примере агрохолдингу (АХ) с применением модификации классического алгоритма метода группового учета аргументов (МГУА), представлено сравнение эффективности комбинаторного и нейросетевого алгоритмов МГУА.

Результаты. Сделан анализ методов прогнозирования и обоснован выбор нейросетевого алгоритма МГУА при выполнении исследований. Составлена оптимальная структура модели и зависимость исходных параметров от избранных входных параметров системы. Выполнен анализ экономических показателей АХ. Сделана графическая визуализация результатов исследований. Доказана эффективность применения модификации алгоритмов МГУА для прогнозирования производственных трендов на срок до 3-х лет. Обнаружена закономерность изменения данных. Рассчитана оценка точности полученных результатов.

Научная новизна. На основе содержательного анализа основных показателей производственной деятельности АХ предложены новые подходы к построению их оптимальной модели с учетом особенности предметной области, что позволяет повысить качество принятия управленческих решений, усовершенствовать алгоритмическое обеспечение системы поддержки принятия решений (СППР) относительно управления агрохолдингами. Разработана информационная технология краткосрочного прогнозирования на основе нейросетевого алгоритма МГУА.

Практическая значимость. На основе предложенной технологии было проведено краткосрочное прогнозирование основных экономических показателей производственной деятельности хозяйственного субъекта (реализация товаров и услуги, себестоимость реализованной продукции, валовый доход, чистая прибыль, коммерческие, общехозяйственные и административные расходы). Получена оценка точности результатов прогнозирования, которая находится в интервале от 1 до 5%.

Ключевые слова: *информационная технология, агрохолдинг, метод группового учета аргументов, прогнозирование, нейросетевой алгоритм, система принятия решений, экономические показатели*

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AN IMAGE RETRIEVAL AND SEMANTIC MAPPING METHOD BASED ON REGION OF INTEREST

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МЕТОД ПОШУКУ ТА СЕМАНТИЧНОГО ВІДБОРУ ЗОБРАЖЕНЬ ЗА ОБЛАСТЮ ЗОБРАЖЕННЯ, ЩО ПРЕДСТАВЛЯЄ ІНТЕРЕС

Purpose. In order to increase the precision and recall rate of image retrieval method, a new image retrieval method is proposed, which bases on the idea that different parts of an image have different discriminative capabilities and contribute to the image retrieval to different extents. The region of interest method was used to improve the effectiveness of the semantic mapping of content and image retrieval.

Methodology. Based on the region of interest, we got a semantic class range in the feature space by semi-supervised learning. The semantic class range is the mapping of image and class. In view of the different image features, the most suitable distance measurement was chosen.

Findings. The region of interest was divided from image by the improved Harris detection method and extract the low-level image features. The features in database were used as training data for semi-supervised learning to build the mapping of images and semantic classes which is updated iteratively by the relevance feedback.

Originality. The map between an image region of interest and class labels was studied. Two kinds of distances were applied to calculate the different feature's similarity. The semantic mapping is updated in real time. The research realizes a novel and comprehensive image retrieval system.

Practical value. Different needs of users were considered, and the very good experiment results have been received. The image retrieval method proposed in this paper is quicker and more effective than other methods.

Keywords*: non-subsampled contourlet transform, semantic gap, relevance feedback, image retrieval, Canberra distance*

Introduction. Due to the continuous development of network and storage technology, the number of images on the internet is constantly increasing. Users in all areas have an urgent need for efficient tools to search images from a large amount of image data on the network. So, how to meet their needs quickly and accurately has become a focus point of multimedia processing research.

The text-based image retrieval (TBIR) method retrieves images by keywords directly, but the images to be searched require manual annotation first, which spend a lot of work. The content-based image retrieval (CBIR) method retrieves images by extracting the low-level features. These image features usually include color, texture and shape. Therefore, CBIR overcomes the shortcomings of the manual annotation's heavy workload and represents the content of image better than TBIR. Semantic-based image retrieval (SBIR) method can understand the semantic information of images, but it still exists the "semantic gap" between the low-level features and the high-level semantic information [1].

