Практическая значимость. Доказана эффективность использования модели на основе нейронной сети с нечёткой логикой, оптимизированной методом роя частиц, в качестве подхода к оптимизации опережения зажигания. Она позволяет обходиться без большого количества калибровочных испытаний, значительно уменьшает трудоемкость экспериментов и повышает эффективность.

Ключевые слова: *нейронная сеть с нечёткой логикой, оптимизация методом роя частиц, двигатель на водородном топливе, опережение зажигания, оптимизация*

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IMAGE FEATURE CLASSIFICATION BASED ON PARTICLE SWARM OPTIMIZATION NEURAL NETWORK

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ОЗНАКОВА КЛАСИФІКАЦІЯ ЗОБРАЖЕННЯ НА ОСНОВІ НЕЙРОННОЇ МЕРЕЖІ ІЗ ЗАСТОСУВАННЯМ МЕТОДУ РОЮ ЧАСТОК

Purpose. The purpose of image feature classification is to divide an image into several meaningful regions according to certain features, making these features the same or similar in a certain region but significantly different in different regions. In this paper, we will investigate the role of neural network and particle swarm optimization (PSO) in the image feature classification.

Methodology. We propose the image feature classification method that combines PSO with neural network. BP neural network has been extensively applied in feature classification and it can classify specific objects or features through early learning, however, BP neural network algorithm also has many defects, including slow convergence speed and easiness to be trapped in local optimum. PSO optimized neural network fully exhibits its global search ability and parallel operation ability.

Findings. Firstly, we take the gray image with specific object as the object to be segmented, study the samples with PSO neural network and get the training network. Secondly, we take the pixel matrix of the image as the input vector and put in the well-trained network for classification. Finally, the image feature classification can be realized.

Originality. We made a study of image feature classification based on the particle swarm optimization neural network. We discussed the theory of image feature classification, basic principles of PSO and neural network.

Practical value. We have also conducted the simulation experiment to confirm that the method suggested in this paper is a feasible one. We have proved that it has higher convergence speed and stronger robustness. Through the highly-efficient processing, this method can obtain important information and achieve excellent effect when used in the segmentation of the objects in complicated scenes.

Keywords: *gray image, feature classification, particle swarm optimization, BP, neural network, segmentation*

Introduction. Image feature classification is one of the basic questions of image processing and computer vision, and it has gained more and more attention in the field of image analysis and processing in recent years. Due to gray scale, frequency spectrum, texture and so on, posed in images, it becomes a complex task to be solved [1]. Image segmentation, object separation, feature extraction and parameter measurement will transfer the original image into a more abstract and compact form, making it possible for high-level analysis and understanding. Image feature classification is the foundation of image understanding and recognition and the research on image feature classification has always been a research hotspot of digital image processing techniques, and it is also a key step of image analysis [2].

Image feature classification serves as a connecting link in the image engineering and it lies between the low- and high-level processing. Although foreign scholars have made extensive research on the techniques of image feature classification, it is still very difficult to find a reliable image feature classification method. Every segmentation algorithm performs the segmentation by using certain specific characteristics of the image. The algorithm suitable for the segmentation of a certain kind of image may not be able to do the segmentation on another kind or it is possible that different segmentation methods are required in segmenting different regions of the same image [3]. Many current techniques are not fit for real-time or approximate real-time processing. So far, an increasing number of scholars have begun to apply such research achievements as intelligent algorithm theory, neural network, fuzzy theory and wavelet transform theory into the image feature classification, thus bringing advanced image feature classification techniques, which integrate specific mathematical methods into being. This paper considers image feature classification as a kind of classification problem. With such advantages as self-organization and intelligence, PSO optimized neural network fully exhibits its global search ability and parallel operation ability, classifies and recognizes the image pixels at the tiny cost, realizes the segmentation and improves the performance of image feature classification.

This paper firstly introduces the theory of image feature classification and then it analyzes the basic principles of PSO and neural network. After that, it designs an image feature classification method based on the optimized neural network of PSO. Finally, it proves that the method of this paper works through the analysis and summarization of the experimental simulation.

Image feature classification. ***Definition of image feature classification.*** The purpose of the classification of image features is to divide an image into several meaningful regions according to certain features (i.e. gray scale, frequency spectrum and texture), making these features the same or similar in a certain region but significantly different in different regions. Image feature classification shall include the following characteristics:

(1) Different separated regions have similarity towards certain feature (i.e. grayscale and texture) and the regions are interconnected without too many holes.

