Hindawi Publishing Corporation
Mathematical Problems in Engineering
Volume 2016, Article ID 3593975, 17 pages
http://dx.doi.org/10.1155/2016/3593975

Research Article

A New Approach for Large-Scale Scene Image Retrieval Based on Improved Parallel k-Means Algorithm in MapReduce Environment

Jianfang Cao,[1] Min Wang,[2] Hao Shi,[2] Guohua Hu,[1] and Yun Tian[1]

[1] *Department of Computer Science & Technology, Xinzhou Teachers University, Xinzhou 034000, China*
[2] *School of Computer Science & Technology, Taiyuan University of Science and Technology, Taiyuan 030024, China*

Correspondence should be addressed to Jianfang Cao; caojianfangcn@163.com

Received 8 May 2016; Revised 21 July 2016; Accepted 11 August 2016

Academic Editor: Anna Vila

The rapid growth of digital images has caused the traditional image retrieval technology to be faced with new challenge. In this paper we introduce a new approach for large-scale scene image retrieval to solve the problems of massive image processing using traditional image retrieval methods. First, we improved traditional k-Means clustering algorithm, which optimized the selection of the initial cluster centers and iteration procedure. Second, we presented a parallel design and realization method for improved k-Means algorithm applied it to feature clustering of scene images. Finally, a storage and retrieval scheme for large-scale scene images was put forward using the large storage capacity and powerful parallel computing ability of the Hadoop distributed platform. The experimental results demonstrated that the proposed method achieved good performance. Compared with the traditional algorithms with single node architecture and parallel k-Means algorithm, the proposed method has obvious advantages for use in large-scale scene image data retrieval in terms of retrieval accuracy, retrieval time overhead, and computational performance (speedup and efficiency, sizeup, and scaleup), which is a significant improvement from applying parallel processing to intelligent algorithms with large-scale datasets.

1. Introduction

Image retrieval is to find the images with the specified feature or the specified content according to the description of the image content in the image set. Due to the complexity of image content and the subjectivity of human cognition, establishing efficient and universal image retrieval has been a very difficult task. Therefore, image retrieval has been the research hotspot in the computer vision and information retrieval fields in recent years [1]. Since the late 1990s, aiming at frame images in videos, Doulamis et al. [2, 3] designed an automatic extraction framework of characteristic frames or scenes for a video sequence and proposed a fuzzy representation of visual content which was useful for content-based image retrieval. Avrithis et al. [4] also presented a content-based indexing and retrieval framework for videos. These works have laid a good foundation for the research of image retrieval. In order to obtain more satisfactory retrieval results, Yang et al. [5] proposed a new semisupervised algorithm and a semisupervised long-term relevance feedback algorithm to design a multimedia retrieval framework and implemented cross-media retrieval, image retrieval, and 3D motion/pose data retrieval. Subrahmanyam et al. [6] introduced a new descriptor called local maximum edge binary patterns to represent the local region of images for image retrieval, which was applied to object tracking. Through experiments on four different small-scale datasets, the retrieval accuracy was improved compared with other existing algorithms. Color is one of the basic features of images, which is one of the most widely used visual features by image retrieval. Liu and Yang [7] proposed the color difference histograms to represent color feature of the image. It was different from the existing histogram techniques, which not only counted the number or frequency of pixels but also counted the perceptually uniform color difference between two points under different backgrounds concerning colors and edge orientations in $L^*a^*b^*$

color space. The results of the experiment confirmed strong discriminative power. Aiming at images of social media websites, Gao et al. [8] put forward a social image search method based on visual-textual joint relevance learning, which used visual and textual information simultaneously to estimate the relevance of user tagged images and utilized a dataset including 370+ images to validate the effectiveness of the proposed approach. Zheng et al. [9] studied image retrieval methods using statistics projection algorithm and Robert algorithm. To retrieve the most relevant images optimizing the time complexity, Madhusudhanarao et al. [10] constructed a model for image retrieval using fusion and relevancy methodology, which integrated the features corresponding to multiple modalities and feature level fusion technique. The performance of the proposed model was evaluated using brain web data of UCI database. Ashraf et al. [11] introduced a new image representation technology, namely, Bandelets transform, used Support Vector Machine for image retrieval, and evaluated the performance on three standard datasets. Ramana et al. [12] analyzed different concepts used to improve the image retrieval efficiency and presented a kind of scope that could improve the performance issues in image retrievals.

However, the production of digital images has rapidly increased with advances in multimedia technology and network technology. Faced with massive amounts of image data, determining how to retrieve the images that users require rapidly and precisely has become the focus of considerable efforts. The abovementioned traditional image retrieval methods based on single-node architecture can largely meet user requirements regarding access time when the number of users who access image database simultaneously is low. With the rapid growth of the number of images, the image feature database has become extremely large, and the number of users who access online image databases simultaneously has also increased, thereby resulting in a rapid decline in retrieval speed. Moreover, because the calculation of image feature similarity is a complex operation, a long computing time and a large amount of computing resources will be consumed when using traditional image retrieval methods. These problems cause the running efficiency of the system to decrease rapidly, even if the response to the user must be performed in a timely manner, when a large number of users attempt to retrieve images from the database simultaneously [13]. Therefore, the traditional image retrieval methods have been unable to complete the processing of large-scale images and cannot easily satisfy the people's requirements on retrieval performance. Therefore, the technology of retrieving large-scale images faces a significant challenge and exploring new methods to retrieve images has become a popular research topic in the digital imaging field. The development of cloud computing technology provides a new concept for the processing of large-scale images. Cloud computing technology has a close relationship with big data. Therefore, using a cloud computing platform to enable distributed parallel processing is an effective solution for realizing the efficient retrieval of large-scale images. Hadoop, which is a software framework of distributed parallel processing for all types of large-scale data, has been widely applied in numerous fields due to its excellent large-scale data processing ability, good extensibility, high reliability, and low cost [14]. In recent years, researchers have begun to focus on large-scale image processing. Almeer [13] realized the analysis and processing of massive remote sensing images using the Hadoop Distribute File System (HDFS) of Hadoop. From the perspective of mass image processing technology, Wiley et al. [15] realized the analysis and processing of astronomical images using Hadoop through converting images into serialized binary files. However, the application is subject to certain restrictions due to its inability to read and write images randomly. Zhu [16] proposed an image classification method by defining an image interface to read and write the entire image. However, the method does not consider the problem of low efficiency for small documents, which causes resource waste; thus, it is only suitable for processing remote sensing images. Sweeney et al. [17] proposed a new method that converted image data information into a float array and stored the array in a file with an index file. The method effectively solved the problem of low efficiency for small documents and supported random access through the index file; however, the method is limited to certain fields because the method is unable to store the original complete information of images and only supports RGB color space and images with JPG, PNG, and PPM format and the method of coding and decoding conversion between image and array is more complex. Scholars also put forward some methods to deal with different types of large-scale images. Chen et al. [18] proposed a new approach to estimate a set of possible ages according to a facial image for large image database. Considering landmark image search, Cheng and Shen [19] developed a very large-scale test collection to support robust performance evaluation. Makantasis et al. [20] realized retrieval for 31,000 cultural heritage images by exploiting and fusing two unsupervised clustering techniques: DBSCAN and spectral clustering. There are no relevant literatures on large-scale scene image processing currently.

Clustering is a common data analysis method under the unsupervised learning environment, the purpose of which is to divide the data on the basis of the degree of mutual dependence between data and further help users correctly analyze and extract the potential rules and patterns existing in the data [21]. k-Means algorithm [22] is a popular clustering method and commonly used for feature clustering in image retrieval. But its performance heavily depends on the initial starting conditions [23]. In view of this, researchers put forward a lot of improved k-Means algorithms. Pelleg and Moore [24] proposed x-Means algorithm, Likas et al. [25] presented the global k-Means algorithm, and Arthur and Vassilvitskii [26] brought forward k-Means++ algorithm. In image retrieval field, Górecki et al. [27] investigated the problem of visually similar image retrieval, proposed a novel k-Means Voting algorithm, and obtained more accurate results compared with a classical similarity measure based on the Euclidean metric. Aiming at extremely high-dimensional and sparse image vectors, Cao et al. [28] presented a summation-based incremental learning algorithm for Info-k-Means clustering for image indexing. Belhaouari et al. [29] proposed optimized k-Means algorithm which could find the optimal centers for each cluster to recognize human face. Younus et al. [30] integrated PSO algorithm and k-Means clustering algorithm to realize content-based image retrieval, which used PSO algorithm to optimize initial cluster center of k-Means algorithm. However, the improvement of the above traditional k-Means clustering algorithm mainly focuses on the determination of the initial cluster centers or distance function. With the rapid increase of the image number, the time efficiency of the above algorithms would drop dramatically. In recent years, scholars have performed research studies on the parallel k-Means clustering algorithm. The Hadoop distributed platform, which uses the MapReduce parallel programming model to realize storage and calculation of large-scale data, is widely applied in current research fields. Zhao et al. [31] proposed a parallel k-Means clustering algorithm based on the cloud platform using the Hadoop distributed platform, which performed local combination using the combine function of the MapReduce parallel programming model and increased the iteration speed of the algorithm. Jin and Wang [32] reduced repeated communication traffic and increased the data transfer rate through the addition of a communication module in the computational model. For the sake of Synthetic Aperture Radar (SAR) image change detection and real-time demand, Zhu et al. [33] proposed a parallel fast global k-Means algorithm, which parallelized the selection of initial cluster centers. Experiments got a good speedup ratio. Although these algorithms can process large-scale data, the clustering quality of these algorithms is not high, and they do not effectively address the problem of the large numbers of calculations in the process of performing one of these algorithms.