Traditional content-based image retrieval method can't express and locate the semantic information of images well, so the accuracy of the image retrieval is not high. Kavitha et al. [2] proposed an equal-size rectangular sub-block image retrieval algorithm based on the color features, considering the semantic difference of spatial distribution, but it has the problem of the fixed space partition. Stöttinger et al. [3] proposed the low-level features of interest points of image retrieval algorithm based on the spatial distribution of certain extent, which improves the retrieval precision, but the method does not consider the classified images. Akgül et al. [4] summarized the feedback method in the content-based image retrieval. The relevant feedback can realize the iterative update of image retrieval, which meets the needs of users to interactively retrieval image.

Color features have great stability in the aspects of image rotation, scaling, and translation. The common similarity calculating methods for color features are Color histogram, the Main color method, Color moment, Color set, Color coherence vector, etc. The simple color-based image retrieval method only focuses on the color information of the whole image and cannot represent the space layout of color feature. Texture feature describes distribution of image pixel grayscale, which is a global feature. The main texture extraction methods include GLCM texture, Tamura texture, Gabor wavelet transform, Contourlet transform, etc. Among them, Arthur and Minh extended the Contourlet transform to Non-Subsampled Contourlet Transform (NSCT) by cancelling the sampling operations [5]. The NSCT can improve the translation invariance and be a great description of texture features.

In this paper, we divide the region of interest and combine the region of interest and non-interest area. The features of texture and color are extracted by color equal quantify method and non-subsampled Contourlet transform method. We adopt the quadratic formula distance and improved Canberra distance to measure the texture and color features respectively. Then the normalized and fused image features are regarded as the underlying features. In order to implement the map between the image and classes, this research also establishes areas of the image classes in the feature space through semi-supervised learning. The similarity between images is used to retrieve. The new image is added into the database based on the result of positive feedback which users mark and the class regional center is updated iteratively in feature space. Furthermore, according to the distance with the class regional center, we retrieve images by using keywords, which will improve the speed and accuracy of image retrieval.

Image feature extraction. In this part, we take an improved Harris algorithm proposed by Misra et al. [6], which effectively avoids the problem of setting the threshold by the secondary non-maxima suppression and has a good rotational invariance.

Region of interest division. The region of interest is divided as follows:

(1) Extracting the Harris feature points by the improved Harris algorithm and calculating the centroid of all the feature points, for instance (a,b).

(2) Calculating the four largest distance $|d_{y1}|$, $|d_{y2}|$ and $|d_{x1}|$, $|d_{x1}|$ between the feature points and the centroid in the horizontal and vertical directions.

(3) After several experimental comparisons, only 95% of the selected feature points are calculated in order to remove the noise points and extract the image region of interest better. We treat the point $\left(a-|d_{x1}|, b-|d_{y1}|\right)$ as the left vertex to draw a rectangle with the length $0.95\left(|d_{x1}|+|d_{x2}|\right)$ and width $0.95\left(|d_{y1}|+|d_{y2}|\right)$. The rectangle area we draw is regarded as the image region of interest.

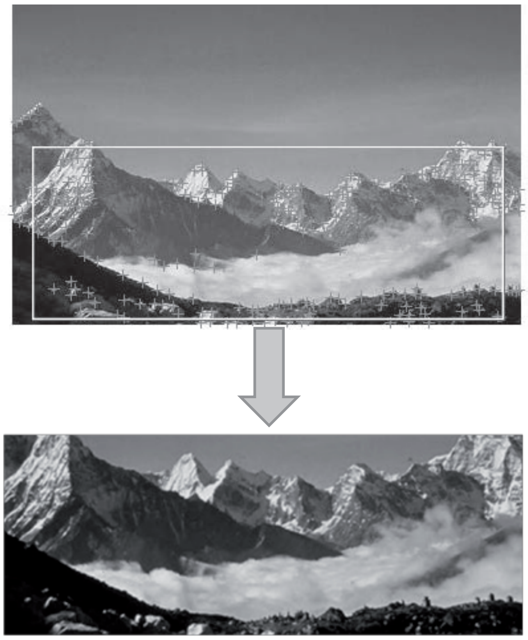


Fig.1. Region of interest extraction

Extracting region of interest in four direction and different distance can ensure its high accuracy.

