIPIS for recognizing an image with superimposed noise of the "blur" type. Blur mask parameters:

- Type: Gaussian noise;
- Mask size: (7×7) pixels;
- The standard deviation of the mask: $\sigma = 3$.

The initial blurred image and the results of center detection are shown in Fig. 11.

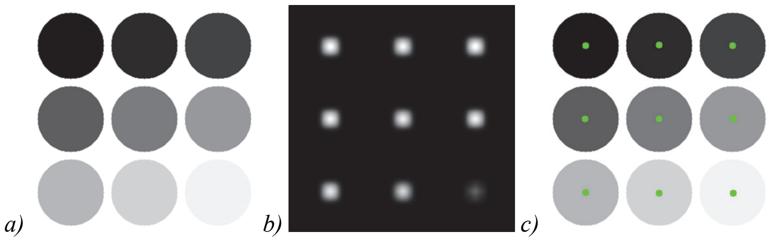


Fig. 11. Result of blurred object recognition for different brightness using LOSO modification: (a) original blurred image; (b) visualization of the integral matrix of average weights S(i,j), (c) found coordinates of the circles centers

You can see that when the LIPIS modification is applied, blurring does not affect the detection performance of circle centers.

3.4. Configuring a set of methods for different shooting conditions and computing resources.

The developed methods can be used both individually and in combination. The decision about which methods and combinations to use in each specific case depends on prior information about the shooting conditions and the available computing resources. In the simplest case, when the radii of the circles in the image are known in advance, and the spread of these values is small, there is no need to apply additional processing in the form of constructing a series of scaled images, and preference should be given to the FRODAS method. If, on the contrary, we know that the image will contain many circles of different radii, the use of PaRCIS is advisable. At the same time, we can obtain the most excellent efficiency from using this method if we have a computer with the ability to parallelize calculations at our disposal.

The LIPIS modification cannot be used independently. This window modification should be used if shooting occurs in variable lighting conditions, such as at the junction of water and air, contrast lighting with shaded areas, or similar transitional conditions.

The following Fig. 12 represents the logic of the unified complex for fast and accurate recognition of a set of multiple-sized objects of radial shape in conditions of variable brightness.

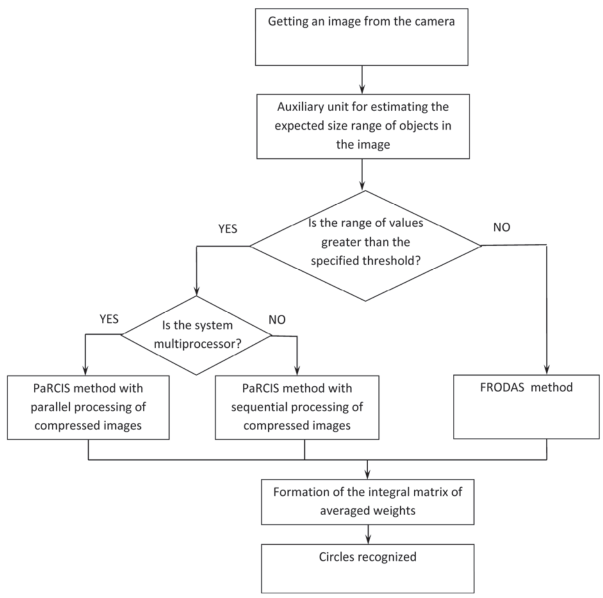


Fig. 12. Scheme of complex recognition methods functioning for different operating conditions

If the researcher has no preliminary information regarding the shooting conditions, we can recommend using the maximum range of methods.

3.5. Comparative analysis of the effectiveness of the developed algorithms in recognizing several multi-sized objects of varying brightness in authentic noisy images

The developed algorithms FRODAS, PaRCIS, and a LIPIS modification were applied to recognize real photos containing several objects of round and close to round shape, with a complex background, blurring, and different brightness of objects in one frame.

To compare the performance, we recognized the same images using the classical Hough method and the FCD method described in [49]. We chose the latter method because of its high speed and accuracy, exceeding Hough's method dozens of times, as noted by the authors of the method.

Three series of experiments were conducted:

1. Recognition of aerial images of landing round markers at different angles taken from a quadrocopter like DJI M100 at low altitude (up to 100m). The original images are presented in [51]. Ten 96 dpi resolution, 1140 by 885 pixel images, taken at night time, with noise reduction, are selected for experiments.
2. Recognition of aerial photographs of traffic circles taken from a helicopter-type unmanned aerial vehicle at medium altitude (up to 1km). The dataset provided by the authors of [52] and is freely available at: https://www.kaggle.com/datasets/javiersanchezsoriano/roundabout-aerial-images-for-vehicle-detection. The set contains 61,896 photos with a size of 1920×1080 pixels, 96 dpi resolution, in jpg format. The images were taken during the daytime in clear weather. One hundred images were randomly selected for the experiments.
3. Recognition of arbitrary photographs taken in various environments containing 8 or more round objects of various sizes at various angles with noise. Each photograph has individual characteristics. A total of 9 images were used.