In summary, no suitable, effective feature clustering method and retrieval method exists for large-scale scene images currently. Therefore, based on the above studies and taking the traditional k-Means algorithm and large-scale scene images as research objects, this study considers the feature clustering optimization method using improved parallel k-Means algorithm for scene images in MapReduce environment and provides an analysis of how to retrieve the user needs of images from the massive scene image database in an accurate, rapid, and efficient manner and realize “people-oriented” efficient retrieval. Compared with the traditional image retrieval methods, the originality of this paper is reflected in the following two aspects. (1) This paper designs distributed parallel k-Means clustering algorithm and realizes the parallel feature clustering for large-scale scene images using MapReduce parallel programming model. In the process of parallel design, we not only apply Canopy algorithm to optimize the initial clustering centers of k-Means algorithm, but also design the combine ( ) function to optimize the iterative process of clustering, which effectively reduces the communication overhead between node computers in the cluster. (2) This paper presents a distributed parallel storage and retrieval scheme for large-scale scene images in Hadoop platform. The validity is verified from different angles (e.g., storage consuming, retrieval accuracy, retrieval time, the system speedup, and efficiency) by several sets of experiments.

2. Theoretical Background

2.1. k-Means Algorithm. The k-Means algorithm [34] is a classical clustering algorithm based on distance; this algorithm takes distance as evaluation index of similarity; in other words, objects that are closer to one another are more similar. The main concept behind this algorithm is as follows: first, randomly select k points as the initial cluster centers; next, calculate the distance between each sample point and central point and then classify the sample points into the nearest cluster; finally, calculate the new cluster centers of the adjusted classes. If the cluster centers of adjacent twice do not change, then do not change the sample; in this case, the sample adjustment ends, and the clustering criterion function E converges:

$$E = \sum_{i=1}^{k} \sum_{p \in C_i} \left\| p - M_i \right\|^2 , \tag{1}$$

where M_i is the mean of the data objects in class C_i and p is the space point of C_i.

The main concept of the parallel k-Means algorithm [34] is as follows: first, randomly select a site as the main point; second, the main point uses the k-Means algorithm to divide it into k clusters; third, the main point broadcasts the central point of every cluster to the remaining $k - 1$ subsites; finally, for each subsite, the distance between data objects of itself and the central point of each cluster is calculated, and then, the sample points are classified into the nearest central point, with transfer of the sample points that do not belong to the subsite to the corresponding site that is the cluster of the sample object. This process is repeated until the discriminant function E converges.

However, the performance of k-Means algorithm depends on the initial centers and the sample discrimination to a large extent. For sample discrimination, the experimental data in this paper is SUN Database which is a scene image database and the feature distinction of different kind of scene image is better. To reduce the influence which is caused by the randomicity of initial clustering centers on algorithm performance, we optimize the selection of the initial cluster centers using Canopy algorithm in advance.

2.2. MapReduce Parallel Programming Model. As one of the core technologies of Hadoop distributed processing, MapReduce provides a type of underlying distributed parallel computing mode for processing big data and a set of complete programming interfaces and an execution environment for developers. MapReduce [35] uses a standard programming and computing mode that can take a function called a high-order function as a parameter to transfer and convert the computational process of data into the executive process of function.

MapReduce divides the computational process of data into two stages, Map and Reduce, corresponding to the two functions mapper and reducer, respectively. First, the original data are split into segments and treated as inputs to the mapper function. Next, after being filtered and converted, the original data become middle results, which are

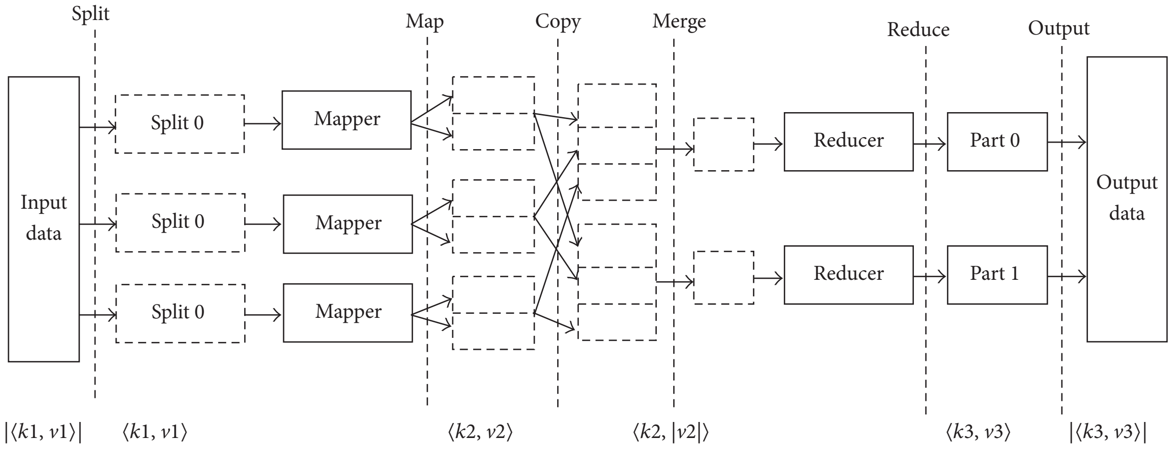


Figure 1: The MapReduce programming model process.

regarded as inputs of the reducer function in the Reduce stage. The final results are obtained after the polymerization process. A flowchart of the MapReduce process is shown in Figure 1.

In the Map stage, MapReduce divides the user's input data into fixed-size segments (called Split), and then, every Split is decomposed into a number of key value pairs $\langle k1, v1\rangle$. Hadoop establishes a Map task for every Split, which executes a user-defined mapper function and produces intermediate results; next, the intermediate results are sorted according to the value of $k2$, which collects the values with same *key* value together to form a new list $\langle k2, list(v2)\rangle$; finally, these tuples $(\langle k2, list(v2)\rangle)$ are divided into groups according to the range of the *key* value, and the corresponding different Reduce tasks are formed.

In the Reduce stage, the Reduce tasks integrate and sort the received data from different mapper functions and then call the corresponding reducer function, take $\langle k2, list(v2)\rangle$ as the input, perform the corresponding processing, and obtain the key value pair $\langle k3, v3\rangle$ which is output to the HDFS.

The process is expressed as follows:

Map: $(k1, v1) \rightarrow list(k2, v2)$.

Reduce: $(k2, list(v2)) \rightarrow list(k3, v3)$.

3. Parallel k-Means Feature Clustering Algorithm

3.1. Parallel Feature Extraction for Scene Images. SURF algorithm [36] can not only maintain independent characteristics in scale, rotation, and illumination change, but also enable the calculation process to be more efficient. It has become the widely used image local feature extraction method in the field of image retrieval due to its robustness and many researchers [37–43] often regard SURF algorithm as the main feature extraction method when processing digital images. Therefore, this paper applies the SURF algorithm to extract the features of the scene images. The process is as follows.

Step 1. Calculate the Hessian matrix of each pixel $X = (x, y)$ of the scene image under the scale σ:

$$H(X,\sigma) = \begin{bmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma) \end{bmatrix}, \quad (2)$$

where $L_{xx}(X,\sigma)$ is the convolution between the Gauss second derivative $(\partial^2/\partial x^2)g(\sigma)$ and the pixel X of the scene image. The other elements of the matrix are obtained in a similar manner.

The matrix is composed of second derivatives and is calculated by an approximate Gauss kernel of the different scales σ. Therefore, Hessian value is a function containing three variables: $H(x, y, \sigma)$.

Step 2. Calculate the corresponding position and scale that can reach the maximum value in the spatial domain and scale domain simultaneously.

For every feature point, perform the following tasks: calculate the response dx and dy of the Haar wavelet for which the radius of circle is 6σ in the direction of x and y; add the response with the range of 60° and higher; rotate the window and determine the direction of the longest vector (main direction).

Structure a square area of size 20σ according to the obtained main direction; split the square area into 4×4 small regions; for every small region, select 25 sampling points, calculate the responses dx and dy in the directions of x and y, respectively, and take the sum of these quantities; next, extract the values of the 4 descriptors: $(\sum dx, \sum dy, \sum |dx|, \sum |dy|)$; finally, the 64-dimensional feature vector is obtained.

Step 3. Normalize the 64-dimensional feature vectors.

The MapReduce parallel computational process of feature extraction on scene images in the Hadoop distributed platform is described as follows.

Map Task

Input: ⟨image_id, image_data⟩

Output: ⟨image_id, image_feature⟩.

The Mapper function utilizes the SURF algorithm to extract the feature vectors for each scene image and count the feature number to facilitate the normalization process.

Reduce Task. The reducer function regards each output key value of the mapper function as its input and then passes the value to the output section.

3.2. Feature Clustering Using Improved Parallel k-Means Algorithm. The k-Means clustering algorithm is an iterative algorithm, in which each iteration process requires considerable time and traffic in the distributed environment. Moreover, the time complexity of the traditional parallel k-Means algorithm applied in the feature clustering for images increases because of the higher property dimensions and higher quality of the images. This paper describes the improvement of the traditional parallel k-Means algorithm. First, the Canopy algorithm is used to select the initial cluster centers, and then, the Combine function is used to perform local merging in the process of generating clustering centers, which not only optimizes the initial cluster centers but also optimizes the iterative process and greatly reduces the time complexity of the parallel k-Means algorithm.