Color feature extraction and quantification. Here the HSV color histogram method is taken to extracting the color feature vector of image by converting images to HSV mode. The range of its three components is $H \in [0,360]$, $S \in [0,1]$ and $V \in [0,1]$ [7].

Usually, the color image has many pixels and the dimensions of its histogram are very high. So, in order to improve the efficiency of image retrieval, the HSV color space is quantified by dividing the H, S and V into 8, 3 and 3 parts respectively. Then a 72 dimensional vector L is calculated though counting the number of pixels in each bin.

The color histogram vector of region of interest is L_a, and the color histogram vector of non interest area is L_b. At last, we normalized the color feature vector of the region of interest and non-interest area by the following formula. α is the normalized weight.

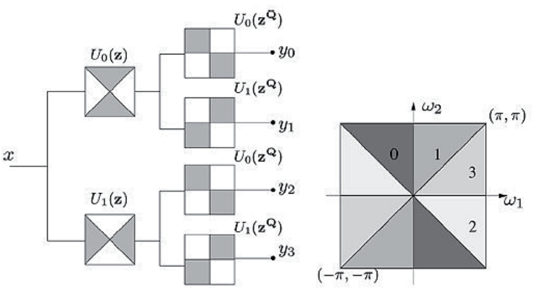
$$L = \alpha L_a + (1-\alpha)L_b, \alpha \in (0,1) \ . \tag{1}$$

Texture feature extraction. Non-subsampled Contourlet transform method has many advantages, such as multi directional, anisotropy and great conversion translation invariance. The sub-band coefficients of image are regarded as its texture. The texture feature vector is formed by calculating the mean and standard deviation sub band coefficients [5].

Texture feature vector is represented as

$$T = [E_1, \sigma_1, E_2, \sigma_2, E_3, \sigma_3, ..., E_n, \sigma_n] \ .$$

Its dimension is determined by the number of decomposition levels and break down directions. E_n is the mean of the sub-band coefficients, α_n is the standard deviation of sub-band coefficients.



a *b*

Fig.2. Decomposition of first and second layers by NSCT: a – filtering structure; b – corresponding frequency decomposition

The 14 sub-bands is obtained from the image though NSCT method with 1, 2, 3 decomposition levels. The mean and variance of these sub-band coefficients is texture features, so we can get a 28 dimensional texture feature vector V.

Image retrieval. ***Similarity calculation.*** In this part, the fusion of color feature and texture feature is used to represent the image. Assuming that the n dimensional feature vector presents color and texture of images, and then each image is a point in n dimensional feature space. The distance of the images that belong to the same class in the feature space should be small. Therefore, the images that have the smallest distance with one class center can be divided into this category in the feature space.

The commonly used similarity measurement methods for color feature are Euclidean distance, Histogram intersection distance, Quadratic distance, etc. It is proved that the widely used Quadratic distance is more effective than the Euclidean distance and Histogram intersection distance. The Quadratic distance of image histograms between the query image P and image Q from database is defined as

$$D_{\text{col}} = (L_p - L_q)A(L_p - L_q)^{\text{T}} \ .$$

Where $\mathbf{L}_p$ is the color histogram vector of image $\mathbf{P}$ and $\mathbf{A}$ is the color similarity matrix, it shows the relationship weight between colors. The similarity between the i th color and the j th color is defined as formula (2).

$$a_{ij} = 1 - d_{ij} / d_{\max} \ . \tag{2}$$

The distance d_{ij} of two kinds color i and j is calculated by Euclidean distance. a_{ij} is the element of color similarity matrix A. The 72×72 color similarity matrix can be obtained by calculating the 72-dimensional color of HSV color space [8].

