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CIRCLE DETECTION BASED ON ARTIFICIAL BEE COLONY ALGORITHM

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ВИЯВЛЕННЯ КРУГЛИХ КОНТУРІВ НА ОСНОВІ АЛГОРИТМУ БДЖОЛИНОЇ КОЛОНІЇ

Purpose. This paper presents an algorithm for the automatic detection of multiple circular shapes from complicated and a noisy image, which does not take into consideration the conventional-Hough transform principles with large amount of calculation.

Methodology. The approach is based on the artificial bee colony algorithm, a swarm optimization algorithm inspired by the intelligent for aging behavior of honey bees. A new objective function has been derived for the edge map of a desired image.

Findings. A matching function determines if such circle candidates are actually present in the image. By the use of artificial bee colony algorithm the objective function is minimized and this leads to automatic circle detection in digital images. The proposed method is able to detect single or multiple circles from a digital image through only one optimization.

Originality. The industrial product calibration card image is chosen as actual image to test the approach which includes a circular-shape object of different sizes in each image. The research on industrial product has not been found at present.

Practical value. Compared with Hough transform algorithm, the amount of calculation and the occupied memory space is reducing greatly, therefore operation speed is improved. The experimental results show that the improved algorithm meets the requirements of industrial real-time detection with a good application effect.

Keywords: *circle detection, artificial bee colony algorithm, intelligent image processing, Canny algorithm, fitness function*

Introduction. In the field of industrial inspection, the circular feature is widespread. Therefore, it has received extensive attention in the machine vision how to identify and locate the circle quickly and accurately. Circle detection is one of the important tasks in machine vision and pattern recognition [1]. It has been widely used in industrial manufacturing, traffic monitoring, human face detection, GPS measurement and weapon manufacturing. Currently there are a lot of algorithms for circle detection which can mainly divided into two classes, one is based on Hough transform, and another one is roundness detection algorithm [2]. These methods can detect the circle in the image, but Hough transform needs large amount of calculation, and circle detection algorithm is more suitable for image with simple background round [3]. Therefore, domestic and foreign scholars have been working to quickly detect circle algorithm research in image with complex background.

This paper presents an algorithm for the automatic detection of multiple circular shapes from complicated and noisy image, which does not take into consideration the conventional-Hough transform principles. Artificial Bee Colony algorithm (ABC) is applied for identifying and extracting circles in digital image. Canny algorithms are chosen to generate the edge-map from a gray-scale image [4]. The detection process is approached as a multi-modal optimization problem. The ABC algorithm searches the entire edge-map looking for circular shapes by considering a combination of edge points that represent candidate circles (food source locations) in the edge image of the scene. An objective function is used to measure the existence of a candidate circle on the edge map. Guided by the values of such an objective function, the set of encoded candidate circles are evolved through the ABC algorithm so that the best candidate can be fitted into the most circular shape on the edge image.

Experimental evidence shows the effectiveness of the method for detecting circles under various conditions. Compared with Hough transform algorithm, the amount of computation and the occupied memory space is reducing greatly, therefore operation speed is improved. The experimental results show that the improved algorithm meets the requirements of industrial real-time detection with a good application effect.

Artificial bee colony algorithm. ABC algorithm was proposed by Turkey scholar Karaboga in 2005, which is a new bionic optimization algorithm [5]. This algorithm has a superior optimization performance than genetic algorithm, particle swarm optimization, and colony algorithm etc., which is applied in many fields such as digital filtering, neural network training and clustering analysis. ABC algorithm is well global convergent with high solving precision, which is briefly introduced as follows.

In ABC algorithm, feasible solutions in Search space are taken as nectar source. The nectar source and functional value of the problem to be solved are in close correlation, while the nectar source quality is measured by the profit value. When the bee colony is initialized, the whole bee colony is divided into two large groups, employed bees and onlookers. Suppose bee population is N_s, in which employed bees quantity is N_e, onlookers quantity is N_u. In general condition $N_e = N_u = \frac{1}{2} N_s$, the search space of each bee is solution variable space of the problem to be solved, which number of dimensions is D. Suppose x = (x_1, $x_2, \ldots, x_{N_e}$, is the bee colony, and x_i is one of the bees. In the bee colony initialized phase, according to formula (1), the feasible solution N_e is generated randomly as below formula (1)

$$x_{i,j} = x_j^{\min} \text{ rand}(0,1)\left(x_j^{\max} - x_j^{\min}\right), \tag{1}$$

where $j \in \{1, 2, \ldots, D\}$, $i \in \{1, 2, \ldots, N_e\}$ and $x_j^{\max}$ are the determined maximum and minimum limits. Each solution vector profit value is calculated respectively. Take these N_e solution as employed bee. For the minimum solution of the optimization solution problem, the profit value formula is as below formula (2).