3.2.1. Parallel Optimization of Initial Clustering Centers for k-Means Based on Canopy Algorithm. Canopy algorithm [34] is a simple, fast, and accurate algorithm for grouping objects into classes. The algorithm divides clustering into two stages: first, a simple and fast method of computing the distance is used to divide the data into overlapping subsets, each of which is called a "canopy"; second, the distances are calculated using a precise and rigorous distance calculating method for all data vectors that belong to the same "canopy" that appeared in the first stage. In this paper, the Canopy algorithm and k-Means algorithm are integrated; the Canopy algorithm is used to optimize the initial clustering centers of the k-Means algorithm. The parallel optimized process for the initial clustering centers using the Canopy algorithm is as follows:

> Input: Scene image dataset *List* (form as $\langle image\_id, image\_feature\rangle$).
>
> Output: k initial clustering centers (form as $\langle canopy\_id, image\_feature\rangle$).

Step 1 (Data preprocessing). Sort the scene image dataset *List* according to the image_id of the images, and set the initial distance thresholds $T1$ and $T2$ (obtained by cross validation), $T1 > T2$.

Step 2. The mapper function randomly selects a sample vector of scene image as a central vector of the canopy and then traverses the scene image dataset. If the distance between the scene image data and central vector of the canopy is less than $T1$, then the image data are classified the canopy; if the distance between the scene image data and the central vector of canopy is less than $T2$, then the image data are removed from the original dataset. Proceed with this processing until *List* is a null set. Finally, all of the central vectors of the canopy are output.

Step 3. The reducer function processes the output of the mapper function, integrates the central vectors of the canopy in the Map stage, and generates new central vectors of canopy, that is, the initial clustering centers.

Thus, we obtain the k initial clustering centers.

3.2.2. Parallel Optimization of the Iterative Process for Feature Clustering Based on k-Means Algorithm. The iterative optimization process using the k-Means algorithm for feature clustering is as follows:

> Input: scene image dataset *List* (form as $\langle image\_id, image\_feature\rangle$).
>
> Output: k clustering centers (form as $\langle image\_id, image\_feature\rangle$).

Step 1. The mapper function receives the output of the reducer function of the Canopy algorithm, calculates the distance between every scene image data and the nearest clustering center of canopy, and outputs scene image data and the respective cluster, such as $\langle cluster\_id, image\_feature\rangle$.

Step 2. The combine function receives the output of the mapper function and combines the objects belonging to the same cluster locally, which sums the corresponding dimensions of the scene image data in every cluster and then counts the number of data objects, resulting in the outputs, such as $\langle cluster\_id, sum, num\rangle$.

Step 3. The reducer function receives the output of the combine function, takes the sum of corresponding dimensions of all scene images of every cluster, determines the total number of scene image data, obtains new values of the cluster centers as the stable cluster center of k-Means such as $\langle cluster\_id, image\_feature, canopy\_id\rangle$, and determines whether the k-Means algorithm is convergent.

Step 4. Perform clustering according to the stable cluster centers. The mapper function receives the scene images to be clustered as inputs, loads the stable cluster centers of the k-Means, calculates the distance between every scene image data and k cluster centers, and then determines the final cluster of the scene image data; the reducer function receives the output of the mapper function, performs data collection, and then obtains the final clustering result.

In addition, for the calculation of similarity between scene image features, this paper uses the Euclidean distance formula, which is a widely used distance definition:

$$d(X,Y) = \left(\sum_{i=1}^{n}(x_i - y_i)^2\right)^{1/2}. \quad (3)$$

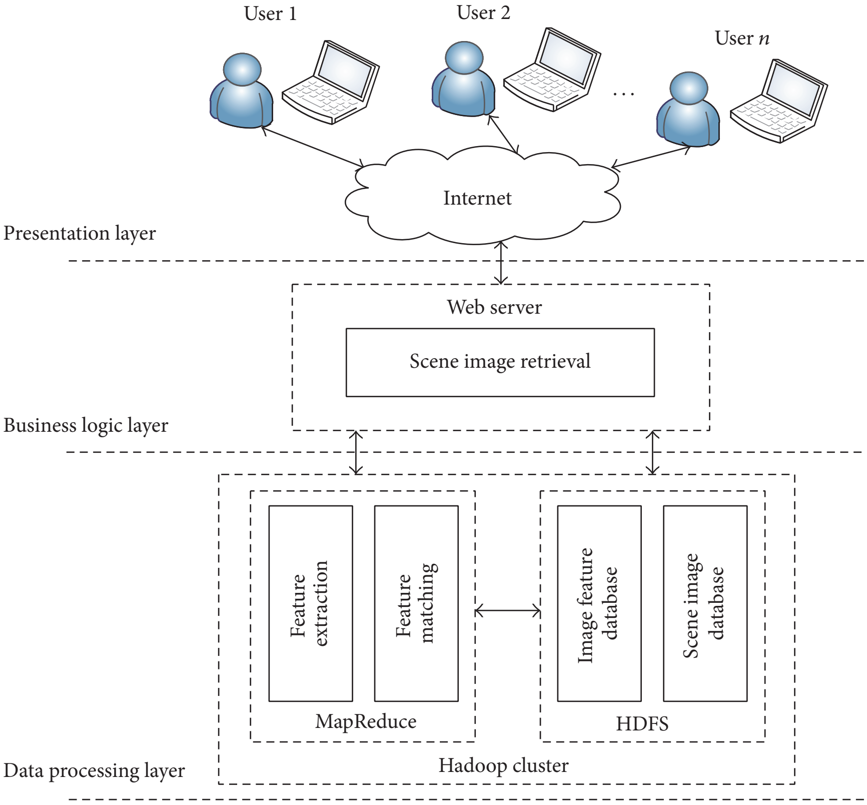


Figure 2: Architecture for large-scale scene image retrieval.

4. Implementation of Large-Scale Scene Image Retrieval

4.1. The Overall Architecture of Retrieval System. To solve the bottleneck problem in the traditional single node architecture due to the rapid growth of scene images, we develop a retrieval scheme for large-scale scene images based on the Hadoop distributed platform. The overall system architecture is shown in Figure 2.

The overall system architecture is divided into three layers:

(1) *The Presentation Layer*. Users obtain services through the Internet and submit sample images or receive retrieval results.

(2) *The Business Logic Layer*. The Web server executes the corresponding business processing tasks according to the users' retrieval requests.

(3) *Data Processing Layer*. This layer is the core of the entire system and is mainly responsible for storage, management, feature extraction, feature matching, and result output for large-scale scene images. Users submit sample images or retrieval keywords to the Hadoop distributed system, which then performs feature extraction (for a sample image) and feature matching. If a sample image is used to retrieve images, then the system uses the sample image to match features in the database stored in the HDFS of scene images; if keywords are used to retrieve images, then the system uses keywords to match the annotation information stored in the scene image database. Finally, the retrieval results are output.

4.2. The Feature Storage Method for Large-Scale Scene Images. As the core subproject of Hadoop, HDFS adopts the master-slave (Master/Slave) mode and stores large-scale data in a plurality of the associated computers, which, in addition to increasing the storage capacity, also realizes automatic fault tolerance, automatically detects and rapidly recovers hardware failures, and conveniently accesses flow data on large-scale dataset. If the images are all stored in HDFS when the image set is large, then reading these images would require a considerable period of time. HBase is a distributed database-oriented column above HDFS and can read and write in real time. Therefore, the storage path and the features of scene images are stored in HBase in this paper. The structure is described in Table 1.

Take the image ID as the primary key of the HBase table and take the source file of the image and the image features and the annotated information as the two-column family of the HBase table. Due to the implementation of the atomic operation, the HBase table places all information of the image in the same row for reading and writing.

4.3. Large-Scale Scene Image Retrieval. The retrieval process is shown in Figure 3.

Table 1: Design of the storage table for large-scale scene images.