(2) Similar regions are greatly different in the features on which threshold segmentation is based.

(3) There is a clear-cut boundary between the regions.

The mathematical form of image feature classification is defined as follows: A is the image, g means having similar characteristics and image feature classification decomposes A into n, namely Ti, $i = 1, 2, 3, ..., n$, which meet the following conditions:

(1) $\bigcup_{i=1}^{n} Ti = A, T_i \cap T_j = \Phi, \forall i, j, i \neq j$.

(2) $\forall i, j = 1, 2 \ldots, n, g(Ti) = Ture$.

(3) $\forall i, j \neq j, g(Ti \cup Tj) = Falase$.

Condition (1) shows that the segmented regions need to cover the entire image, but different regions do not overlap with each other, Condition (2) suggests that every region has similar property and Condition (3) indicates that the neighboring two regions cannot be merged as one region due to different properties. If the constraints to maintain regional connectivity are canceled, the division of the pixel set is called pixel classification and every pixel set is a Class [4].

Image feature classification methods based on a threshold. Image thresholding segmentation is a traditional and commonly-used image feature classification method and it is especially suitable for the images with object and background occupying different grayscale ranges because of its simple realization, little computation and stable performance. The boundary of a system is a threshold, its numeral value is called threshold value and the "threshold value" command of the image is to convert a gray or colored image into black-and-white image with high contrast. The command of "threshold value" is of great significant to determine the brightest and the darkest regions. The purpose of image thresholding is the divide the pixel sets according to the grayscale and every sub-set forms a corresponding region to the real scenery. Every region has the same property while the neighborhood region has a similar property. Such division can be realized by selecting one or more thresholds starting from the grayscale.

Thresholding method is a common image feature classification method which splits the interested objective from the background of the image. Assume that the original image is $I(x, y)$ and the threshold method determines several threshold value $T_1, T_2, \ldots, T_N, (N \geq 1)$ in the image $I(x, y)$ according to certain rules. Classify the image features into several parts with these thresholds and the segmented image can be represented as follows

$$R(x,y) = \begin{cases} L_N & if\ I(x,y) \geq T_N \\ L_{N-1} & if\ T_{N-1} \leq I(x,y) < T_N \\ & \vdots \\ L_1 & if\ T_1 \leq I(x,y) < T_2 \\ L_0 & if\ I(x,y) < T_1 \end{cases}. \quad (1)$$

Here, $L_0, L_1, \cdots, L_N$ are the grayscale of the resulting image. If $N = 2$, the segmentation steps above are also called the image binarization based on thresholding method. The selection of threshold is determined according to the specific questions. As for the given image, the optimal threshold can be determined by analyzing the histogram. For example, when the histogram lies in two peaks, the midpoint of the two peaks is selected as the optimal threshold [5].

It is especially suitable for the image the object and background of which occupy different grayscale ranges. It can greatly compress the amount of data and significant simplifies the analysis and processing steps. In the specific implementation of thresholding segmentation, the selection of local segmentation threshold is usually realized by controlling the selection range of threshold, namely to divide the original image into smaller images and segment every smaller image with different thresholds according to the local characteristics of the image [6]. Thresholds are divided into global threshold, local threshold, and dynamic threshold.

(1) Global threshold: This threshold depends on the image grayscale and it is only related to the characteristics of the pixels of every image.

(2) Local threshold: This threshold relies on the image grayscale and certain local characteristics of the neighborhood, namely it is related to the characteristics of a local region.

(3) Dynamic threshold: This threshold is determined by the space coordinate, which means that the threshold is related to the coordinate.

Description of particle swarm optimization. Similar to other evolutionary algorithms, PSO also uses the concepts such as swarm and evolution and it searches the optimal solution in the complicated space through the collaboration and competition among the individuals. PSO generates the initial population, namely randomly initializes a group of particles in the space of feasible solutions. Every particle may be a feasible solution to the optimization problem and a fitness value is determine by the object function. PSO considers every individual as a particle with no volume and weight in an n-dimensional search space. Every particle moves in the solution space and its direction and distance are determined by a speed. Generally, the particle will move by following the current optimal particle and get the optimal solution through search generation by generation. In every generation, the particle will track two extremums: one is the optimal solution $pbest$ it has found and the other is the optimal solution $gbest$ the entire population has found.