Guang et al. [9] have modified the Canberra distance by adding smoothing factor which is the mean of feature vector. Here we add the smoothing factor coefficients based on the above methods to adjust it more appropriate on the image data and describe the similarity between texture features better.

The texture feature of image in database is $T = \{T_1, T_2, ..., T_m\}$ and $Q = \{Q_1, Q_2, ..., Q_m\}$ is texture feature vector of query image. The distance between T and Q is calculated by the following formula.

$$D_{\text{tex}} = \sum_{i=1}^{m} \frac{|T_{\text{i}} - Q_{\text{i}}|}{|T_{\text{i}} + \omega u_{\text{T}}| + |Q_{\text{i}} + \omega u_{\text{Q}}|} \ .$$

Among them, $u_T = \sum_{i=1}^{m} \frac{T_{\text{i}}}{m}$ $u_Q = \sum_{i=1}^{m} \frac{Q_{\text{i}}}{m}$ is the smoothing factor, ω is the coefficient of smoothing factor.

The similarity between images is external normalized of quadratic distance on image color feature and modified Canberra distance on the texture feature. The normalized weight is λ.

$$\text{Dis}(i,j) = \lambda D_{\text{col}}(i,j) + (1-\lambda) D_{\text{tex}}(i,j), \lambda \in (0,1) \ .$$

We set the coordinate of image in the feature space to be $P(i) = \{L, V\}$. Then, the regional center of th class A is

$$P(A) = \frac{1}{n} \sum_{n} P(i), i \in A \ ,$$

where n is the number of images belonging to the class A. The regional center is iteratively updated with users' positive feedback by adding the new images into database.

The distance between image i, which belongs to the class A, and its regional center a is

$$d(i) = \sqrt{\text{Dis}(i,a)\text{Dis}(i,a)^{\text{T}}} \ ,$$

where $\{P(A), d_{\min}, d_{\max}\}$ can represent the image area of the class A. If the location of image in the feature space is in a region, the image most likely belongs to that class. The set of images for the class A is

$$C = \{i \mid a \times d_{\min} \le d(i) \le b \times d_{\max}\} \ . \tag{3}$$

The values of $a, b(0 < a,\ b < 1)$ are determined according to the actual situation to improve the classification accuracy of region.

Process of image retrieval. Our algorithm extracts the underlying features of the image in the database, then the image and the underlying features we extract are used as training data for class region semi-supervised learning, realizing the semantic mapping of image and categories.

Algorithm 1: Semi-supervised learning for region of a class

Input: Image dataset

Output: Features database and region of class

Step 1: Loading image dataset, saving image into the library. Preprocessing the image and extracting low-level features, saving the features into database.

Step 2: Calculating regional center of each classes using the low-level features of images.

Step 3: Determining the region of image class in the feature space according to the distance between the class center and the image, choosing the most suitable value of a, b in formula (3) though experiment.

Users can use either the example image or keywords to retrieve images.