Image ID	Image	Image feature information	
	Source file of image	Extracted features	Annotated information
…	…	…	…

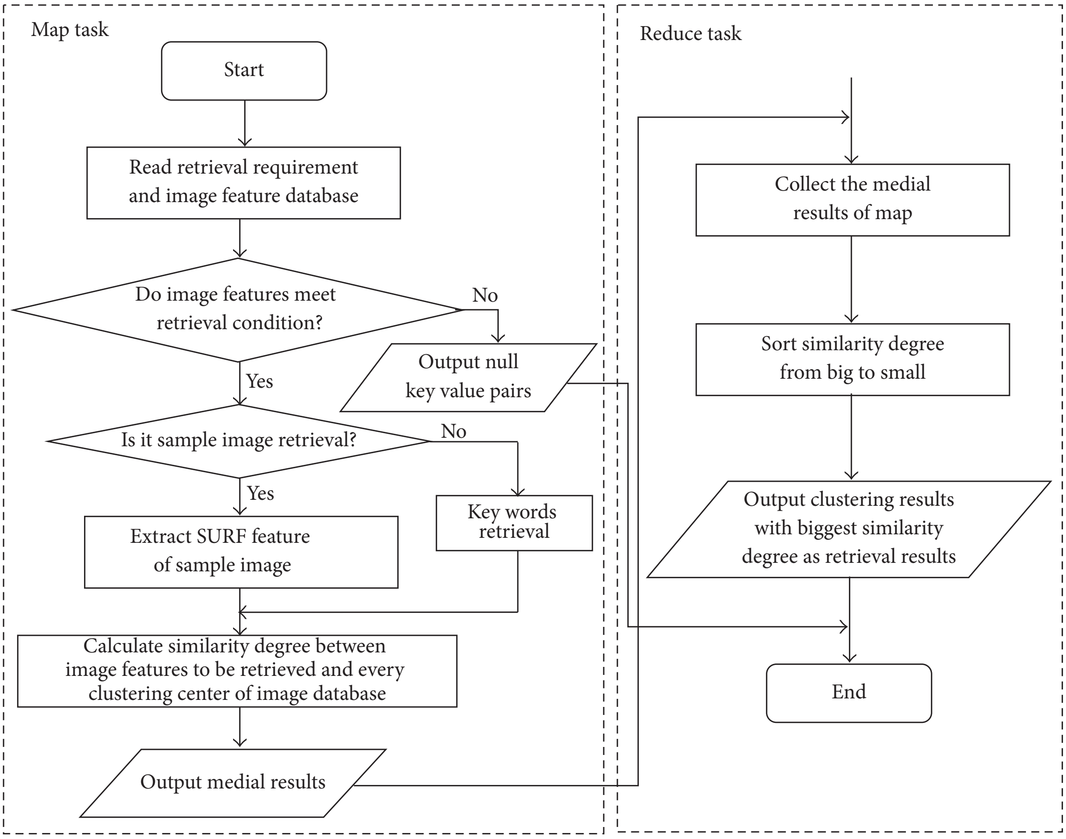

Map task
Start
Read retrieval requirement and image feature database
Do image features meet retrieval condition?
No
Output null key value pairs
Yes
Is it sample image retrieval?
No
Yes
Key words retrieval
Extract SURF feature of sample image
Calculate similarity degree between image features to be retrieved and every clustering center of image database
Output medial results
Reduce task
Collect the medial results of map
Sort similarity degree from big to small
Output clustering results with biggest similarity degree as retrieval results
End

Figure 3: Retrieval flow for large-scale scene images.

Large-scale scene image retrieval based on the improved distributed k-Means feature cluster algorithm is based on describing images according to the SURF feature of scene images combined with the annotation information of the scene images. The steps are as follows:

(1) Store the scene image database and annotation information in the HBase distributed database of HDFS to extract features and cluster and obtain the retrieval results.

(2) Extract the image features in a distributed and parallel manner using the SURF algorithm for scene images in the database; cluster the extracted features using the proposed improved k-Means algorithm, and store the clustered image data and features in the HDFS.

(3) At the image retrieval stage, the Map task receives the user's retrieval requirement, reads the image feature database, adjusts the retrieval requirement, extracts the features of the sample image, calculates the similarity degree between the image feature to be retrieved and every clustering center in the image database, and takes the calculation results as the intermediate results to the output.

(4) The Reduce task receives the output of the Map task and sorts the similarity degree from large to small and outputs the retrieval results, which are scene images with the greatest similarity degree.

5. Results and Discussion

5.1. Experimental Environment and Test Data. In this paper, the experimental environment adopts the Hadoop cluster consisting of 5 computers (1 computer as the Master node and the remaining 4 computers as the Slave nodes). The basic configuration of every node computer is as follows: 4 G dual core processor, 500 GB of hard disk space, and the Ubuntu operating system.

The experimental data are obtained from the COREL Database and the SUN Database on the Internet. The COREL Database published by COREL Corporation consists of 60,000 images (about 100 images represent one image categories, that is to say, 600 image categories altogether) based on 600 CD-ROMs. We download freely a subset of 60,000 images containing 10,000 images and 100 categories from http://wang.ist.psu.edu/docs/related/. To construct the larger datasets, we duplicate the 10,000 images (about 100 images per category, 100 categories altogether) to 30,000 images (about 300 images per category, 100 categories altogether) so as to satisfy the experimental requirement. We construct 8 datasets by random selection according to image category and image number and name them as "Data 1" through "Data 8." The category number and image number included in these datasets are, respectively, as follows: 10 categories, 1,500 images; 10 categories, 3,000 images; 20 categories, 3,000 images; 20 categories, 6,000 images; 50 categories, 6,000 images; 50 categories, 15,000 images; 100 categories, 15,000 images; 100 categories, 30,000 images. The SUN Database currently contains 131,067 scene images and 908 scene categories. Due to the limitations of the experimental conditions, we selected 50,000 scene images as the experimental datasets from the SUN Database. These scene images are publicly available at http://groups.csail.mit.edu/vision/SUN/. The selected 50,000 images are constructed 5 datasets (using a combination of random selection by computers and artificial selection) and we name them sequentially as "Data 9" through "Data 13." These datasets include the following number of scene images, respectively: 1,000 images, 5,000 images, 15,000 images, 30,000 images, and 50,000 images. In this way, a total of 80,000 scene images are selected as the experimental data in this paper and we have dealt with all experimental images into the format of 384 $*$ 256 pixels.

5.2. Experimental Results and Analysis

5.2.1. Storage Performance Test and Analysis. When performing the storage performance test, we experimentally contrasted the time consumption of storing different scene image sets according to the node number of the Hadoop cluster. We conducted the performance test of the storage time when the number of nodes is 1, 2, 3, and 4. The experiment results are shown in Figure 4.

When the size of scene images is less than 5,000, the growth of node number does not clearly affect the performance of the amount of time consumed for scene image storage; when the size of scene images is more than 5,000, the performance on distributed parallel storage is more clearly observed. With the same size of the image database, the amount of time consumed for storage decreases with an increasing node number. When the size of the scene images becomes larger, the amount of time consumed for storage also becomes larger. However, the single node cluster increases most rapidly, and the rate of growth of the 4-node cluster is reduced. That is, when the image database is small, the use of a multinode cluster for distributed storage is not appropriate; when the image database is large, the efficiency of using distributed parallel storage is higher.

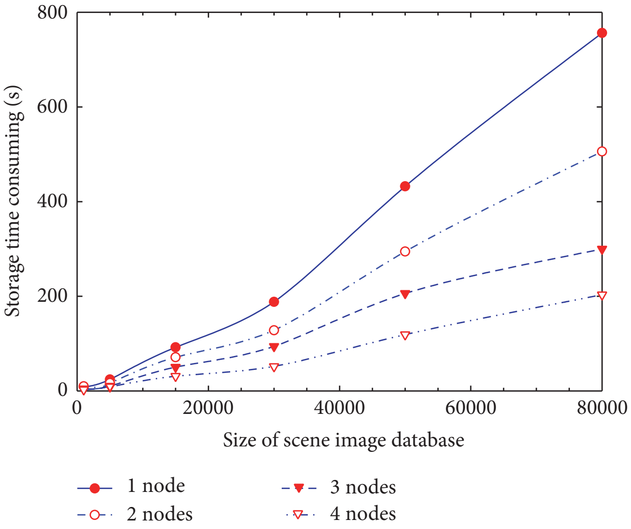
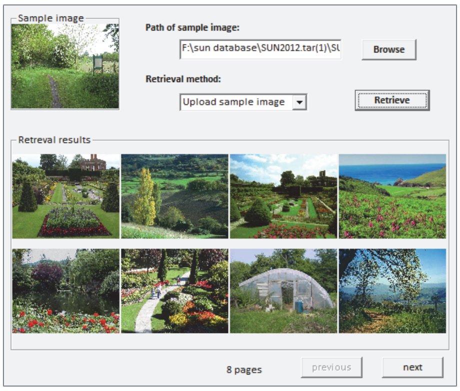


FIGURE 4: Comparison of the amount of time consumed for large-scale scene image storage.



Path of sample image: F:\sun database\SUN2012.tar(1)\SU

Retrieval method: Upload sample image

FIGURE 5: The interface of retrieval result for large-scale scene images.

5.2.2. Retrieval Performance Test and Analysis. We developed an image retrieval prototype system based on Hadoop platform using Java. Figure 5 is the interface of the retrieval results aiming at the uploaded sample image retrieval.

To verify the retrieval performance, experiments are performed to compare the following three aspects: retrieval accuracy, retrieval time consuming, speedup and efficiency, sizeup, and scaleup.

(1) Retrieval Accuracy. Under different datasets of COREL Database and SUN Database, the traditional k-Means algorithm, x-Means algorithm in literature [24], global k-Means algorithm in literature [25], k-Means++ algorithm in literature [26], the parallel k-Means algorithm in literature [33],

Table 2: Contrast of the retrieval accuracy (%) of different methods based on COREL datasets.

Dataset	Retrieval precision rate (%)					
	k-Means	x-Means	Global k-Means	k-Means++	Parallel k-Means	The proposed method
Data 1	90.79	91.42	91.57	92.31	94.46	98.71
Data 2	88.59	89.83	89.81	90.62	93.83	98.03
Data 3	87.87	88.14	89.01	89.54	93.76	98.00
Data 4	85.83	85.96	86.25	87.49	92.17	96.57
Data 5	84.81	85.07	85.49	85.91	92.17	96.56
Data 6	82.35	83.89	83.96	83.97	90.73	94.99
Data 7	79.64	81.44	81.97	82.35	90.06	94.55
Data 8	74.91	76.87	77.28	77.40	89.45	93.76
Max	90.79	91.42	91.57	92.31	94.46	98.71
Min	74.91	76.87	77.28	77.40	89.45	93.76
Mean	84.35	85.33	85.67	86.20	92.08	96.33
Standard deviation	4.87	4.39	4.34	4.57	1.75	1.70

and the proposed algorithm in this paper were compared in terms of their retrieval precision rates.

