Eng Int Syst (2023) 2: 105–113

Engineering
Intelligent Systems

Visual Feature Clustering Method for Image Based on Cloud Computing Technology

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In order to significantly improve the performance of image classification, a visual feature clustering method for image based on cloud computing technology is proposed. The energy regression filtering algorithm is used to filter and denoise the image, the features of the denoised image are extracted from the global features and local features, and the mutation features and static features in the image are standardized. The multiple visual features integration of the image is achieved by means of multi-feature statistics, spectrum integration processing and structure integration. The K-means clustering algorithm is used to cluster the integrated image visual features. The parallel processing process in cloud computing technology is used to convert each iteration of the serial K-means algorithm into a Map Reduce calculation, to realize the image visual feature clustering. Experimental results show that this method can effectively achieve image denoising, has high feature integration and good clustering performance.

Keywords: cloud computing technology, image visual features, clustering algorithm, filtering algorithm, feature integration, parallelization.

1. INTRODUCTION

The aim of feature extraction is to extract the essential features of the research object with a certain transformation, which is the key research content in the field of image and machine vision [1]. As a key problem of image retrieval, image matching and image fusion, feature extraction and application has become the focus and hotspot of current research. The extraction of features from a visual information image is an important field of technology associated with intelligent image and computer vision [2, 3]. Relevant information is extracted from an image by means of an appropriate computer algorithm to determine whether the image has a specific recognition factor. The visual feature clustering method applied to an image creates groups or classes of objects through unsupervised learning (clustering), supervised learning (classification) and semi-supervised learning methods, so that the objects in the class are very similar, but very different from the objects in other classes [4]. Although many clustering algorithms have been proposed, clustering is still a challenging problem. A clustering algorithm will obtain different clustering results due to the selection of data set features and different algorithm parameters [5]. Li et al. [6] studied the clustering method based on adaptive weighting feature K-means, and used adaptive weighting technology to optimize the K-means clustering method so as to improve the performance of the K-means clustering method. For the analysis of big data, JIANG Y. W. [7] studied the efficient clustering method of multidimensional discrete data, applied the spatial reconstruction analysis method to the nonlinear mapping of big data, selected the minimum embedding dimension and the best time delay to construct the information flow model of big data time series, and established the clustering search objective function based on extracting eigenvalues. In addition, the fuzzy clustering algorithm was used to solve the search objective function of the initial clustering center, so as to obtain the optimal clustering center of big data and achieve clustering optimization. Yu et al. [8] applied the non-negative matrix decomposition

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algorithm of $L2, 1$ norm of kernel to the clustering process, and used the sparse robust nonnegative matrix decomposition method based on kernel to obtain good sparsity and robustness of the algorithm and improve the clustering performance. Rahimzad et al. [9] applied the enhanced convolutional automatic encoder to image clustering, and preprocessed the image by using the minimum noise fraction transformation. After training, the convolutional automatic encoder can automatically encode the upgraded function and enhance the manual function, making the clustering process easier. The small batch K-means algorithm is used to cluster the depth features. Cloud computing is a kind of distributed computing, which involves the decomposition of huge data computing and processing programs into countless small programs through the 'cloud' network. When the results are obtained, they are returned to users through the system's processing and analysis functions comprising multiple servers. The clustering algorithm based on cloud computing technology takes cloud computing technology as a container for the calculation of large-scale target clustering. The development of cloud computing technology provides new ideas for the processing of massive amounts of image data. The development of cloud computing technology has been closely associated with the processing of large-scale data. Therefore, using the cloud computing platform for distributed parallel processing is an effective solution for the processing of huge numbers of images. Hadoop is a software framework capable of distributed parallel processing of large-scale data. Since its inception, it has been widely used because of its excellent large-scale data processing ability, good scalability, high reliability and low cost. Hence, in this paper, the visual image-feature clustering method based on cloud computing technology is applied to cluster the image's visual features and improve the performance of image processing.