Assume that in D-dimensional search space, there are m particles forming a group, the position of the ith particle is represented as $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ in D-dimensional space, the best position (with the best fitness) the ith particle has passed is marked as $P_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$ and the flying speed of every particle is $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$, $i = 1, 2, \ldots m$. In the entire group, the best positions which all particles have passed are $P_g = (p_{g1}, p_{g2}, \ldots, p_{gD})$ and the particles of every generation will update their own speeds and positions according to the following formulas:

$$v_{id} = wv_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}); \quad (2)$$

$$x_{id} = x_{id} + v_{id}. \quad (3)$$

Here, w is the inertia weight, c_1 and c_2 are learning factors and r_1 and r_2 are random numbers within $[0,1]$. The inertia weight w describes the influence the speed of the particle in the last generation has on that of the current generation. To control its value can adjust the global and local optimization abilities of PSO [7].

Basic principle of BP neural network. BP (Back Propagation) network is a multi-layer feed forward network and it is one of the most extensively used neural network models at present. BP network can learn and save plenty of input-output mode mapping relations without revealing the mathematical equation, which describes such relation in advance. Its learning rule is to use the steepest descent method, which keeps adjusting the weight and threshold of the network through back propagation so as to minimize the sum of the squared network error [8]. The topological structure of BP neural network model includes: the input layer, the hidden layer and the output layer, as indicated in fig. 1.

A standard BP network model is consisted of three neuron layers: the input layer, the hidden layer and the output layer (from left to right). Neuron is the most fundamental component of neural network. The neighboring neurons are fully-connected, that is to say, every neuron of the next layer is fully connected with every neuron of the current layer and the neurons of the same layer are also fully connected [9]. BP neurons are similar to other neurons and the difference is that the transmission function of BP neurons are non-linear functions. The commonly used functions include logsig and tan-sig and some output layer may select linear function like purelin.

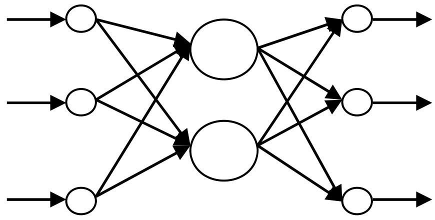

Fig. 1. BP network model

Image feature classification based on PSO neural network. The training sample in the simulation experiment of this paper is one-dimensional vector of P=[0:1:255] and it represents the 256 grayscale of the image. The object sample of this experiment is a 256x1 matrix with 1−100 as 0 and 101−256 as 1. The main parameters of this experiment is as follows: the maximum number of network training is 5000, the maximum number of generations is 200, the number of individuals is 30, the number of independent variables of the fitness function is 5 and the fitness limit is 0.00001. The construction process of PSO neural network is indicated as fig. 2.

Put the above input samples and object samples into the built BP neural network and PSO neural network respectively and get the following results.

Through the comparison of fig. 3, 4, it can be seen that BP neural network has numerous trainings, long training time and it is difficult to converge to the minimum error. Its trainings are as many trainings as 5000 and its error is only converge to 0.01, which is far away from 0.00001, therefore, it is obvious that BP neural network is low in training and learning efficiency and its operating time is low. On the contrary, PSO neural network can converge to the preset minimum error after only 180 trainings. Through this simulation experiment, it can be seen that PSO algorithm can greatly optimize the performance of neural network, find the optimal solution at a shorter time and resolve the problems in a faster and more accurate manner [10].

Experimental simulation and analysis. The image feature classification method based on the neural network of PSO mainly includes two parts: the first is to conduct learning training on the samples with PSO neural network, the second is image feature classification, and its main steps are as follows:

(1) After determining the object to be segmented, abstract the samples of various classes as the initial training samples of the neural network.

(2) Train PSO neural network. This is an extremely important step because it manifests the differences from the traditional segmentation algorithms and it is a learning and training process. Through continuous learning and training, it enhances the understanding of PSO neural network on the segmentation problem and it can naturally separate different classes.