First, we made the experimental contrast using COREL Database and the experimental results are shown in Table 2.

The data in Table 2 show that, no matter which algorithm is used, the retrieval accuracy would decrease with the increase of image category under the circumstances of the same image number; and the retrieval accuracy would also decrease with the increase of image number under the circumstances of the same image category. This suggests that the larger the image number is and the more the image categories are, the more complicated the retrieval process would be, which leads to the decline of the retrieval accuracy. However, the growth of image categories has less influence on retrieval accuracy than the increase of image number, especially for the two parallel algorithms. In addition, it can be concluded that the retrieval accuracy would drop dramatically for the traditional algorithms (k-Means, x-Means, global k-Means, and k-Means++) with single node architecture, yet the retrieval accuracy of the two parallel algorithms declines slower, which fully reflects the superiority of distributed parallel computing. From the point of view of the statistical results of the standard deviation, the proposed algorithm in this paper has the fewest sample fluctuations and shows the best retrieval performance.

Next, we use the traditional quantities of precision rate, recall rate, and $F1$ value to evaluate the retrieval effect on datasets of SUN Database. The precision rate reflects the ability of rejecting irrelevant scene images according to the following formula:

$$P_{\text{precision}} = \frac{\text{the number of the retrieved relevant images}}{\text{the number of retrieved images}} \times 100\%. \tag{4}$$

The recall rate reflects the ability of a system to classify relevant images according to the following formula:

$$P_{\text{recall}} = \frac{\text{the number of retrieved relevant images}}{\text{the number of all relevant images in the retrieval system}} \times 100\%. \tag{5}$$

For large-scale data analysis and retrieval, when the precision and recall rate appear contradictory, a comprehensive evaluation standard, namely, F-measure index is usually used to evaluate the system in order to evaluate retrieval performance. It combines the results of precision rate and recall rate and is the weighted harmonic mean of precision rate and recall rate. The higher the F value is, the better the retrieval performance is. The calculation formula is as follows:

$$F = \frac{\left(\alpha^2 + 1\right) \times P_{\text{precision}} \times P_{\text{recall}}}{\alpha^2 \times \left(P_{\text{precision}} + P_{\text{recall}}\right)}, \tag{6}$$

where α is adjusting parameter. When $\alpha = 1$, that is the most commonly used $F1$ value evaluation index:

$$F1 = \frac{2 \times P_{\text{precision}} \times P_{\text{recall}}}{P_{\text{precision}} + P_{\text{recall}}}. \tag{7}$$

It is generally believed that the higher $F1$ value shows that the system reaches the optimal balance between precision rate and recall rate and achieves the better analysis and retrieval effectiveness.

Under different sizes of scene images, different algorithms appearing in Table 2 are compared in terms of their classification precision ratios, recall rates, and $F1$ value. The experimental results are shown in Table 3 and Figure 6.

Table 3 shows the retrieval accuracy of different methods and Figure 6 shows the average retrieval accuracy of

Table 3: Contrast of the retrieval accuracy (%) of different methods based on SUN database.

Dataset	Clustering algorithm	Precision rate (%)	Recall rate (%)	$F1$ value
Data 9	k-Means	89.29	92.16	0.907
	x-Means	91.47	94.06	0.927
	Global k-Means	91.91	94.87	0.934
	k-Means++	92.38	94.99	0.937
	Parallel k-Means	92.54	95.43	0.940
	The proposed method	96.48	98.87	0.977
Data 10	k-Means	86.41	89.25	0.878
	x-Means	87.96	90.81	0.894
	Global k-Means	87.83	90.81	0.893
	k-Means++	88.37	91.04	0.897
	Parallel k-Means	91.90	94.81	0.933
	The proposed method	95.85	98.36	0.971
Data 11	k-Means	81.29	84.18	0.827
	x-Means	82.35	85.02	0.837
	Global k-Means	83.81	86.81	0.853
	k-Means++	85.26	87.94	0.866
	Parallel k-Means	90.86	93.83	0.923
	The proposed method	94.93	97.89	0.964
Data 12	k-Means	74.10	76.92	0.755
	x-Means	76.05	78.89	0.774
	Global k-Means	76.72	79.28	0.780
	k-Means++	79.31	81.69	0.805
	Parallel k-Means	89.53	91.90	0.907
	The proposed method	93.77	96.71	0.952
Data 13	k-Means	64.83	66.43	0.656
	x-Means	66.59	67.91	0.672
	Global k-Means	67.28	69.05	0.682
	k-Means++	69.05	72.0	0.705
	Parallel k-Means	88.14	91.03	0.896
	The proposed method	92.49	95.59	0.940

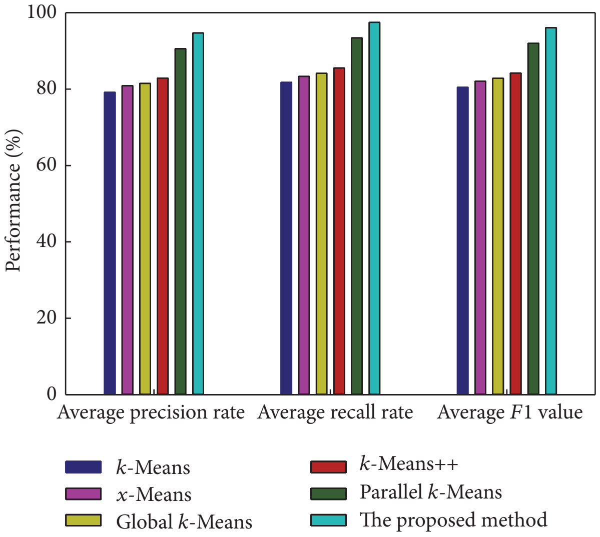
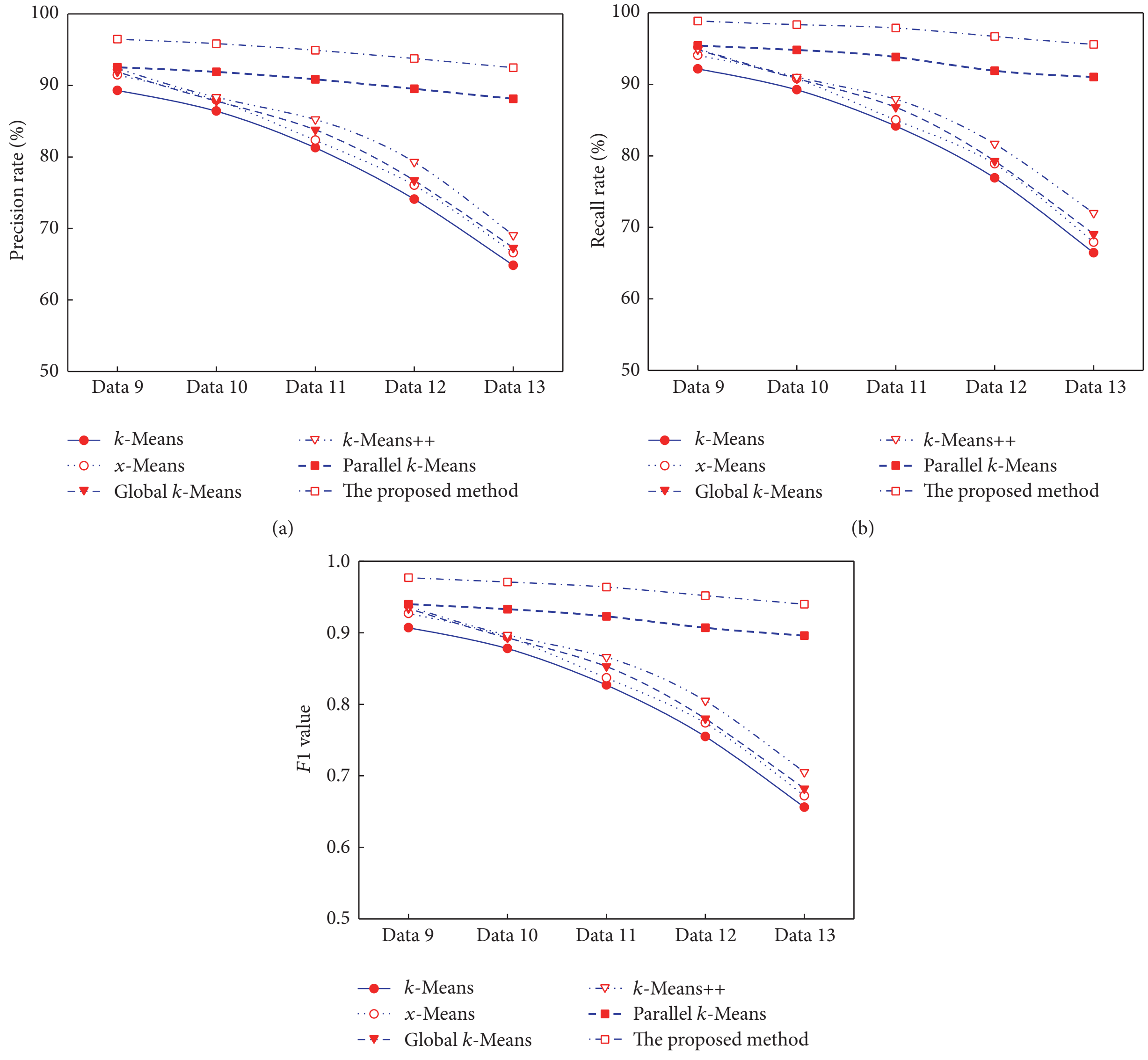


Figure 6: Comparison of the average retrieval accuracies (%) based on SUN Database.

different methods based on the datasets of SUN Database. In Table 3, for five different scene image datasets, the method proposed in this paper is preferable to the method of the traditional algorithms (k-Means, x-Means, global k-Means, and k-Means++) with single node architecture and parallel k-Means algorithm in literature [33]. Furthermore, the average retrieval accuracy using the proposed method is the highest with respect to the traditional algorithms with single node architecture and parallel k-Means algorithm in Figure 6. These phenomena describe that the improvement in the accuracy is not by chance. The optimization of initial clustering center of k-Means algorithm and the parallel design of the proposed method in MapReduce environment are important factors of improving the retrieval accuracy. In addition, $F1$ value is greater than 0.9 and the average $F1$ value is greater than 0.95 using the proposed method in this paper, which also describe that the proposed method reaches the very good balance between precision rate and recall rate and we have obtained desired retrieval performance.