2. MATERIALS AND METHODS

2.1 Image filtering Based on Energy Regression Filtering Method

2.1.1 Spatial Scale Filtering

With the increase of the scale, the amplitude of the abrupt edge of the image increases, while the amplitude of the noise decreases. Therefore, the correlation $G_{2}^{k}, (n)(k = 1, 2)$ of wavelet transform on some adjacent scales can accurately locate the edge and noise, and $n = (n_1, n_2)$ in $G_{2^J}^{k}(n)(k = 1, 2)$. The principle of wavelet correlation on an adjacent scale is:

$$G_{2^j}^{k}(n) = E_{2^j}^{k}(n) * E_{2^{j+1}}^{k}(n) \tag{1}$$

In Formula (1), $*$ represents the quadrature of relative elements of two matrices. Through the correlation of wavelet transform, it can compare $G_{2^j}^{k}(n)$ with $E_{2^j}^{k}(n)$, because the amplitude of image edge coefficient on scale 2^{j+1} is greater than that on scale 2^j, and the amplitude of noise on scale 2^{j+1} is less than that on scale 2^j, $G_{2^j}^{k}(n)$ is sharp and reduces the modulus maxima of noise while increasing the modulus maxima of the image edge [10].

In the 2-dimensional discrete image $f(n) = f(n_1, n_2)$, the energy of image $f(n_1, n_2)$ is expressed as $Pf = \sum_{n_1,n_2} (f(n_1, n_2))^2$, and then the high-frequency image transformed by dyadic wavelet on scale 2^j is obtained, which is expressed as:

$$PW_{2^J}^{k} = \sum_{n_1,n_2} E_{2^j}^{2} * \sum_{n_1,n_2} f(n_1, n_2)^2 \tag{2}$$

$$PC_{2^J}^{k} = \sum_{n_1,n_2} G_{2^1}^{2} * \sum_{n_1,n_2} f(n_1, n_2)^2 \tag{3}$$

From Formulas (2) and (3), it can be obtained that on the same scale, the energy $PC_{2^j}^{k}$ of the correlation image $G_{2^j}^{k}(n)$ is higher than the energy $PW_{2^j}^{k}$ of the high-frequency image $E_{2^j}^{k} f(n)$, that is, $PC_{2^j}^{k}$ is inconsistent with the order of magnitude of $PW_{2^J}^{k}$. Therefore, it is necessary to adjust the correlation image $G_{2^J}^{k}(n)$ and the high-frequency image $E_{2^J}^{k} f(n)$ so that they can be compared at the same level of brightness. Assuming the regression factor $R_{2^J}^{k}(n)$, the correlation image $G_{2^j}^{k}(n)$ is scaled again, and expressed as:

$$G_{2^J}^{k}(n) = G_{2^J}^{k}(n) * R_{2^J}^{k} \tag{4}$$

2.1.2 Selection of Regression Factors

Taking the arithmetic square root of the ratio between the energy of the wavelet coefficient and the energy of the correlation image as the regression factor [11], the correlation image $G_{2^j}^{k}(n)$ can be compared with the high-frequency image $E_{2^J}^{k} f(n)$ in the same order of magnitude. The preset regression factor is:

$$R_{2^j}^{k} = \frac{\sqrt{PW_{2^j}^{k}}}{\sqrt{PC_{2^j}^{k}}} \tag{5}$$

Then:

$$G_{2^j}^{\prime k}(n) = \frac{G_{2^J}^{k}(n) * \sqrt{PW_{2^j}^{k}}}{\sqrt{PC_{2^j}^{k}}} \tag{6}$$

When the source image $f(n) = f(n_1, n_2)$ is filtered by this method, the scale space filtering algorithm can be known as an energy regression filtering algorithm.

By storing the edge information extracted from the wavelet coefficient $E_{2^j}^{k}(n)$ in $E_{new2^j}^{k}(n)$ and replacing $E_{2^j}^{k}(n)$ with $E_{new2^j}^{k}(n)$, the wavelet transform data obtained by the energy regression filtering algorithm can be obtained [12]. These wavelet-transform data have been denoised and the edge information of most source images has been saved.