$$f(x_i) = \begin{cases} \dfrac{1}{1 + f(x_i)}, & f(x_i) \geq 0 \\ 1 + abs\left(f(x_i)\right), & f(x_i) < 0 \end{cases}, \tag{2}$$

where $f(x_i)$ is position x_i objective function value. During the optimization, the employed bee search in the neighborhood of the current position according to formula (3)

$$\upsilon_{i,j} = x_{i,j} + \varphi_{i,j}(x_{i,j} - x_{k,j}), \tag{3}$$

where $j \in \{1, 2, \ldots, D\}$, $k \in \{1, 2, \ldots, N_e\}$ are generated randomly and $k \neq j$. $\varphi_{i,j}$ is the random value between [–1, 1]. Each onlooker follows a employed bee according to the employed bee profit value, and then search in the neighborhood for better profit value position.

If the new nectar source is more profitable, then the employed bee position is replaced by new nectar source position. Its chosen probability formula is as formula, showed below (4).

$$p_m = \frac{f(x_i)}{\sum_{m=1}^{N_e} f(x_m)}. \tag{4}$$

If one employed bee search time is over the limit but the better nectar source is not found yet, this nectar source is abandoned and a new random nectar source is taken as this employed bee position. If the bee colony optimization process meets the stop condition, then the best objective function value and its position are output, otherwise, the bee colony turn into the next optimization search process.

By searching for better positioned neighborhood, we are abandoning the worse position and generating the new one, ABC algorithm can search the best problem solution during bee colony gradual position optimization. The performance of artificial bee colony algorithm is very outstanding. Its proposer compared the ABC algorithm with genetic algorithm, particle swarm algorithm, differential evolutionary algorithms and the other high performance bionic intelligence algorithm for abundant common benchmark function. The computer experiment showed that artificial bee colony algorithm is better than these above algorithms for global optimization ability and solution accuracy. Therefore, the ABC algorithm is adopted in this paper for character image edge search, and then the good effect result is get.

Artificial bee colony algorithm applied for circle detection. The ABC circle detector involves a preprocessing stage that requires marking the object's contour by applying a single-pixel edge detection method. In this paper, such a task, is accomplished by the classical Canny algorithm [6]. Then, the locations of the found edge pixels are stored within the P = $=\left\{p_1, p_2, \ldots, p_{E_p}\right\}, E_p$ being the total number of edge pixels in the image.

The popular canny edge detector applies the following steps to search contours in the image. The first stage is Gaussian smoothing. The resulting image is imported to the PC that is transfered back to the gradient filter, but the gradient filter is modified, due to this gradient magnitude is not applied that is given by previous operator, however the separately G_x and G_y are needed. The phase or orientation of the gradient which is obtained using the following formula

$$\theta = \text{arctg}\,(G_y/G_x). \tag{5}$$

In which, formula (5) contains an arctg and a division calculation. These operators are very difficult to implement using hardware. Arctg and the division calculation can be eliminated by simply comparing G_x and G_y values. If they have similar length, a diagonal direction is obtained, if one is at least 2.5 times longer than the other, a horizontal or vertical direction are obtained.

After the edge directions are acquired, non maximum suppression is applied. Non maximum suppression is used to trace pixels along the gradient in the edge direction and compare the value perpendicular to the gradient. Two perpendicular pixel values are compared with the value in the edge direction. If their value is lower than the pixel on the edge, then they are suppressed i. e. their pixel value is changed to 0, or else the higher pixel value is set as the edge and the other two are suppressed with a pixel value of 0.

Finally, hysteresis is used as a means of eliminating *streaking which is the breaking up of an edge contour* caused by the operator output fluctuating above and below the threshold. If a single threshold, T1 is applied to an image, and an edge has an average strength equal to T1, then due to noise, there will be instances where the edge dips below the threshold.