To perform comparative experiments using the FCD method, we independently programmed the method based on the description given in [49]. Since the methods proposed in this paper were developed by us using C++ programming language and Microsoft Visual Studio and OpenCV library [53], to ensure equal conditions during testing all methods, including the classical Hough method, were implemented by us independently using these software tools. All experiments were performed on a computer with an Intel Core i5-3230M 2.60GHz processor. No parallelization was used.

Series of experiments No. 1.

The conditions for recognition here are pretty simple. Each image contains one circle, and all circles in all images have approximately the same radius; the marker is applied with light paint on a dark background. We showed thumbnails of the images used in the experiment in Fig. 13.

a) b) c)

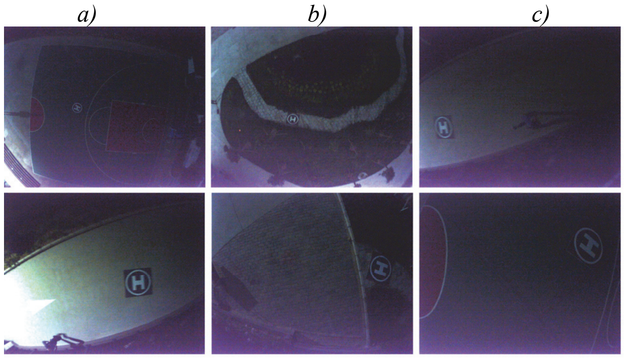


Fig. 13 Photos of the round landing marker at night. a) Uniform background, b) Variable brightness background, c) Deformed marker

In Table 2, we show comparative results using Hough, FCD, and PaRCIS with LIPIS modification.

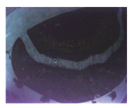
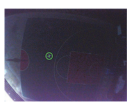
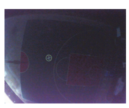
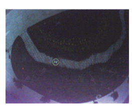
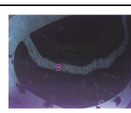
Tab. 2. Comparative performance indicators of circle recognition methods for experiment №1

	Correctly recognized objects for all images	**False recognitions per 1 image**	**Average recognition time per image (ms)**
Hough method	100%	0	192
FCD [49]	100%	0	869
PaRCIS+ LIPIS	100%	0	835

For simple recognition conditions with a predetermined approximate size of the radius of a single target circle, all three methods give equally high accuracy. The speed of our method is intermediate.

An example of round marker recognition for three images is given in Table. 3.

Tab. 3. Type and number of recognized circles using the PaRCIS+ LIPIS method in comparison with the Hough method for experiment №1

Original image			
PaRCIS+ LIPIS method			
FCD method			
Hough method			

Series of experiments No. 2.

The conditions for recognition were complicated. The photographs show circles of different sizes and contrasts.

We showed thumbnails of the images used in the experiment in Fig. 14.

a) b) c)

Fig. 14. Photos of traffic circles taken from a UAV. a) Contrasting background, b) Blending background, c) Background of variable brightness

The results of the accuracy and speed of recognizing circles in an image using three methods: the classical Hough method, the FCD method, and the PaRCIS method proposed in this article are shown in Table 4.

Tab. 4. Comparative performance indicators of circle recognition methods for experiment №2

	Correctly recognized objects for all images	**False recognitions per 1 image**	**Average recognition time per image (ms)**
Hough method with one-time tuning	82%	19	868
Hough method with individual tuning	100%	0	304 340
FCD [49]	100%	0	731
PaRCIS	100%	0	723

At the same time, for the classical Hough method, we carried out two series of experiments: in the first series of experiments, the method parameters were adjusted once, before recognition, and the parameters remained the same for all images. In the second series of experiments, we adjusted the parameters for each image separately. For this case, the recognition time is also indicated taking into account the setup time. For the other two methods, we performed a one-time setup before starting a series of experiments. Examples of four traffic circle recognition can be seen in Table. 5.

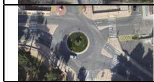
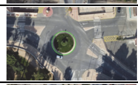
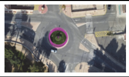
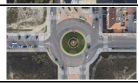
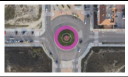
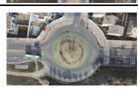
You can see that our proposed method is not inferior in accuracy to the others, and is significantly faster than the Hough method and slightly faster than the FCD method. The PARCIS method found all the circles correctly.