The specific process of energy regression filtering algorithm is:

(1) Set the two-dimensional discrete image $f(n_1, n_2)(1 \le n_1, n_2 \le N)$ and the number of decomposition layers $J(1 \le J \le Iog_2 N)$;

(2) Obtain a set of matrix $\{EE_{2}^{k}, (n_1, n_2)\}(1 \le j \le J)$ that can realize $EE_{2^j}^{k}(n_1, n_2) = E_{2^J}^{k}(n_1, n_2)$ and a set of scale filter matrix $Sfilter_{2^J}^{k}(n_1, n_2) = 0$;

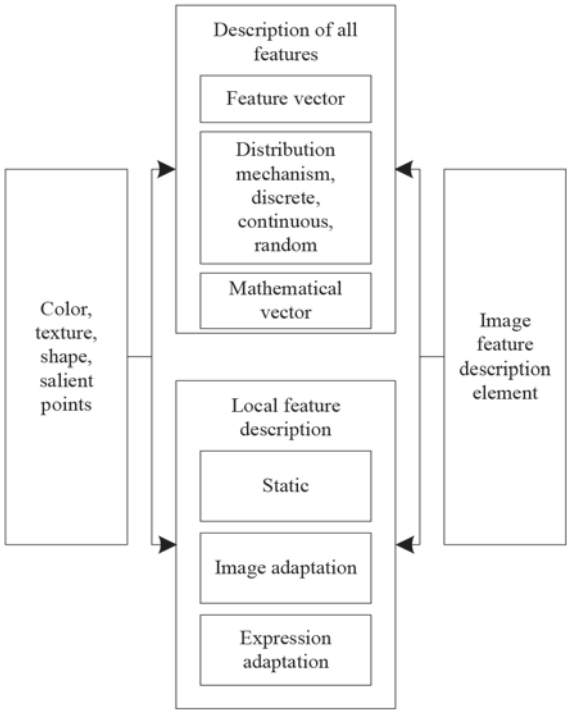

Figure 1 Description process of image feature table.

(3) Wavelet transform coefficient $\{E^k_{2^j}(n)\}_{1\le j\le J}$ and low-frequency rough component $s_{2^j}f(n)$ are obtained by J-scale dyadic wavelet decomposition of noisy image [13];

(4) Calculate Formulas (7), (8), (9) on different scales;

$$G_{2^j}(n_1,n_2) = E_{2^j}(n_1,n_2) * E_{2^{j+1}}(n_1,n_2) \quad (7)$$

$$PC^k_{2^J} = \sum_n (E^k_{2^j})^2 * \sum_n (n_1,n_2)^2 \quad (8)$$

$$PW^k_{2^J} = \sum_n (E^k_{2^j})^2 * \sum_n (n_1,n_2)^2 \quad (9)$$

(5) Scale $G^k_{2^j}(n_1,n_2)$ again through the preset regression factor:

$$G'^k_{2^j}(n_1,n_2) = \frac{G^k_{2^j}(n_1,n_2) * \sqrt{PW^k_{2^j}}}{\sqrt{PC^k_{2^j}}} \quad (10)$$

$G'^k_{2^j}(n_1,n_2)$ is compared with $E^k_{2^j}(n_1,n_2)$, if:

$$|G'^k_{2^j}(n_1,n_2)| \ge |E^k_{2^j}(n_1,n_2)| \quad (11)$$

Then the edge information obtained in $E^k_{2^J}(n)$ and $G^k_{2^J}(n)$ is stored in $Sfilter^k_{2^J}(n)$, and the wavelet coefficients are calculated by energy regression filtering method:

$$E^k_{new2^j}(n) = Sfifter^k_{2^j}(n) * EE^k_{2^j}(n) \quad (12)$$

(6) Reconstruct $\{\{E^1_{new2^j},(n), E^2_{new2^j},(n)\}_{1\le j\le J}, S_{2^j}f(n)\}$ to obtain the filtered image.