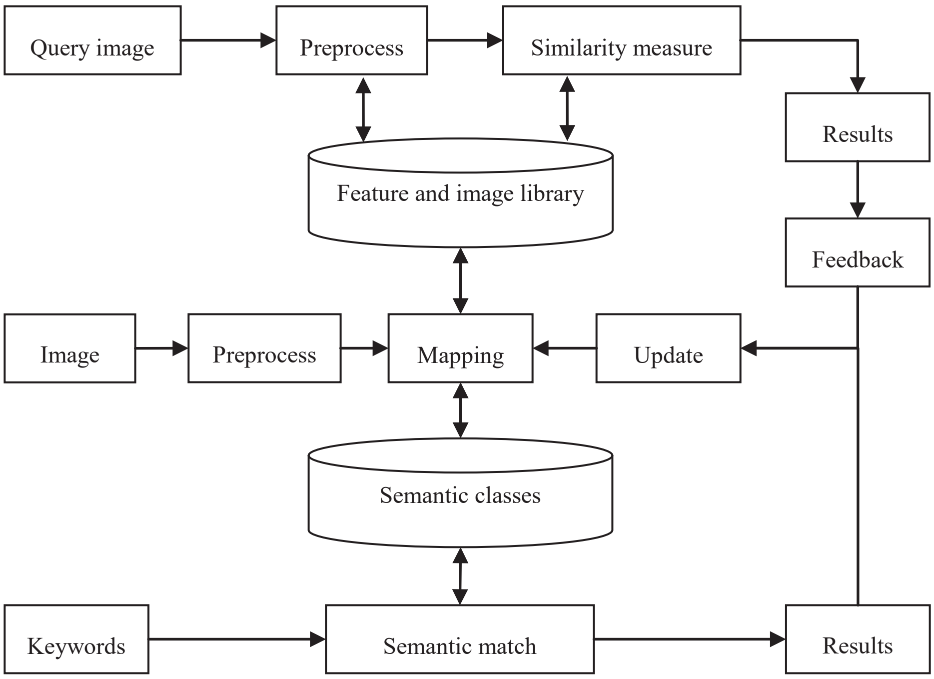


Fig.3. Image retrieval system

Keywords retrieval method matches keywords that users input with knowledge database, and then we can find the class labels of retrieved images and return images belong to this class according to the distance with the center of class region in ascending order.

Algorithm 2: Image retrieval

Input: New query image

Output: Retrieval result and class label

Step 1: Preprocessing query image Q, dividing the region of interest and extracting 72-dimensional color feature vector of image Q as well as 28-dimensional texture feature vector.

Step 2: Calculating the similarity $Dis(i, j)$ of image Q and various class centers in the feature space. Outputting similar images according to the similarity $Dis(i, j)$ in ascending order and determines the class label of the query image Q. When image Q satisfies more than one class regions, we select the class label for Q with the highest scale class of images return.

Step 3: Users feedback satisfaction of the query results. If users are satisfied with the results, image Q will be stored into image library, whose features will be saved into the feature library and added to the image collection of the corresponding class. At the same time, the regional center of the class is recalculated.

Experimental and results. In order to test the effectiveness of the image retrieval algorithm we proposed, 1000 images of Corel image dataset were used as an experimental test dataset, which included flowers, mountains, Africa peoples, beach, architecture, food, buses, horses, dinosaurs and elephants. Altogether ten categories, 100 images of each class [10]. The experimental simulation platform was MATLAB2013a.

First, the image dataset was preprocessed. The image dataset for each class was randomly divided into five groups, 20 images per each group, preparing for five cross-validation. Taking four of five groups of images as experimental training data and the remaining group was regarded as test data. Then, we used a total of 800 classified training data, 80 pictures per class, and the remaining 200 unclassified images as test data. The training image dataset was saved into the library and the features were saved into the feature database. By semi-supervised learning, we learned the class center and class region of each image class and established the semantic mapping of images and class labels.

In the experiment, the internal normalized weight α of formula (1) was 0.83, the normalized weight λ of color feature and texture feature was 0.68. The values of the class region parameters a, b in formula (3) were 0.85 and 0.72.

Precision and recall were used to measure the performance of image retrieval algorithm in this paper. The recall and precision are defined as follows

$$P(N)=\frac{I_{\mathrm{N}}}{N}, R(N)=\frac{I_{\mathrm{N}}}{M} \quad ,$$

where I_N represents the number of images which consistent with the class of query image in the retrieval results, M is the number of images consistent with the class of the query image in the image database, N is the number of images that retrieval return. In the experiment, $N=36$, $M=80$. The higher precision and recall rate means that the image retrieval algorithm has a better performance.