Equally it will also extend above the threshold for making an edge which is shown as a dashed line. To avoid this, 2 thresholds are set in hysteresis. Any pixel in the image that has a value greater than T1 is presumed to be an edge pixel, and which is marked immediately. Then, any pixels that are connected to this edge pixel and that have a value greater than T2 are also selected as edge pixels. If the following point is estimated as an edge, a gradient of T2 is applied until a gradient below T1 is shown. The procedure is shown in Fig. 1.

Step 1: In order to implement the canny edge detector algorithm, a series of steps must be followed. The first step is to filter out any noise in the original image before trying to locate and detect any edges. Because the Gaussian filter can be computed using a simple mask, it is used exclusively in the Canny algorithm. Once a suitable mask has been calculated, the Gaussian smoothing can be performed using standard convolution methods. Aconvolution mask is usually much smaller than the actual image. As a result, the mask is slid over the image, manipulating a square of pixels at a time. The larger the width of the Gaussian mask, the lower the detector's noise sensitivity. The localization error in the detected edges also increases slightly as the Gaussian width is increased. Image smoothing is the first stage of the canny edge detection. The pixel values of the input image are convolved with predefined operators to create an intermediate image. This process is used to reduce the noise within an image or to produce a less pixilated image. Image smoothing is performed by convolving the input image with a Gaussian filter. A Gaussian filter is a discrete version of the 2-dimensional function shown in formula (6).

$$G_\sigma(x,y)=\frac{1}{2\pi\sigma^2}\exp\left(-\frac{(x^2+y^2)}{2\sigma^2}\right). \qquad (6)$$

In formula (6), σ is the standard deviation of the Gaussian filter, which describes the narrowness of the peaked function, and x and y are spatial coordinates.

Step 2: After smoothing the image and eliminating the noise, the next step is to find the edge strength by taking the gradient of the image. The Sobel operator performs a 2-D spatial gradient measurement on an image. Then, the approximate absolute gradient magnitude (edge strength) at each point can be found.The Sobel operator uses a pair of 3 × 3 convolution masks, one estimating the gradient in the x direction(columns) and the other estimating the gradient in the y-direction (rows).

In this stage, the blurred image obtained from the image smoothing stage is convolved with a 3 × 3 Sobel operator. The Sobel operator is a discrete differential operator that generates a gradient image. Sobel operators used to calculate the horizontal andvertical gradients. The Sobel operators are shown in Fig. 2.

In order to construct each candidate circle C (or food-source within the ABC framework), indexes i_1, i_2 and i_3 are representing three edge points previously

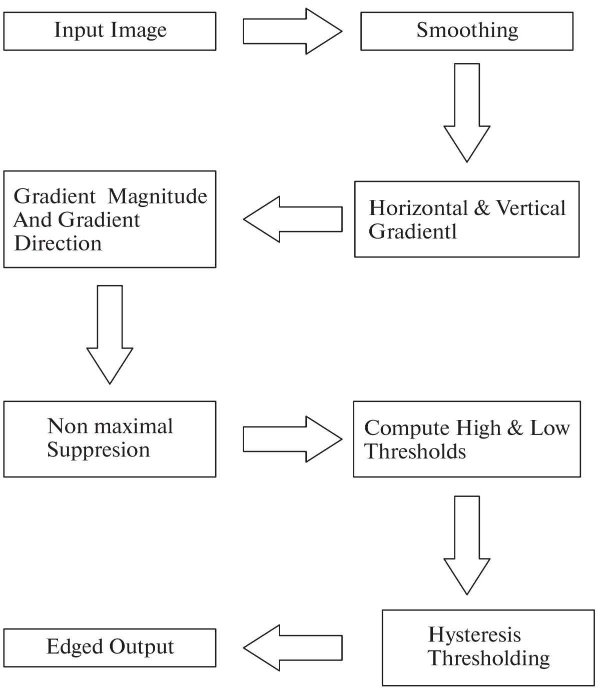

Fig. 1. Block diagram of canny edge detection

$$G_x=\begin{array}{|c|c|c|}\hline -1 & 0 & +1\\\hline -2 & 0 & +2\\\hline -1 & 0 & +1\\\hline\end{array}$$

$$G_y=\begin{array}{|c|c|c|}\hline -1 & -2 & -1\\\hline 0 & 0 & 0\\\hline +1 & +2 & +1\\\hline\end{array}$$