2.2 Visual Feature Integration of Image

2.2.1 Visual Feature Description of Image

After feature annotation, the filtered image will generally complete the image's multi-feature expression in the preprocessing stage [14]. The visual features obtained by extraction can be used as the basis for image feature analysis and expression. The process of image feature expression is shown in Figure 1.

The visual feature expression of an image is divided into two steps:

(1) express the global feature of the image, and

(2) express the local features of the image.

In the process of image global feature expression, the whole image is calculated and extracted to obtain the color, texture, shape and other feature expression elements of the filtered image. The local feature expression process calculates the characteristic local area of the image to obtain the visual feature expression elements of this area. The expression elements of local features are fed back to the global image features, and the two visual effects are integrated to obtain a unified expression. This expression method does not need to segment the image, so the feature expression rate is high. However, due to the relatively single distribution of spatial information in the image, the position translation, multi-feature rotation and expression intensity of feature integration effect change [15]. Using multiple local features and global features to represent images in both directions can prevent the above problems. The bi-directional expression method can obtain smaller feature elements and facilitate substantive feature expression. In the process of multi feature expression, it lays a foundation for multi feature integration.

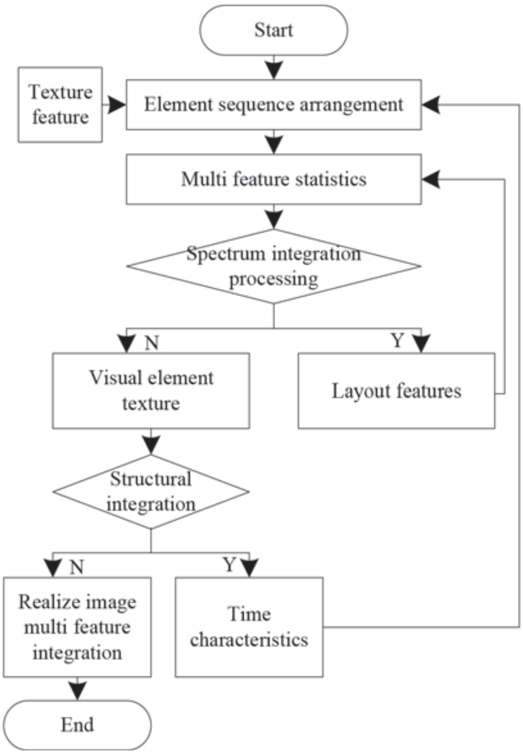

Figure 2 Image visual feature integration process.

2.2.2 Realization of Image's Visual Feature Integration

Image feature annotation labels the Mutational features and static features in the image [16], prevents feature disappearing in feature integration, selects the image feature sequence, and introduces time elements, so as to achieve the expression of various image visual features, and select the elements for multi-feature integration. After the preprocessing, image's multi-feature integration is carried out for textural features. The surface granularity and feature arrangement structure of the image are certain. In the corresponding range, the texture and smoothness of the target area are different from other scene features. Therefore, image's multi-feature integration using textural features consists of three steps: (1) multi-feature statistics; (2) integrated processing of spectrum; and (3) structural integration. The textural feature is the main clue in the process of visual feature integration. For areas with large distribution of image feature density, the textural feature can be obtained by feature statistics. In the statistical process, the relationship between image gray distribution and texture feature is used to build the relationship. The statistical results are relatively accurate, and multiple feature authentication statistics can be avoided. In the process of spectrum integration. The Fourier change principle is used to build the relationship with image texture feature distribution, and ensure that all the spectrum in the integration covers the integration range. The textural features in the structural integration will describe the geometric relationship of the features in the pixels, and multi-feature integration is carried out through the arrangement rules.