Fig. 4 is the experimental interface of our image retrieval system, the image in the upper left corner is the query image, behind which are the system return results in order of priority according to similarity with the query image. Precision and recall rate are calculated and displayed in Fig. 4. For example, in Fig.4, *a* the query image is "Dinosaur". The retrieval result includes mostly dinosaurs, its precision and recall rate are 97.22 and 43.75%. Fig. 4, *b* shows the result for the query image "Food", the retrieval result contains small number of pictures of other classes, its precision and recall rate are 88.89 and 40.00% respectively.

Fig. 4. Results of the image retrieval system: a – dinosaur; b –food

In order to compare the performance of the similarity measure method proposed in our research, the experiment has been carried out that compared our method with Euclidean distance and Canberra distance [9], and its results are presented in the table. As can be seen in the table, our method is more effective than Euclidean distance and Canberra distance.

Fig. 5 reflects the performance of the similarity measurement by three methods. Our method appeared more suitable when compared to the other methods.

Table

Performance of the Comparison of Distance Measures in the Image Retrieval for Different Classes

Algorithm		Horse	Flower	Dinosaur	Mountain	Average
Euclidian	Precision	0.5769	0.6025	0.6217	0.4962	0.5743
	Recall	0.2596	0.2711	0.2797	0.2232	0.2584
Canberra	Precision	0.6261	0.6342	0.6528	0.5192	0.6081
	Recall	0.2817	0.2853	0.2937	0.2336	0.2736
Our method	Precision	0.6623	0.6755	0.6897	0.5682	0.6489
	Recall	0.2980	0.3039	0.3103	0.2557	0.2920

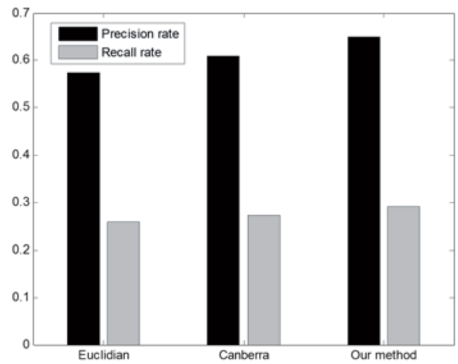


Fig. 5. Comparison of the precision and recall rate of retrieval for different distances

In order to reflect the effectiveness of the region of interest we extracted, in the experiment, the quadratic distance and Canberra distance were used for similarity measurement and extract the region of interest or not to retrieve respectively. The experimental results were compared and analyzed. As can be seen from Fig. 6, the result of the method that extracts the region of interest has higher accuracy than the method that does not extract the region of interest. Thus, the effectiveness of the region of interest was verified. The results are shown in Fig. 6. For the images with main outstanding content, such as the flowers, dinosaurs and so on, the accuracy has been improved greatly, but for the images with sophisticated content, such as buses, mountains and so on, the accuracy increase is not obvious.

Fig. 7 reflects the loss of precision of 3 different distance measurements with the increase of image number that returns. In Fig. 7, we can see that the precision of the Euclidean distance and Canberra distance decreases rapidly. The precision of the method combining Quadratic distance and the improved Canberra distance decreases slowly compared with the previous two.

The semantic map in image retrieval system has increased the precision and recall rate compared with the European distance and Canberra distance.

Discussion and conclusion. The region of interest image retrieval algorithm based on the semi-supervised learning is presented in this paper. We have found that the images with same semantic have certain similarities in the underlying features. The developed algorithm combines the region of interest and non-interest areas of an image and calculates the similarity by Quadratic formula distance and modified Canberra distance. By using semi-supervised learning methods, the semantic map between image and the class label has been build. The algorithm performed well in the experiment, but the "semantic gap" still exists. The image retrieval algorithm, which is able to articulate and represent all the emotion semantic information, is still a difficult problem to be put forward.