Fig. 2. The Sobel Operators

stored in vector P, must be combined. Therefore, each food-source is encoded as one circle the $C = \{p_1, p_2, p_3\}$, which is characterized by three points.

p_1, p_2 and p_3 are lie on its own circumference. Such candidate circle is labeled as a potential solution for the detection problem. Considering the configuration of the edge points in Fig. 1, the circle centre (x_0, y_0) and the radius r of C can be calculated using simple geometric equations shown in formula (7).

$$(x_i - x_0)^2 + (y_i - y_0)^2 = (2r)^2. \qquad (7)$$

In this algorithm each individual food source in each step shows a trial circle. Each sample circle is represented as a food source position,

$$\text{food}_i = [x_i, y_i, r_i]^T. \qquad (8)$$

In formula (8), where x_i and y_i are the coordinates of the center of the circle and r_i stands for radius. Let (x_i, y_i, r_i) will be the test circle. It is obvious that all the points on a complete circle in the edge-map have an intensity value equal to one while the intensity values belong to an interval between [0, 1]. So if we have a test circle which pixels exactly match with the edge-map, the objective value must become minimum. The number of pixels for representing the circle that i^{th} food source is indicated by N_C. In other words, N_C is the number of dots that generate a circle with radius on white paper while the dots are connected together and there is no dot on the other one. A circle with radius is defined and then is moved to the coordinates (x_i, y_i).

Simply, the objective function can be defined as formula (9),

$$\text{Object Value}_i = 1 - \frac{N_m}{N_c}. \qquad (9)$$

N_m is the number of pixels that are exactly matched with the test circle that can be constructed by information from their food source. As the number of matched pixels increase the object value decrease, so the object value is equal to zero if all the pixels match with the test circle. A value near to zero of Object Value$_i$ implies a better response from the "circularity" operator and represents a better nectar-amount within the ABC framework.

Fig. 3 illustrates how pixels match with test circle and how objective function is calculated. This example

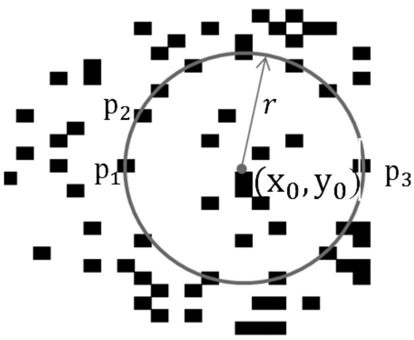

Fig. 3. Circle candidate (individual), built from the combination of points

shows that the objective value is equal to 0.75 because only one quarter pixels are on the test circle.

Fig. 4 shows the procedure to evaluate the objective function Object Value$_i$. At first, three edge points encode a candidate circle. Then, a circular virtual shape is built. Such virtual shape, which is characterized by pixel groups a determined number N_m of pixel coordinates that are shown by Fig. 2. Finally, the virtual shape is compared with the original edge-map, point by point, in order to find matches between virtual and edge pixels. As a result, only eighteen edge pixels are common for both circle images.

The fitness functions such that at the optimal situation of objective function (minimization) becomes maximum value. Formula (10) determines the fitness amount of each solution (food source).

$$\text{fit}_i = \frac{1}{1 + \text{Object value}_i}. \qquad (10)$$

The implementation of the proposed algorithm can be summarized by the following steps:

Step 1: Apply the Canny filter to the original image and store edge image.

Step 2: Initialize required parameters of the ABC algorithm. Set the colony's size, the abandonment limit and the maximum number of cycles.

Step 3: Initialize circle candidates and clear all counters.

Step 4: Obtain the matching fitness (food source quality) for each circle candidate.

Step 5: Repeat steps 6 to 10 until a termination criterion is met.

Step 6: Modify the circle candidates and evaluate its matching fitness (send employed bees onto food sources). Likewise, update all counters.

Step 7: Calculate the probability value for each circle candidate. Such probability value will be used as a preference index by onlooker bees.

Step 8: Generate new circles candidates from current candidates according to their probability (Send onlooker bees to their selected food source). Likewise, update counters.

Step 9: Obtain the matching fitness for each circle candidate and calculate the best circle candidate.