The textural features of an image are an important element of the image's visual feature integration. The reason that textural features are selected as the clue of the integration method is that texture features can contain the hidden features of the image [17], and will not be disturbed or changed during image preprocessing, visual calculation and other steps. When integrating the textural features, the use coefficient of the original pixel value will be transformed, and the integrated threshold value is obtained through wavelet transform and discrete cosine transform. The integrated image will retain the clarity of the original image, avoid the interaction of adjacent pixels, and ensure that the Markov parameters are within a reasonable integration range. The process applied for the integration of image features is shown in Figure 2.

2.3 Image's Visual Feature Clustering

An image's visual feature clustering involves composing a set of physical or abstract images into multiple classes or clusters composed of similar objects [18]. The cluster generated by clustering is a set of data objects. The image objects in the same cluster are as similar as possible, while the image objects in different clusters are as different as possible.

2.3.1 K-Means Clustering Algorithm

The general process of clustering the integrated image features by K-means clustering algorithm is as follows:

(1) Randomly select k centers from the visual feature set D of the sample image as the initial center point of clustering.

(2) Iteration.

    (a) According to the central point coordinates of each cluster, assign each image's visual feature sample to the nearest cluster;

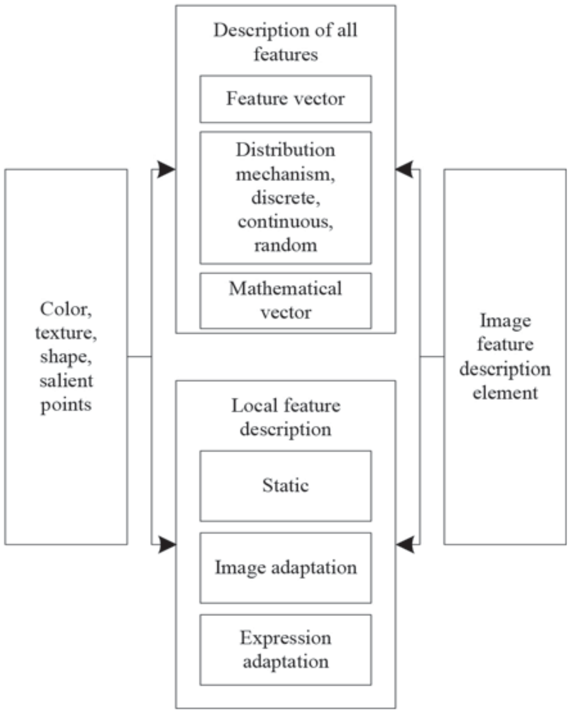

Figure 3 Implementation process of K-means algorithm based on cloud computing.

(b) Update the coordinates of the center point of the cluster, that is, calculate the mean value of all image visual feature samples in each cluster;

(c) Re cluster all the elements in D according to the new center.

(3) Continue until the clustering results no longer change, that is, converge.

2.3.2 K-Means Clustering Based on Cloud Computing

The K-means algorithm is parallelized based on cloud computing in order to convert each iteration of the serial K-means algorithm into a Map Reduce calculation, which can be calculated and implemented in parallel independently, including the distance between the image's visual feature sample and the cluster center and the local calculation of the new cluster center. The parallelization process of the K-means algorithm based on cloud computing involves the Map process, the Combine process and Reduce process. Its flow chart is shown in Figure 3.

(1) Design of Map function

The Map function takes each line of the file as a sample, which is expressed in the form of key/value pairs, calculates the distance from each image visual feature sample to each cluster center, selects the cluster center with the smallest distance, assigns the image visual feature sample to the cluster, and marks the image's visual feature sample as the new cluster category to form the output form of key/value pairs. The visual features of the input image represent $< key, \ value >$ pairs in the form of <line number, record line>, *key* input by the Map function is the offset of the current record relative to the starting point of the visual feature file of the input image [19], and *value* is the coordinate value of each dimension of the current record; The output intermediate result is expressed as $< key', \ value' >$ pairs in the form of <cluster id, record attribute vector>; The output results are also $< key', \ value' >$ pairs, key' represents the cluster id, and $value'$ represents the image's visual feature object most similar to the cluster center.