(a)

(b)

(c)

FIGURE 7: (a) Decline curve of the precision rate (%) based on SUN Database. (b) Decline curve of the recall rate (%) based on SUN Database. (c) Decline curve of $F1$ value based on SUN Database.

In order to better observe the fluctuation of the retrieval accuracy, we drew a decline curve of the retrieval performance for different algorithms, as shown in Figures 7(a)–7(c).

Figures 7(a)–7(c) shows the decline curves of precision rate, recall rate, and $F1$ value based on SUN Database. It can be concluded that the fluctuation of the proposed method in this paper and the parallel k-Means algorithm is much less than the traditional algorithms with single node architecture according to the curve change; moreover, as the data scale increases, although the retrieval accuracy rates of all methods decreased, the proposed method in this paper and the parallel k-Means algorithm obviously decreased only very slightly, which indicates that the parallel programming model based on MapReduce achieves an excellent performance level, particularly with large-scale data.

In addition, we also made the experimental contrast of the average retrieval accuracy for COREL Database (30,000 images), SUN Database (50,000 images), the mixture of COREL Database, and SUN Database (80,000 images) using different algorithms. The experimental results are shown in Figure 8.

Figure 8 is a sharp contrast of average retrieval accuracy of different methods in different datasets. When image number increases from 30,000 to 80,000, the average retrieval accuracies of the traditional algorithms (k-Means, x-Means, global k-Means, and k-Means++) with single node architecture all decrease by more than 25%, yet that of the parallel k-Means algorithm and the proposed method only decreases by 3.35% and 2.66%, respectively, which further shows that the retrieval performance of the traditional algorithms based on

Table 4: Comparison of retrieval times for the different methods based on COREL database.

Retrieval method	Image category	Retrieval time (S)			
		3,000 images	6,000 images	15,000 images	30,000 images
k−Means	10	16	52	1,766	6,258
	20	16	53	1,772	6,297
	50	19	53	1,785	6,322
	100	23	57	1,809	6,413
x-Means	10	16	50	1,752	6,259
	20	17	51	1,770	6,295
	50	18	53	1,784	6,319
	100	22	56	1,801	6,410
Global *k*-Means	10	14	51	1,750	6,264
	20	14	54	1,776	6,294
	50	17	56	1,788	6,320
	100	22	59	1,800	6,408
k-Means++	10	15	47	1,758	6,253
	20	15	49	1,769	6,282
	50	18	53	1,783	6,318
	100	23	55	1,803	6,411
Parallel *k*-Means++ (using 4 slave nodes)	10	2.8	6.1	43	101
	20	3.0	6.5	45	106
	50	3.3	7.0	48	109
	100	3.9	7.8	50	112
The proposed method (using 4 slave nodes)	10	0.79	1.3	10	65
	20	0.80	1.5	11	68
	50	0.83	2.0	14	69
	100	0.84	2.7	15	71

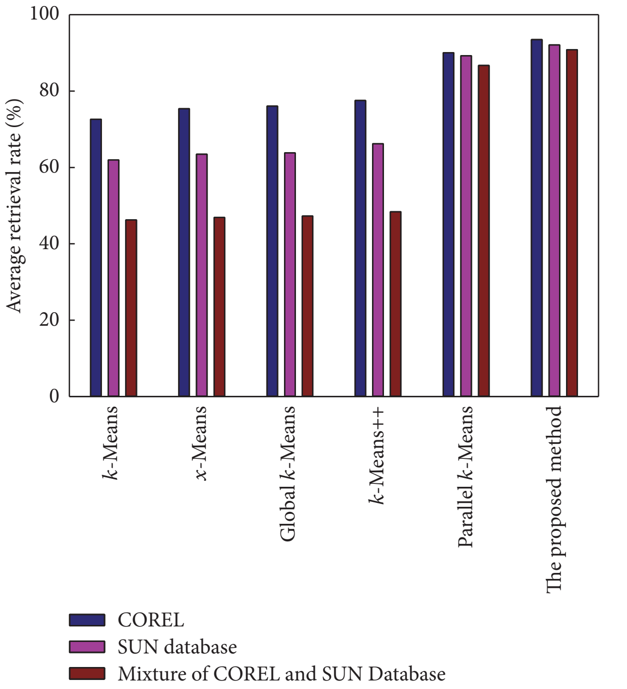


Figure 8: Average retrieval accuracy (%) comparison of different methods.

stand-alone architecture would become worse and worse with the dramatic increase in the amount of data, and the retrieval performance of the algorithms based on MapReduce model decreases slightly because this paper applies distributed parallel processing, in which the larger the amount of the data is, the more computational ability the function of nodes in cluster has can be, especially when this paper improved the initial clustering centers in the process of parallel design.

(2) Retrieval Time Consuming. To further verify the effectiveness of the proposed method in this paper, we make the experimental contrast of retrieval time. The experimental results are shown in Tables 4 and 5.

Furthermore, to test the time performance of the method proposed in this paper in MapReduce environment, we randomly selected 60,000 images from 80,000 images database (the mixture of COREL Database and SUN Database) to make comparison in the case of different slave node computers only using the parallel *k*-Means algorithm and the proposed method in this paper. The experimental results are shown in Figure 9.

Tables 4 and 5 present the contrast results of retrieval time consuming for different data scale using different methods. Aiming at the parallel computing environment, Figure 9 compares the time performances of the two parallel

Table 5: Comparison of retrieval times for the different methods based on SUN database.

Image number	Retrieval time (S)					
	k-Means	x-Means	Global k-Means	k-Means++	Parallel k-Means	The proposed method
1,000	0.9	0.8	0.9	0.9	0.2	0.026
5,000	51	53	54	54	7	1.2
15,000	1,793	1,796	1,794	1,799	54	13
30,000	6,257	6,285	6,277	6,289	110	69
50,000	12,109	12,132	12,133	12,129	187	149

Explanation: The parallel k-Means algorithm and the proposed method in this paper used 4-slave-node computers.

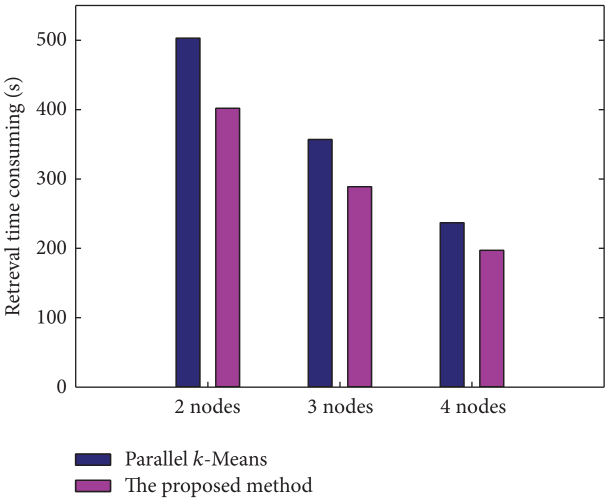


Figure 9: Comparison of retrieval time consuming for randomly selected 60,000 images.

algorithms under different computing nodes. We note that the retrieval time of the traditional algorithms (k-Means, x-Means, global k-Means, and k-Means++) is much longer than that of the other two parallel algorithms. This is because the two parallel algorithms adopt distributed parallel processing technology, while the traditional algorithms use the single node architecture with low processing capacity. As can be seen in Tables 4 and 5 and Figure 9, the retrieval time of the method proposed in this paper is less than that of the parallel k-Means algorithm, which is mainly because the method proposed in this paper not only optimizes the initial clustering center of k-Means algorithm, but also optimizes the iterative process of the algorithm in the MapReduce environment. Therefore, desired retrieval time performance is obtained.

Figure 8 shows the contrast results of retrieval time consuming for 50,000 scene images in different nodes using parallel k-Means algorithm and the proposed method, respectively.

(3) Speedup and Efficiency, Sizeup, and Scaleup. For the parallel programming model based on MapReduce, we evaluate the computational performance of the proposed algorithm in terms of speedup and efficiency, sizeup, and scaleup. To test the computational performance, we randomly selected 5 different datasets: 5,000 images, 10,000 images, 20,000 images, 50,000 images, and 80,000 images.