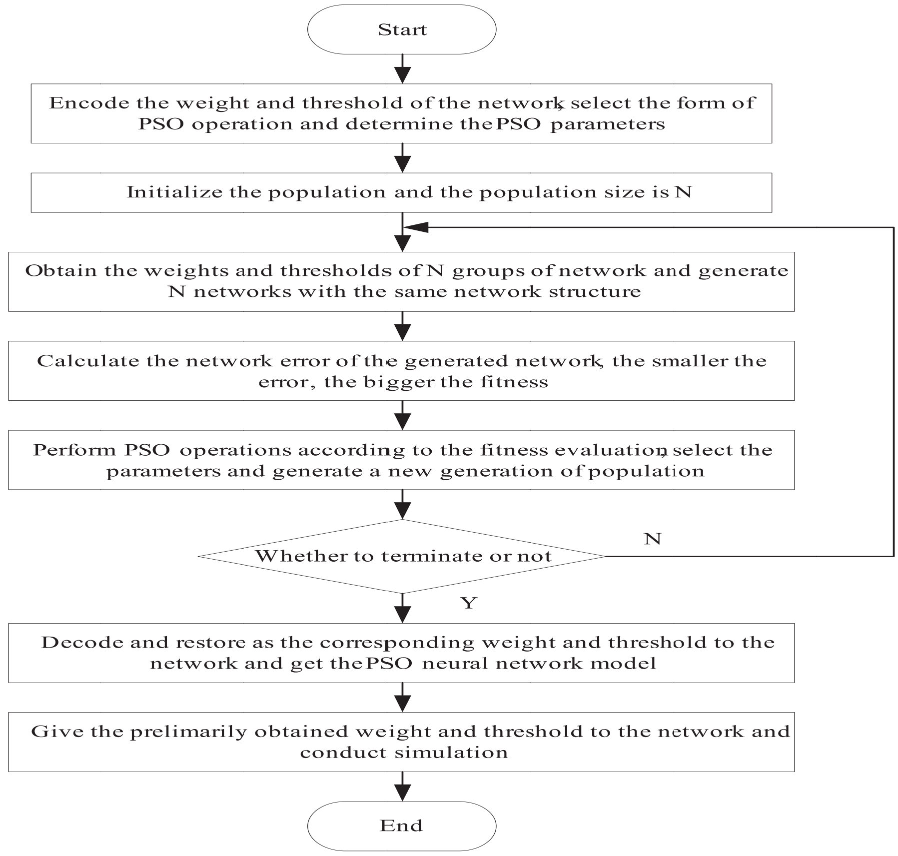

Fig. 2. Flowchart of BP neural network optimization by PSO

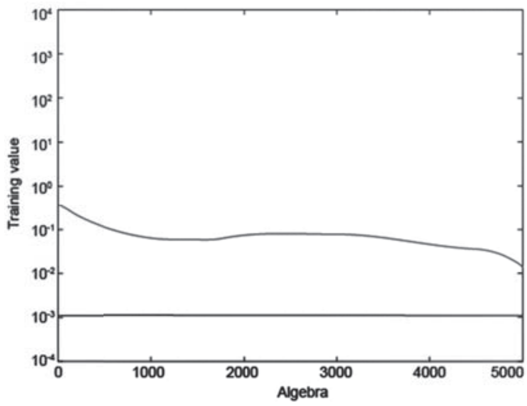

Fig. 3. BP neural network training chart

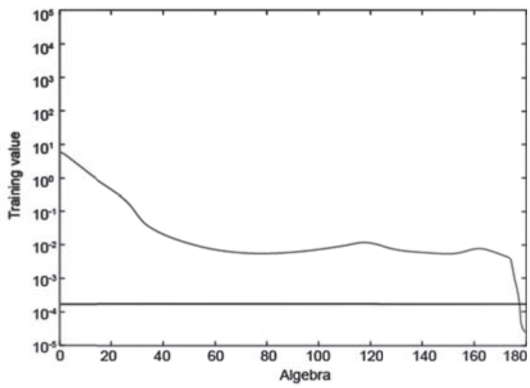

Fig. 4. PSO network training chart

(3) Read the image, get its pixel matrix and obtain the input vector by conducting dimensionality reduction on the matrix.

(4) Train the input vector by using the well-trained PSO neural network and the final output vector is the classification result of the image. Every sample to be classified is a corresponding pixel point I_{ij} in the image I, send this sample into the PSO neural network *psonn* for classification, get an output value O_{ij} and classify the pixels according to this out-put value.

$$O_{ij} = psonn(I_{ij})\,; \qquad (4)$$

$$I_{ij} = \begin{cases} U, O_{ij} \geq 0.4 \\ G, O_{ij} < 0.6 \end{cases}. \qquad (5)$$

Here, U is the objective region, G is the background region and I is the segmented image.