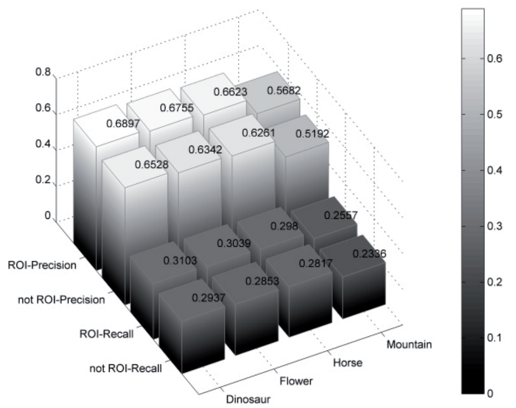


Fig. 6. Comparison of the effect resulted by the region of interest extraction

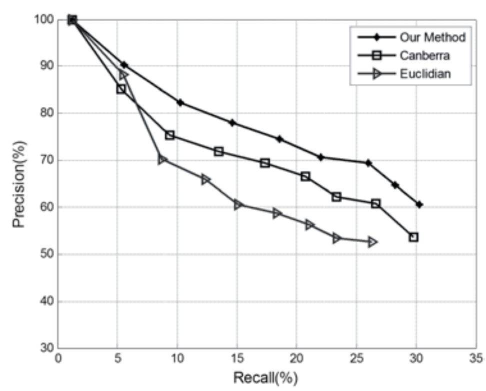


Fig. 7. Relationship between precision rate and recall rate

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Мета. Для підвищення показників точності та повноти пошуку зображень, у статті запропонований новий метод пошуку зображень. Він ґрунтується на тому, що окремі частини зображення по-різному піддаються пізнанню, їх вклад у результативність пошуку різний. Для підвищення ефективності пошуку й семантичного відбору використаний метод пошуку за областю зображення, що представляє інтерес.

Методика. На основі області зображення, що представляє інтерес, отриманий семантичний діапазон класу в ознаковому просторі за допомогою алгоритму наполовину керованого навчання. Семантичний діапазон класу являє собою відповідність зображення та класу. Беручи до уваги відмінності елементів зображення, оби-ралася найбільш відповідна міра відстані.

Результати. У зображенні область, що представляє інтерес, виділялася за допомогою покращеного детектора Харріса та видалення несуттєвих елементів зображення. Для наполовину керованого навчання використовувалася база характерних ознак для зіставлення зображень і семантичних класів, що ітераційно оновлюються за допомогою релевантного зворотного зв'язку.

Наукова новизна. Вивчена відповідність між областями зображень, що представляють інтерес, і назвами класів. Використовувалися дві міри відстані для обчислення схожості між різними елементами. Семантичний відбір удосконалюється в оперативному порядку. У дослідженні запропонована нова універсальна система пошуку зображень.

Практична значимість. Проаналізовані різні потреби користувачів, експерименти дали гарний результат. У порівняні з іншими методами, запропонований метод пошуку зображень за областю, що представляє інтерес, є швидшим і ефективнішим.

Ключові слова: *NSCT-контурна трансформація, семантичний пролом, релевантний зворотний зв'язок, пошук зображень, міра відстані Канберра*

Цель. Для повышения показателей точности и полноты поиска изображений, в статье предложен новый метод поиска изображений. Он основывается на том, что отдельные части изображения по-разному поддаются опознанию, их вклад в результативность поиска различен. Для повышения эффективности поиска и семантического отбора использован метод поиска по представляющей интерес области изображения.

Методика. На основе представляющей интерес области изображения получен семантический диапазон класса в признаковом пространстве с помощью алгоритма наполовину управляемого обучения. Семантический диапазон класса представляет собой соответствие изображения и класса. Принимая во внимание различия элементов изображения, выбиралась наиболее соответствующая мера расстояния.