Step 10: Stop modifying the circle candidate (food source) whose counter has reached its counter and save it as a possible solution (global or local optimum) in the exhausted source memory. Clear counter and generate a new circle candidate.

Step 11: Analyze solutions previously stored in the exhausted-source memory. The memory holds solutions

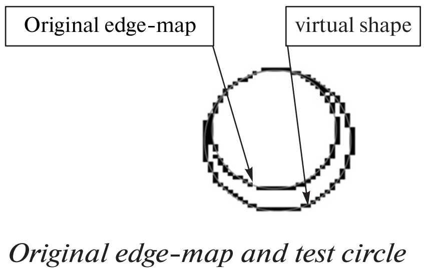

Fig. 4. Original edge-map and test circle

(any other potential circular shape in the image) generated through the evolution of the optimization algorithm.

In ABC algorithm, the steps 6 to 10 are repeated until a termination criterion is met. Typically, two stop criteria have been employed for meta-heuristic algorithms: either an upper limit of the fitness function is reached, or an upper limit of the number of generations is attained. The first criterion requires an extensive knowledge of the problem and its solutions. On the contrary, by considering the stop criterion based on the number of generations, feasible solutions may be found by exploring the search space through several iterations. For our purpose, the number of iterations as stop criterion is employed in order to allow the multi-circle detection. Hence, if a solution representing a valid circle appears at early stages, it would be stored in the exhausted-source memory and the algorithm continues detecting other feasible solutions until depleting the iteration number. Therefore, the main issue is to define a fair iteration number, which should be big enough to allow finding circles at the image and small enough to avoid an exaggerated computational cost. For this study, such a number was experimentally defined as 300.

Expremental results. The calibration card image (Fig. 5) is chosen as actual image to test the approach which includes a circular-shape object of different sizes in each image. Standard canny edge-detector is applied in image-processing Toolbox, MATLAB 7.0, as a pre-processing step. Our approach is very fast due to the small size of computation which needs to carry out in each cycle. The related edge-map image is shown in Fig. 6.

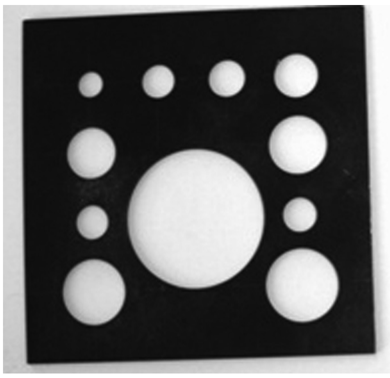

Fig. 5. Calibration card image

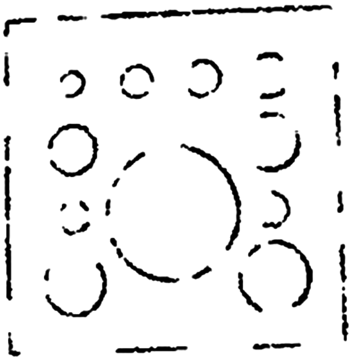

Fig. 6. Edge-map image

Table presents the parameters for the ABC algorithm in this study. They have been retained for all testimages after being experimentally defined.

The experimental setup includes the use of synthetic image of 819 × 460 pixels. The image contains varying amounts of circular shapes and some have also been contaminated by added noise so as to increase the complexity of the localization task. The algorithm is executed over 100 times, successfully identifying and marking all circles in the image. The detection has proved to be robust to translation and scaling, requiring less than 1 s. Fig. 7 shows the outcome after applying the algorithm from the experimental set. The noisy images show our algorithm is robust enough to detect circles on the images which highly affected by a random noise.

Discussion and conclusion. Hough Transform methods for circle detection use three edge points to cast a vote for the potential circular shape in the parameter space. However, they would require a huge amount of memory and longer computational times to obtain a sub-pixel resolution. Moreover, HT-based methods rarely find a precise parameter set for a circle in the image. This work has presented an algorithm for the automatic detection of multiple circular shapes from complicated and noisy images without the conventional Hough Transform principles. The detection process is considered to be similar to a multi-modal optimization. Rather than other heuristic methods that employ an iterative procedure, the proposed ABC method is able to detect single ormultiple circles in a digital image within only one optimization cycle. An objective function is used to measure the existence of a candidate circle from the edge-map. Guided by the values of this matching function, the candidate circles are envolved using the ABC algorithm so that the best