(5) Restore the classification result from one-dimensional vector array into image matrix form and show the segmentation result.

In order to verify the effectiveness of this algorithm, this paper makes comparison experiment between PSO neural network method and Otsu method with Matlab test image as the object. The computer used in this experiment is configured as follows: CPU is Intel (R) Core (TM) i5 CPU@1.40GHz, internal memory is 4G, operating system is Windows7 and the programming environment is 64-bit MATLAB R2012a. The comparison of the image feature classification effects is indicated as fig. 5.

It can be seen from fig.5 that the segmented result of Otsu method is just the outline of the objective and some features in the region can't be extracted while that of PSO neural network is obviously much better. It performs well in the objective outline and the regional details, it makes uniform segmented image regions and accurate boundary shape and it balances the segmentation accuracy and the preservation of the image details well. Therefore, it has higher segmentation accuracy and better segmentation result compared with Otsu method.

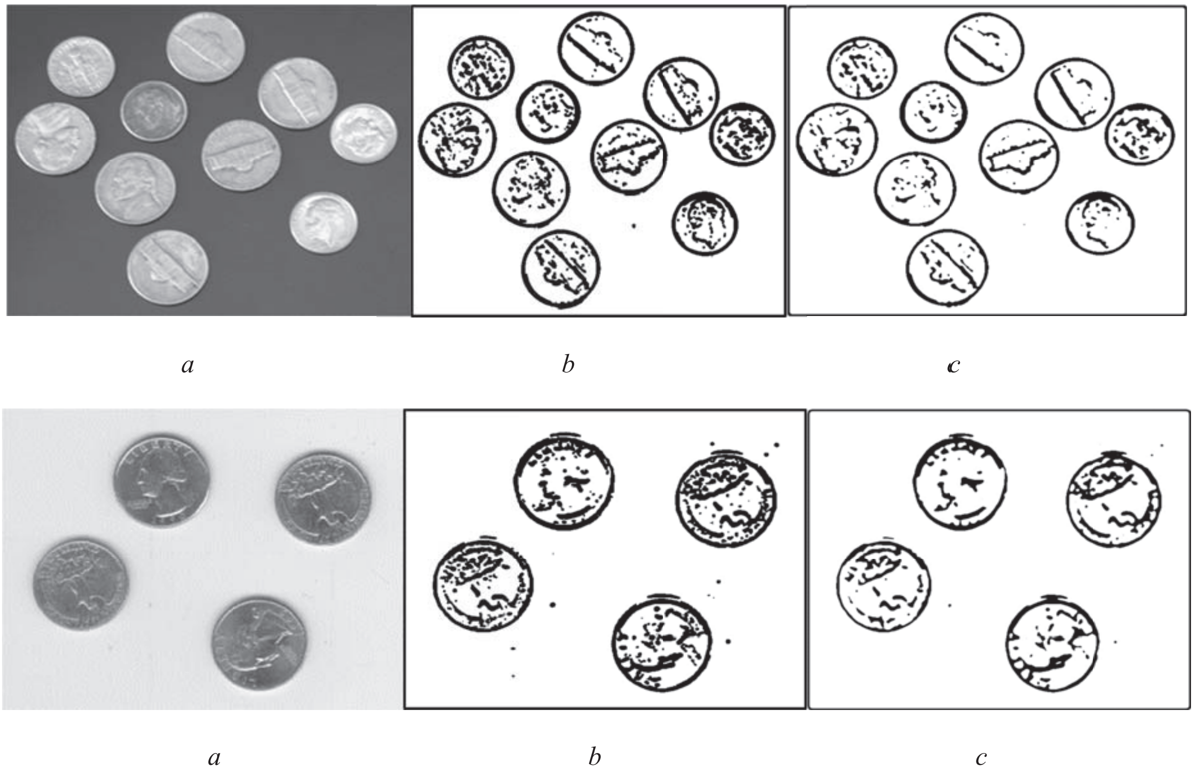

Fig. 5. Image feature classification effect comparison: a – Original image; b – PSO neural network; c – Otsu method

Conclusion. Image feature classification is to estimate the segmented feature graph of the image to be processed. Through the description of the segmentation result, the relating information contained in the image can be understood. This paper has proposed an image feature classification method based on PSO optimized neural network. To design the weight and threshold with PSO can avoid such shortcomings that BP algorithm is easy to be trapped in a local minimum, it has slow training speed, its error function must be derivable and its error is big and greatly improve the learning performance of the network. The simulation experiment proves that PSO neural network has an excellent effect and it is a feasible image feature classification method.