Speedup refers to the ratio of the time required to run a task on a single calculating node to the time required to run that same task on multiple calculating nodes, while efficiency refers to the ratio of the speedup to the number of calculating nodes [14]. In an ideal state, the speedup should increase linearly and the efficiency should remain constant with the increase of the number of nodes. However, the efficiency does not reach 1 because task control is influenced by communication cost and load balance, among other factors. Goller et al. [44] suggested that the system has obtained good performance as long as the efficiency can reach 0.5. Figures 10(a) and 10(b) show experimental comparisons of the speedup ratios and of the efficiencies of the method proposed in this paper, respectively, using datasets of different scales.

In Figure 10(a), the speedup ratio takes on a rising tendency as the number of calculating nodes increases, and increased data scale results in an increased magnitude of the speedup ratio. For the same dataset, the processing speed of the system becomes faster with the increase of the number of computing nodes; that is to say, the processing time become less, so the speedup ratio takes on a rising tendency. For different datasets, the larger the amount of data is, the better the performance of the multicomputing nodes is. So compared to the single node computer, the processing speed would be much faster. This result further indicates that larger datasets better demonstrate the performance of multiple calculating nodes. Figure 10(b) validates the retrieval system's efficiency. As the number of calculating nodes increases, the system efficiency decreases more rapidly than when the dataset is smaller. As the size of the dataset gradually increases, the increase in calculating nodes results in a reduced system efficiency, yet with a smaller magnitude. The main reason for the reduction in system efficiency is that the increase in data size causes the system processing time to increase. In contrast, as the number of calculating nodes increases, the communication overhead between nodes also increases. However, the system efficiency is always above 0.5, which indicates that the method has excellent parallel performance and expandability.

Sizeup is defined as how much longer it takes on a given system when the image size is m-times larger than the original

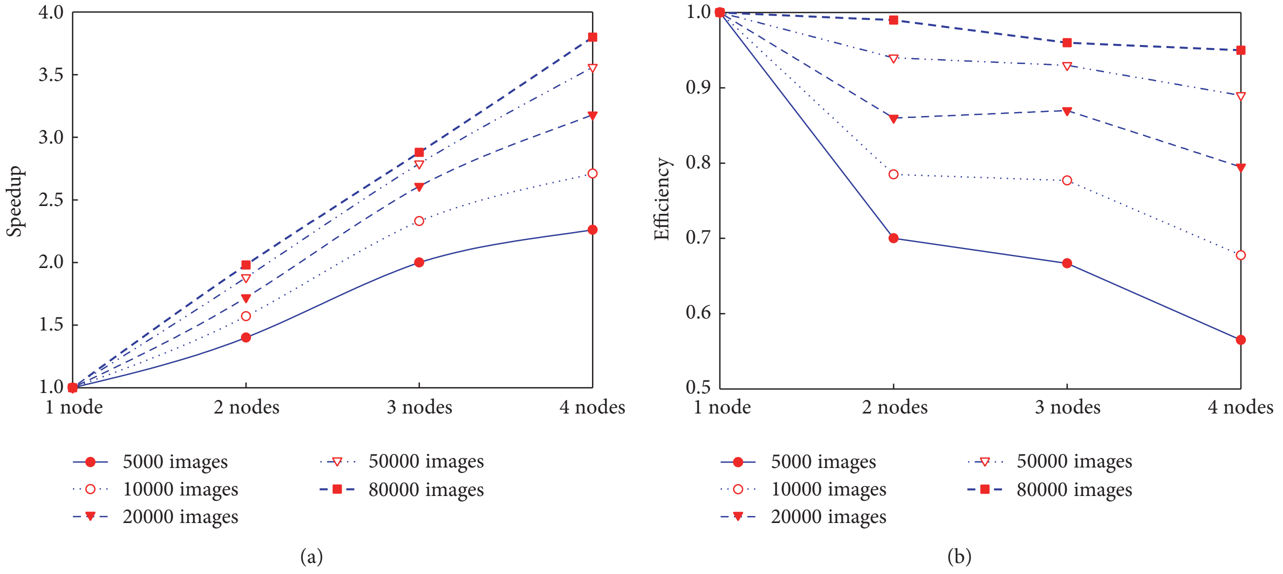


FIGURE 10: (a) Comparison of the speedups. (b) Comparison of the efficiencies.

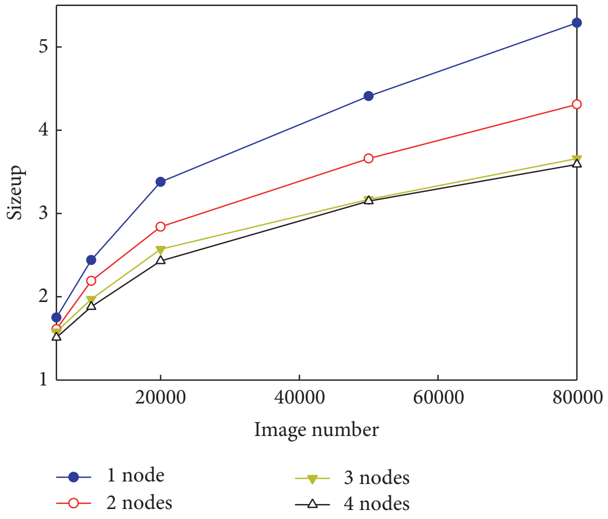


FIGURE 11: The comparison of sizeups.

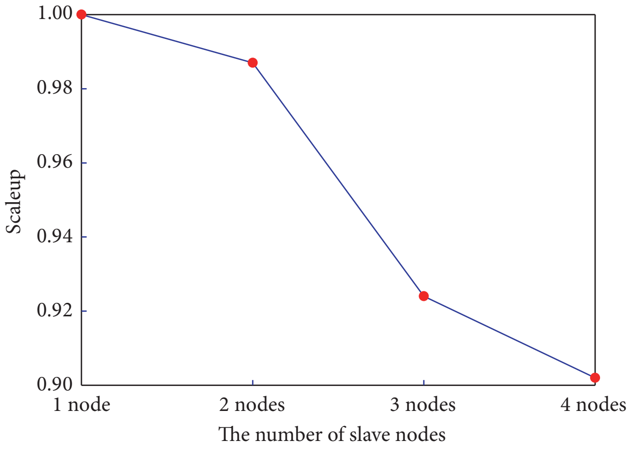


FIGURE 12: The comparison of scaleup.

image size. That is to say, with the increase of image number, the higher the value of sizeup is, the longer the time the cluster system would take. To measure sizeup, we fix the number of the slave nodes to 1, 2, 3, and 4, respectively, and increase the image size from 5,000 images to 80,000 images for each node number. Figure 11 shows the experimental results. It is easy to see that when we increase image size from 5,000 to 80,000, the sizeup of 1-node system is increased by about 3 while it is only increased by 2.3 for 4-node system. This is because the communication time of the 1-node system is smaller than that of the 4-node system, and the communication time would not increase much for the proposed method in this paper when the image number is increased. Therefore, the proposed method in this paper has a good sizeup performance.

Scaleup refers to the ability of an m-times larger system to perform an m-times larger job in the same run time as the original system, which is used to evaluate the ability of the algorithm to grow both the system and the image size. Obviously, the higher value of the scaleup indicates the better algorithm performance. Therefore, scaleup validates how well the algorithm handles larger image size when more node computers are available. For the measure of scaleup, we increase the node computers and image size simultaneously and obtain the different scaleup values for the following combinations (1-node computer, 5,000 images), (2-node computers, 10,000 images), (3-node computers, 50,000 images), and (4-node computers, 80,000 images). The results are shown in Figure 12. The higher the scaleup value, the better the performance we would obtain. The results in

Figure 12 show that the values of scaleup are all higher than 0.90, which demonstrates the proposed method scales well.

6. Conclusions

As a kind of media with visual and integrated information, digital images have more and more penetrated and served in all fields and gradually influence people's work, study, and life. Accordingly, it has become the urgent problem to be solved to organize, manage, and analyze large-scale image data. Scene images are very common image data, which contains extremely rich content. Therefore, how to make the computer understand the image contents like the human and make retrieval results meet users' needs is very important. At the same time, building parallel retrieval framework for large-scale scene images based on big data technology to improve the retrieval efficiency would lay a solid foundation for the effective organization and management of massive image data.

This paper discussed the development of a large-scale scene image retrieval method based on an improved parallel k-Means feature cluster algorithm and better improved the time efficiency and retrieval accuracy for large-scale image retrieval. It studied how to improve the parallel k-Means algorithm and apply it to feature cluster retrieval for scene images. Finally, retrieval for large-scale scene images was realized using the Hadoop distributed processing platform. The experimental results demonstrated that the designed scheme could balance the system load, make full use of the resources of the distributed system, and improve the retrieval speed. When considering large-scale scene images, the retrieval efficiency of the Hadoop distributed system was greatly improved relative to the retrieval efficiency of a system of single-node architecture, which fully embodied the powerful computing capability of the distributed parallel processing architecture.

With the development of parallel technology, parallel computing plays more and more important role in dealing with the complex problems of huge amount calculations. The purpose of this paper is to apply MapReduce parallel programming framework to traditional k-Means algorithm optimized by Canopy algorithm so as to improve the clustering speed of k-Means algorithm through the research on the parallel processing technology of Hadoop cluster. In the field of digital image understanding, using the powerful data processing ability of parallel computing to mine and analyze massive data is helpful to obtain more accurate image information. It has very important value for image annotation, classification, and retrieval. It is of great significance to improve the intelligence for digital image understanding.