Результаты. В изображении представляющая интерес область выделялась с помощью улучшенного детектора Харриса и удаления несущественных элементов изображения. Для наполовину управляемого обучения использовалась база характерных признаков для сопоставления изображений и семантических классов, итерационно обновляющихся посредством релевантной обратной связи.

Научная новизна. Изучено соответствие между представляющими интерес областями изображений и названиями классов. Использовались две меры расстояния для вычисления сходства между разными элементами. Семантический отбор совершенствуется в оперативном порядке. В исследовании предложена новая универсальная система поиска изображений.

Практическая значимость. Проанализированы различные потребности пользователей, эксперименты дали хороший результат. В сравнении с другими методами, предложенный метод поиска изображений по представляющей интерес области является более быстрым и эффективным.

Ключевые слова: *NSCT-контурная трансформация, семантическая брешь, релевантная обратная связь, поиск изображений, мера расстояния Канберра*

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TSP PROBLEM SOLVING METHOD BASED ON BIG-SMALL ANT COLONY ALGORITHM

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МЕТОД РІШЕННЯ «ЗАДАЧІ КОМІВОЯЖЕРА» НА ОСНОВІ АЛГОРИТМУ «ВЕЛИКИХ І МАЛИХ МУРАШОК»

Purpose. The traditional ant colony optimization algorithms have been used to solve the NP-hard problem, Traveling Salesman Problem (TSP), which is based on the rule that ants tend to choose high pheromone concentrated path. The max-min ant system (MMAS) most commonly achieves the nearest neighbouring city and always formulates the local optimal solution.

Methodology. The "big-small ant colony" algorithm with a kind of "jump pit strategies" has been formulated. Where, the big ants can carry much more pheromones and are prone to making mistakes.

Findings. First, the "big-small ant colony" algorithm was employed to accelerate the convergence speed. Then, by using a kind of jump pit concepts, a wider range path searching was provided, where the "small jumping strategy" allowed more than one ant to go along a different path, and the "big jumping strategy" put a barrier on the pheromone convergence path forcing the ants to choose other different paths. The experimental results showed that the modified algorithm always converges to the optimal results unlike the MMAS.

Originality. The modified ant colony optimization algorithm was studied and the effectiveness of the idea, which was put forward, was discussed.

Practical value. The proposed algorithm may be employed to solve other problems, especially together with some deterministic algorithm to realize quick global optimization.

Keywords: *ant colony optimization, traveling salesman problem, max-min ant system, NP-hard problem, global search, pheromones, "jump pit strategy"*

Introduction. In nature, ants crawl out from the cave to find a food source, upon finding it they come back to the colony. They leave a path marked by pheromones substances. In an ant colony, the algorithm of information interaction is based on the pheromones mainly. The ants are able to perceive the existence of this kind of material and its strength in the absence of visual signs. At the initial stage, in the environment there are no pheromone paths, and the ants search for things in a random way. Then the process of the food source search is affected by the previous residues of the ants' pheromone. Ants tend to choose the path with the high concentration of the pheromone. At the same time, the pheromone is a kind of volatile chemicals, which evaporates slowly. The longer is a path, the more time an ant spends on travelling down the path and back, the more time the pheromones have to evaporate. The pheromone residual is relatively higher on a shorter path. Subsequently the probability that other ants will choose the shorter path is large. This leads to the more and more ants walk along the short path. Consequently, the pheromone concentration that remains on the path will also increase. Therefore, the ants' collective behaviour constitutes the pheromone positive feedback process, which allows finding the shortest path. The positive feedback mechanism strengthens the performance of better solutions, but it may cause the ant colony algorithm easily fall in premature phenomenon and stagnant phenomenon when solving problems. In real life, many ants cannot complete complex tasks, but can find the current optimal solution path to adapt to the changes in the environment. Ant Colony Optimization (ACO) algorithm is a method, which is used to find an optimal path through graphs. Marco Dorigo put it forward in