(2) Design of Combine function

The Combine function is intended for the localized Reduce processing of a large number of intermediate results produced by the Map process, which can reduce the transmission time and bandwidth of image visual features between nodes. The task of the Combine function is to preprocess the Map results in the node, process the value with the same key value, and then transfer the processed local clustering results to the Reduce function in the cluster for protocol operation.

(3) Design of Reduce function

The Reduce function calculates a new cluster center by summarizing the local clustering results obtained by the Combine function, and uses it for the next round of iterative operations. The Reduce function first calculates the number of samples of the local clustering results output by each node, analyzes the coordinate values of each dimension of each sample, then adds the corresponding accumulated values of each dimension respectively, and then divides them by the total number of samples just calculated. The calculation result is the new cluster center coordinate. After executing the Reduce task, a new cluster center can be calculated from the output result and update it to the HDFS distributed file system, the file is copied to all nodes in the cluster, and then cycled and iterated to calculate the sum of squares of error criterion function of Map Reduce Job. If the difference is less than the set value, the clustering criterion function has converged and the algorithm ends; Otherwise, the new cluster center is replaced with the original cluster center and a new round of iterative calculation

Figure 4 Original image.

is started, which is also the process of Map task, Combine task and Reduce task. When the iterative output converges in a stable manner, the final image visual feature clustering result can be obtained.

3. RESULTS

In order to verify the effect of applying a clustering method based on cloud computing technology to the actual image's visual feature clustering, taking the image database of a university laboratory as the experimental object, the method proposed in this paper is used to cluster the internal image of the experimental object. The results are given below.

3.1 Denoising Results

Four images are randomly selected from the experimental subjects: a human image, an animal image, a plant image and a vehicle image. The selected experimental object is denoised by the method proposed in this paper, and the results are shown in Figure 2 and Figure 3.

Figure 4, Figure 5 and Figure 6 show that the proposed method can effectively denoise the image in the experimental object, improve the fineness in the image, and make the denoised image as close as possible to the original image.

3.2 Image Feature Integration Test

For the testing process, third-party soft ware is used to analyze the replacement degree of an image's visual feature integration using the proposed method. The replacement degree is the feedback value of an image's visual features after integration. The general data range is between 0.891 and 0.887. Exceeding the upper value range will produce a certain image shadow, and exceeding the lower value range will cause insufficient integration of image's visual features. The test results showing the degree of permutation of the image's visual feature integration obtained by the proposed method are shown in Figure 7.

By analyzing Figure 7, it can be seen that the results of the image's visual feature integration obtained by the proposed method is within the effective range. There is no image transition to the upper value range, indicating that the integration effect is relatively complete, and the image has no shadow, and maintains a certain range with the lower value range, indicating that the integration value is good. Therefore, this method achieves excellent results.

3.3 Clustering Results of Image Visual Feature

3.3.1 Image Clustering Results

Table 1 shows the clustering results for some images used in the experiment.

Table 1 shows that the proposed method can effectively complete image clustering and achieve the purpose of different image classification within the experimental object. At the same time, the classification results are consistent with the actual data types, which shows that the proposed method has practical application performance.

Figure 5 Noisy image.

Figure 6 Denoised image.

3.3.2 Clustering Performance Analysis

Experiments were conducted to determine the clustering performance of the method proposed in this paper from three aspects: network image tendency, network image homology and network image attribution rate. Generally, the trend, homology and attribution rate of the results obtained by image clustering methods are 64.2%–68.8%, 79.3%–85.6% and 49.3%–55.6% respectively. The results obtained for the clustering performance of the proposed method are shown in Table 2.