Table

ABC detector parameters

Colony size	Abandonment limit	Number of cycles	α	Limit
20	100	300	0.05	30

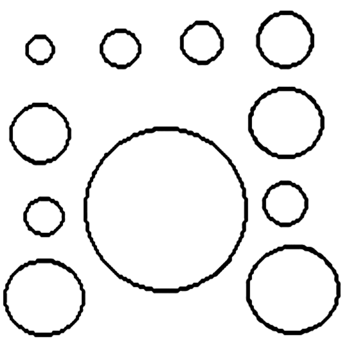

Fig. 7. Simulation results

candidate can be found as an actual circle. Finally, the result indicates that the ABC method can yield better results on complicated and noisy images. The result shows that the ABC algorithm can effectively serve as an attractive method to successfully extract multiple circular shapes.

Acknowledgements. This work was supported by the education department of Jilin Province. The title of research project: research on localization algorithm of mobile robots based on machine vision, and project serial number: (2014) 328.

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Мета. У роботі представлений алгоритм автоматичного виявлення множинних кругових контурів на складних і зашумлених зображеннях, що не бере до уваги загальноприйняті принципи перетворення Хафа з великим об'ємом обчислень.

Методика. Підхід заснований на алгоритмі штучної бджолиної колонії, який є роєвим оптимізаційним алгоритмом, що імітує розумну поведінку бджіл при зборі нектару. Виведена нова цільова функція для країв оброблюваного зображення.

Результати. Функція відповідності визначає, чи дійсно потенційно кругові контури присутні на зображенні. Цільова функція мінімізується з використанням алгоритму штучної бджолиної колонії, внаслідок чого на цифровому зображенні автоматично визначаються круглі контури. Запропонований метод здатний виявити окремі і множинні кругові форми на цифрових знімках за допомогою лише єдиної оптимізації.

Наукова новизна. Для тестування підходу було вибрано зображення промислової калібрувальної карти, що містить об'єкти круглих форм різних розмірів на кожному зображенні. Дослідження на промисловому продукті до теперішнього часу не зустрічалося.

Практична значимість. У порівнянні з алгоритмом Хафа-перетворення, об›єм обчислень і займаної пам›яті помітно скорочується, таким чином, покращена робоча швидкість. Експериментальні результати показують, що покращений алгоритм відповідає вимогам промислового виявлення в реальному часі з хорошим ефектом застосування.

Ключові слова: *виявлення круга, алгоритм бджолиної колонії, інтелектуальна обробка зображень, алгоритм Канні, фітнес-функція*

Цель. В работе представлен алгоритм автоматического обнаружения множественных круговых очертаний на сложных и зашумлённых изображениях, который не принимает во внимание общепринятые принципы преобразования Хафа с большим объёмом вычислений.

Методика. Подход основан на алгоритме искусственной пчелиной колонии, являющемся роевым оптимизационным алгоритмом, имитирующем разумное поведение пчёл при сборе нектара. Выведена новая целевая функция для краёв обрабатываемого изображения.

Результаты. Функция соответствия определяет, действительно ли потенциально круговые очертания присутствуют на изображении. Целевая функция минимизируется с использованием алгоритма искусственной пчелиной колонии, в результате чего на цифровом изображении автоматически определяются круглые очертания. Предложенный метод способен обнаружить отдельные и множественные круговые формы на цифровых снимках посредством только единственной оптимизации.

Научная новизна. Для тестирования подхода было выбрано изображение промышленной калибровочной карты, которая содержит объекты круглых форм разных размеров на каждом изображении. Исследование на промышленном продукте до настоящего времени не встречалось.

Практическая значимость. В сравнении с алгоритмом Хафа-преобразования, объём вычислений и занимаемой памяти заметно сокращается, таким образом, улучшена рабочая скорость. Экспериментальные результаты показывают, что улучшенный алгоритм соответствует требованиям промышленного обнаружения в реальном времени с хорошим эффектом применения.

Ключевые слова: *обнаружение круга, алгоритм пчелиной колонии, интеллектуальная обработка изображений, алгоритм Канни, фитнес-функция*

Рекомендовано до публікації докт. техн. наук В. В. Гнатушенком. Дата надходження рукопису 11.06.15.