Series of experiments No. 3.

We carried out this series of experiments for the most challenging conditions. Each photograph contains several circles of different radii and with different contrasts. Figure 15 shows thumbnails of the images used in the experiment.

Parameters of the recognition algorithms: $\alpha = 3$; $\sigma_r = 0.5$; $\Delta = 5$.

Tab. 5. Type and number of recognized circles using the PaRCIS method in comparison with the Hough method for experiment № 2

Original image	PaRCIS method	Hough (one-time tuning)	
		Image	True/false
			1/0
			1/6
			1/66
			0/0

a) b) c)

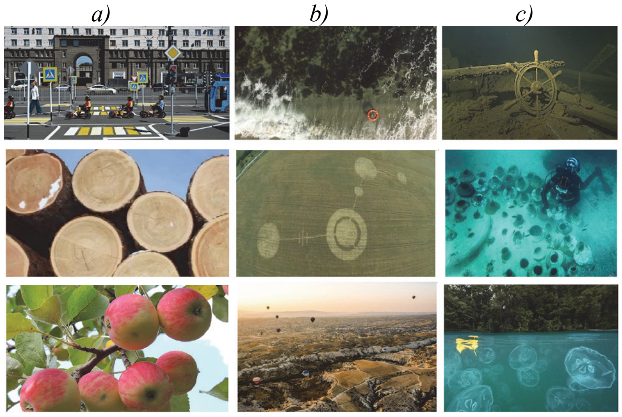


Fig. 15. Photos of real objects taken in various environments. a) Images taken from the ground, b) Images taken from the air, c) Images taken underwater

We present the results of processing three photographs as an example of the proposed algorithms' work. These photos demonstrate the algorithm's characteristic features for various shooting conditions.

Photo №1. Tree trunk cuts of different radii.

Frame size 255×170 pixels; Resolution: 120 dpi; File size: 16 Kb; Shooting conditions: at ground level, close distance; Number of objects of interest: 8; Object radii: 30 to 50 pixels; Frame illumination parameters: uniform illumination; Image clarity rating: High definition; Noise: insignificant.

The PaRCIS method, with two radius ranges for compression and LIPIS modification, successfully recognized all eight objects; no false recognitions were obtained. Fig. 16 presents the results obtained.

The methods recognized smaller radius circles at the first zoom level and larger radius circles at the second zoom level. For this example, the recognition conditions were relatively simple.

Photo №2. Underwater photography of jellyfish.

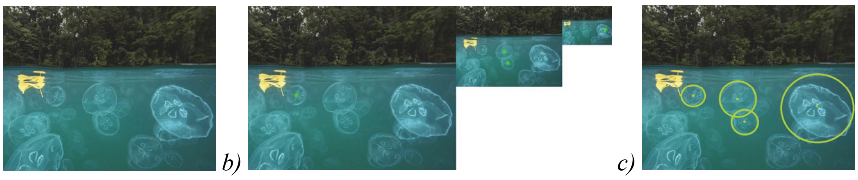
Frame size: 630×485 pixels; Resolution: 72 dpi; File size: 80 Kb; Shooting conditions: underwater shooting, part of the frame is above water; Number of objects of interest: more than 10; Object radii: from 15 to 100 pixels; Frame illumination parameters: uneven illumination, glare; Evaluation of image clarity: low clarity; Presence of noise: blur.

a) b) c)

Fig. 16. The result of recognize circles for simple conditions: (a) the original image; (b) a set of compressed images during processing; (c) the resulting image with recognized circles

Applying the developed algorithms with three ranges of radii in compression, we were able to recognize four objects. No false recognitions were detected. The results are presented in Fig. 17.

Recognition conditions for this photo were more complex than for photo № 1, primarily due to the significant blurring of object contours in the image and uneven illumination and brightness. The lower recognition accuracy was due to the insufficiently close to a circle shape of some objects (ellipses) and the presence of additional details inside the contours (due to the physiology of jellyfish).



a) b) c)

Fig. 17. The result of applying the developed set of methods for recognizing circles in complex conditions: (a) the original image; (b) a set of compressed images during processing; (c) the resulting image with recognized circles

Photo №3. Balloons of different radii.

Frame size: 720×520 pixels; Resolution: 96 dots per inch; File size: 112 Kb; Shooting conditions: from the air, haze; Number of objects of interest: 9; Object radii: from 6 to 15 pixels; Frame illumination parameters: uneven illumination, complex background; Evaluation of image clarity: medium clarity; Presence of noise: salt and pepper, blur.