Table 2 shows the clustering results obtained by the method proposed in this paper. It can be seen that among the four different clustering results for the network image obtained by

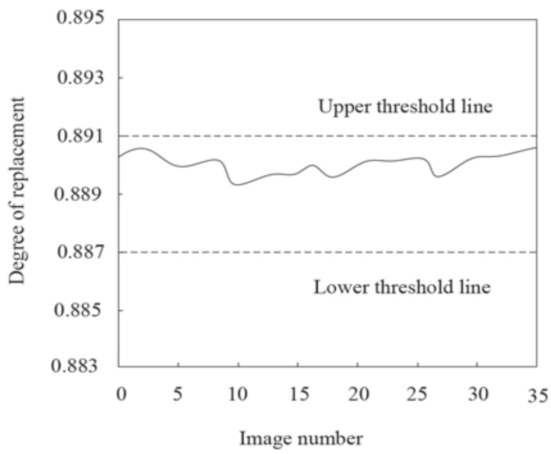

Figure 7 Analysis results of image's visual feature integration permutation.

Table 1 Clustering results of some images.

Image number	The clustering results of this method	Is it consistent with the actual image type
00041	Portrait	Agreement
00287	Botany	Agreement
00684	Automobile	Agreement
01531	Automobile	Agreement
02684	Portrait	Agreement
05740	Animal	Agreement
09716	Botany	Agreement
13816	Animal	Agreement
19842	Botany	Agreement
22090	Botany	Agreement

Table 2 Clustering performance analysis results.

Index	**Image category**			
	Portrait	**Botany**	**Animal**	**Automobile**
Network image tendency/%	68.14	68.67	66.79	67.23
Network image homology/%	84.82	83.90	83.58	84.37
Network image attribution rate/%	54.26	54.95	52.91	52.68

the proposed method, the results of image tendency, image homology and image attribution rate have high values, which shows that the clustering results obtained by this method are better.

3.3.3 Clustering Performance Comparison

To further test the clustering performance of the proposed method, taking the clustering standard rate ACC as the clustering performance evaluation index, the number of clusters is set as 2, 4, 6, 8 and 10 respectively, and the clustering method based on adaptive weighting and the clustering method based on L2,1 norm nonnegative matrix decomposition algorithm of kernel are taken as two comparison methods, to analyze the ACC values of the three methods used for comparison in the actual clustering process, so as to test the clustering performance of the proposed method. The results are shown in Table 3.

Formula (9) shows the calculation formula of clustering standard rate ACC:

$$ACC = \max_{\phi} \frac{1}{n} \sum_{i=1}^{n} 1\{\lambda_i = \phi(\sigma_i)\} \tag{13}$$

In Formula (13), λ_i represents the actual classification label, ϕ represents the 1-to-1 mapping between the clustering result and the actual classification label, and σ_i represents the clustering result obtained by the historical clustering algorithm.

As shown in Table 3, when the number of clusters is 2, the results of the clustering standard rate (i.e., ACC value) of the three clustering methods are not significantly different. With the increase of the number of clusters, the results of clustering standard rate of different methods decrease in varying degrees. Among them, the calculation result of clustering standard rate based on adaptive weighted clustering method decreases

Table 3 Calculation results of different standard clustering methods.

Number of clusters	Paper method/%	Clustering method based on adaptive weighting/%	Clustering method of l2,1 norm nonnegative matrix decomposition algorithm based on Kernel/%
2	99.64	99.45	97.24
4	99.57	99.38	96.47
6	99.33	95.13	95.36
8	99.05	9122	94.15
00	98.38	85.40	92.18

the most significantly. When the number of clusters reaches 10, the clustering standard rate of the method in this paper decreases to 85.49%, which is significantly lower than that of the other two methods. The calculation result of the clustering standard rate of this method is always higher than 98%, which shows that the clustering performance of this method is significantly better than the two other methods.

4. CONCLUSION

Feature extraction plays a key role in the field of image analysis, understanding, and pattern recognition. In order to achieve better image processing, this paper studies the visual feature clustering method for images based on cloud computing technology. The feature integration is implemented for the image after noise reduction, and the image feature clustering is completed by applying the parallel K-means algorithm under cloud computing. The results show that this method has strong clustering performance. In the subsequent optimization process, the clustering efficiency of this method will be studied in depth in order to improve the clustering efficiency and optimize the clustering performance of this method.

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