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Мета. Ознакова класифікація зображення направлена на розділення зображення на декілька інформативних ділянок за певною ознакою, єдиною або схожою для частин зображення всередині однієї ділянки, і що значно відрізняється для різних ділянок зображення. У роботі ми вивчимо роль нейронної мережі та методу рою часток за ознакової класифікації зображення.

Методика. Запропоновано метод ознакової класифікації зображення, що об'єднує метод рою часток та нейронну мережу. Нейронна мережа зі зворотним поширенням помилки широко застосовується для ознакової класифікації та може класифікувати конкретні об'єкти або властивості завдяки легкій навченості. Проте, алгоритм нейронної мережі зі зворотним поширенням помилки має багато недоліків, включаючи повільну збіжність і схильність до попадання в пастку локального оптимуму. Нейронна мережа, оптимізована методом рою часток, демонструє здатності пошуку по всій області та розпаралелюванню обчислень.

Результати. Спочатку для сегментації застосовували півтонове зображення певного об'єкту (у відтінках сірого), вивчали зразки за допомогою нейронної мережі, оптимізованої методом рою часток, й отримували засіб навчання мережі. Далі, в якості вихідного вектора, приймалася піксельна матриця зображення та поміщалася до навченої нейронної мережі для класифікації. Таким чином здійснювалася ознакова класифікація зображення.

Наукова новизна. Вивчена ознакова класифікація зображення, заснована на нейронній мережі, оптимізованій методом рою часток. Розглянута теорія ознакової класифікації зображення, основні принципи методу рою часток і нейронної мережі.

Практична значимість. Проведено експеримент з моделювання з метою підтвердження здійсненності методу, викладеного у статті. Доведено, що метод характеризується швидшою збіжністю та більшою помилкостійкістю. Завдяки високій ефективності цього методу можна отримувати важливу інформацію та досягати відмінних результатів при сегментації об'єктів у складних сценах.

Ключові слова: *зображення у відтінках сірого, ознакова класифікації методом рою часток, зворотне поширення помилки, нейронна мережа, сегментація*

Цель. Признаковая классификация изображения направлена на разделение изображения на несколько иформативных участков по определенному признаку, единому или схожему для частей изображения внутри одного участка, и значительно отличающемуся для разных участков изображения. В работе мы изучим роль нейронной сети и метода роя частиц при признаковой классификации изображения.

Методика. Предложен метод признаковой классификации изображения, объединяющий метод роя частиц и нейронную сеть. Нейронная сеть с обратным распространением ошибки широко применяется для признаковой классификации и может классифицировать конкретные объекты или свойства благодаря лёгкой обучаемости. Однако, алгоритм нейронной сети с обратным распространением ошибки имеет много недостатков, включая медленную сходимость и склонность к попаданию в ловушку локального оптимума. Нейронная сеть, оптимизированная методом роя частиц, демонстрирует способности поиска по всей области и распараллеливанию вычислений.

Результаты. Сначала для сегментации применяли полутоновое изображение определенного объекта (в оттенках серого), изучали образцы с помощью нейронной сети, оптимизированной методом роя частиц, и получали средство обучения сети. Далее, в качестве исходного вектора, принималась пиксельная матрица изображения и помещалась в обученную нейронную сеть для классификации. Таким образом производилась признаковая классификация изображения.

Научная новизна. Изучена признаковая классификация изображения, основанная на нейронной сети, оптимизированной методом роя частиц. Рассмотрена теория признаковой классификации изображения, основные принципы метода роя частиц и нейронной сети.

Практическая значимость. Проведен эксперимент по моделированию с целью подтверждения осуществимости метода, изложенного в статье. Доказано, что метод характеризуется более быстрой сходимостью и большей ошибкостойкостью. Благодаря высокой эффективности этого метода можно получать важную информацию и достигать отличных результатов при сегментации объектов в сложных сценах.

Ключевые слова*: изображение в оттенках серого, признаковая классификации методом роя частиц, обратное распространение ошибки, нейронная сеть, сегментация*

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