The recognition results are shown in Fig. 18. 6 objects out of 9 were detected, with five false recognitions of objects with radii less than 7 pixels. We manually added red frames for those objects that were not found by the algorithm.

a) b) c)

Fig. 18. The result of recognize circles in very complex conditions: (a) the original image; (b) a set of compressed images during processing; (c) the resulting image with recognized circles and unrecognized objects

This image was obtained under the most challenging conditions out of the three considered:

- The objects have a slight radius compared to the frame size;
- They are taken against both dark and light backgrounds with different brightness;
- The contours of the objects merge with the background;
- The image contains noise from various properties.

Despite the expected decrease in efficiency, the developed algorithms recognized 70% of the objects of interest in the photo. False recognitions refer to dark circular areas of small radii in the background image, which are full of similar small contrast details.

The Table 6 presents the comparative effectiveness of the developed method in terms of accuracy and speed relative to the classical Hough method and the FCD method. False recognition was taken into account for objects with a radius of more than 10 pixels.

The developed method PaRCIS with a reduced range of radii and modification of the sliding window LIPIS showed the highest accuracy. At the same time, the average recognition speed for the presented images is somewhat inferior to the classical Hough method but significantly exceeds its accuracy. Compared to the Fast Circle Detection method, the proposed method is superior in accuracy and recognition speed for experimental images.

Tab. 6. Comparative performance indicators of circle recognition methods for experiment №3

	Correctly recognized objects for all images	**False recognitions per 1 image**	**Average recognition time per image (ms)**
Hough method	68,97%	13	417
FCD [49]	75,86%	1	797
PaRCIS+LIPIS	89,66%	0	579

Discussion and conclusions

To study the effectiveness of the proposed methods, we conducted three series of comparative recognition experiments for conditions of varying complexity: for a single circle of the same radius for all photographs, for a single circle of different radii for different photographs, and many circles of different radii in each image. Moreover, the first two experiments we conducted were for photographs taken from the air by the onboard camera of a UAV, and the last one was for the conditions of three environments (from the ground, from the air, and underwater). We found that our method did not provide significant gains for simple conditions. However, we gained accuracy and speed as the conditions became more complex.

In particular, using the hybrid algorithm FRODAS increases the recognition accuracy compared to the basic Hough algorithm by an average of 35 %, primarily due to the reduction of false recognitions. No fine-tuning of the Hough algorithm is required, which reduces the algorithm's running time. Improved accuracy while reducing the time cost is achieved by preliminary fast, low-cost FRST processing. The resulting hybrid method, as a result, combines the advantages of the Hough algorithm in terms of accuracy in recognizing circles as their centers and radii and the FRST algorithm in terms of recognition speed.

Application of the PaRCIS algorithm increases the recognition rate compared to the basic FRST algorithm by an average of 2.1 times for images containing a set of circles of different radii. At the same time, the algorithm's accuracy remains at the basic algorithm's level. The speed increase is achieved by step-by-step compression of the original image, thereby reducing the ranges of the desired radii of circles and reducing the dimensionality of the image during compression. An additional advantage is the robustness of the method to noise.

The LIPIS modification makes any basic algorithm robust to sharp changes in the brightness of the searched objects in one image. The classical algorithms FRST, Hough's method, and the proposed FRODAS and PaRCIS can act as basic algorithms. Comparison with FRST (one of the possible basic ones) demonstrated the comparative efficiency of the proposed modification: for the test image, the primary method failed to recognize two out of nine objects with brightness change from 0 to 20 with a step of 30, whereas the modification allowed to recognize all nine circles.

We can combine the developed methods into a single complex, the blocks of which we can turn on or off in accordance with the peculiarities of external conditions. A single set of methods allows the recognition procedure to be adapted to the external conditions of imaging and/or requirements of the calculator on board the UAV.

Due to the simplicity of implementation, low requirement for computational resources, and high speed of operation, the methods are suitable for computer vision systems of light unmanned vehicles moving at high speed.

A limitation of the proposed approach is the radial shape requirement for the detected object. The algorithms do not apply to objects of interest of arbitrarily complex shapes, such as a human face. However, with appropriate modifications, the proposed methods can be extended to other object shapes that possess the symmetry property to some extent, such as polyhedrons, ellipses, etc.

Another limiting factor for applying the developed methods is the presence of many small details close to circular shapes in the image. Their presence can lead to both missing real circles and false detection. Small details should be specially processed to level out their negative influence.

The solution to these problems is the direction of development of the research described in the article.

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