Analysis and processing of large-scale multimedia data have become popular research topics with the arrival of the big data era and the development of cloud computing and multimedia technology. Future research to improve the results of this paper mainly includes the following: (1) expansion of the node number of the Hadoop distributed platform, adjustment of the relevant parameters of the system, and further improvements to the efficiency of the distributed system; (2) optimization of the feature extraction and clustering algorithm to improve the retrieval accuracy; and (3) optimization of the task design of Map and Reduce to achieve faster and more precise retrieval.

Competing Interests

The authors declare no conflict of interests.

Acknowledgments

This study was supported by the National Natural Science Foundation of China (61202163), the Shanxi Natural Science Foundation (2013011017-2 and 2014011019-3), the Science and Technology Innovation Project of Colleges and Universities in Shanxi Province (2013150), and the Specialized Subject for Key Disciplines of Xinzhou Teachers University, China (XK201308, XK201404).

References

[1] L. Zhuang, Y.-T. Zhuang, J.-Q. Wu, Z.-C. Ye, and F. Wu, "Image retrieval approach based on sparse canonical correlation analysis," *Journal of Software*, vol. 23, no. 5, pp. 1295–1304, 2012.

[2] A. Doulamis, Y. Avrithis, N. Doulamis, and S. Kollias, "Indexing and retrieval of the most characteristics scenes/frames in video-databases," in *Proceedings of the 1st Workshop on Image Analysis for Multimedia Interactive Systems (WIAMIS '97)*, pp. 1054–1110, Louvais-la-Neuve, Belgium, June 1997.

[3] A. D. Doulamis, N. D. Doulamis, and S. D. Kollias, "A fuzzy video content representation for video summarization and content-based retrieval," *Signal Processing*, vol. 80, no. 6, pp. 1049–1067, 2000.

[4] Y. S. Avrithis, A. D. Doulamis, N. D. Doulamis, and S. D. Kollias, "An adaptive approach to video indexing and retrieval using fuzzy classification," in *Proceedings of the International Workshop on Very Low Bitrate Video Coding (VLBV '98)*, pp. 69–72, Urbana, Ill, USA, October 1998.

[5] Y. Yang, F. Nie, D. Xu, J. Luo, Y. Zhuang, and Y. Pan, "A multimedia retrieval framework based on semi-supervised ranking and relevance feedback," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 34, no. 4, pp. 723–742, 2012.

[6] M. Subrahmanyam, R. P. Maheshwari, and R. Balasubramanian, "Local maximum edge binary patterns: a new descriptor for image retrieval and object tracking," *Signal Processing*, vol. 92, no. 6, pp. 1467–1479, 2012.

[7] G.-H. Liu and J.-Y. Yang, "Content-based image retrieval using color difference histogram," *Pattern Recognition*, vol. 46, no. 1, pp. 188–198, 2013.

[8] Y. Gao, M. Wang, Z.-J. Zha, J. Shen, X. Li, and X. Wu, "Visual-textual joint relevance learning for tag-based social image search," *IEEE Transactions on Image Processing*, vol. 22, no. 1, pp. 363–376, 2013.

[9] X. Zheng, Z. Gao, and E. Liu, "Applied study on image retrievals based on statistics projection algorithm and Robert algorithm," *Applied Mathematics and Information Sciences*, vol. 8, no. 2, pp. 787–792, 2014.

[10] T. V. Madhusudhanarao, S. P. Setty, and Y. Srinivas, "Model based approach for content based image retrievals based on fusion and relevancy methodology," *International Arab Journal of Information Technology*, vol. 12, no. 6, pp. 519–523, 2015.

[11] R. Ashraf, K. Bashir, and T. Mahmood, "Content-based image retrieval by exploring bandletized regions through support vector machines," *Journal of Information Science and Engineering*, vol. 32, no. 2, pp. 245–269, 2016.

[12] T. V. Ramana, K. V. Rao, and G. S. C. Prasad, "Literature survey to improve image retrieval efficiency by visual attention model," in *Proceedings of the 3rd International Conference on Information System Design and Intelligent Applications*, Visakhapatnam, India, January 2016.

[13] M. H. Almeer, "Cloud Hadoop mapreduce for remote sensing image analysis," *Journal of Emerging Trends in Computing and Information Sciences*, vol. 3, no. 4, pp. 637–644, 2012.

[14] W. S. Zhu and P. Wang, "Large-scale image retrieval solution based on Hadoop cloud computing platform," *Journal of Computer Applications*, vol. 34, no. 3, pp. 695–699, 2014.

[15] K. Wiley, A. Connolly, and S. Krughoff, "Astronomical image processing with Hadoop," in *Proceedings of the 20th Conference on Astronomical Data Analysis Software and Systems*, pp. 93–96, Astronomical Society of the Pacific, San Francisco, Calif, USA, July 2011.

[16] Y. M. Zhu, "Image classification based on Hadoop platform," *Journal of Southwest University of Science and Technology*, vol. 26, no. 2, pp. 70–73, 2011.

[17] C. Sweeney, L. Liu, and S. Arietta, *HIPI: A Hadoop Image Processing Interface for Image-Based Mapreduce Tasks*, University of Virginia, Charlottesville, Va, USA, 2011.

[18] Y. W. Chen, D. H. Lai, H. Qi, J. L. Wang, and J. X. Du, "A new method to estimate ages of facial image for large database," *Multimedia Tools and Applications*, vol. 75, no. 5, pp. 2877–2895, 2016.

[19] Z. Y. Cheng and J. L. Shen, "On very large scale test collection for landmark image search benchmarking," *Signal Processing*, vol. 124, pp. 13–26, 2016.

[20] K. Makantasis, A. Doulamis, N. Doulamis, and M. Ioannides, "In the wild image retrieval and clustering for 3D cultural heritage landmarks reconstruction," *Multimedia Tools and Applications*, vol. 75, no. 7, pp. 3593–3629, 2016.

[21] L. X. Wang and S. Y. Jiang, "Novel feature selection method based on feature clustering," *Application Research of Computers*, vol. 32, no. 5, pp. 1305–1308, 2015.

[22] J. M. Peña, J. A. Lozano, and P. Larrañaga, "An empirical comparison of four initialization methods for the *K*-Means algorithm," *Pattern Recognition Letters*, vol. 20, no. 10, pp. 1027–1040, 1999.

[23] M. I. Malinen, R. Mariescu-Istodor, and P. Fränti, "K-means*: clustering by gradual data transformation," *Pattern Recognition*, vol. 47, pp. 3376–3386, 2014.

[24] D. Pelleg and A. W. Moore, "X-means: extending k-means with efficient estimation of the number of clusters," in *Proceedings of the 17th International Conference on Machine Learning (ICML '00)*, pp. 727–734, Morgan Kaufmann Publishers, San Francisco, Calif, USA, 2000.

[25] A. Likas, N. Vlassis, and J. J. Verbeek, "The global *k*-means clustering algorithm," *Pattern Recognition*, vol. 36, no. 2, pp. 451–461, 2003.

[26] D. Arthur and S. Vassilvitskii, "k-means++: the advantages of careful seeding," in *Proceedings of the 18th Annual ACM-SIAM Symposium on Discrete Algorithms (SODA '07)*, pp. 1027–1035, Society for Industrial and Applied Mathematics, 2007.

[27] P. Górecki, K. Sopyła, and P. Drozda, "Ranking by K-means voting algorithm for similar image retrieval," in *Artificial Intelligence and Soft Computing*, vol. 7267 of *Lecture Notes in Computer Science*, pp. 509–517, Springer, Berlin, Germany, 2012.

[28] J. Cao, Z. A. Wu, J. J. Wu, and W. J. Liu, "Towards information-theoretic K-means clustering for image indexing," *Signal Processing*, vol. 93, no. 7, pp. 2026–2037, 2013.

[29] S. B. Belhaouari, S. Ahmed, and S. Mansour, "Optimized K-means algorithm," *Mathematical Problems in Engineering*, vol. 2014, Article ID 506480, 14 pages, 2014.

[30] Z. S. Younus, D. Mohamad, T. Saba et al., "Content-based image retrieval using PSO and k-means clustering algorithm," *Arabian Journal of Geosciences*, vol. 8, no. 8, pp. 6211–6224, 2015.

[31] W. Z. Zhao, H. F. Ma, and Y. X. Fu, "Research on parallel k-means algorithm design based on hadoop platform," *Computer Science*, vol. 38, no. 10, pp. 166–168, 2011.

[32] W. J. Jin and C. Z. Wang, "Iteration MapReduce framework for evolution algorithm," *Journal of Computer Applications*, vol. 33, no. 12, pp. 3591–3595, 2013.

[33] H. M. Zhu, Q. Y. Zhang, X. Y. Ren, and L. C. Jiao, "Parallel fast global K-means algorithm for synthetic aperture radar image change detection using OpenCL," in *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium*, Milan, Italy, July 2015.

[34] A. R. Konicek, J. Lefman, and C. Szakal, "Automated correlation and classification of secondary ion mass spectrometry images using a *k*-means cluster method," *Analyst*, vol. 137, no. 15, pp. 3479–3487, 2012.

[35] C. Doulkeridis and K. Nørvåg, "A survey of large-scale analytical query processing in MapReduce," *The VLDB Journal*, vol. 23, no. 3, pp. 355–380, 2014.

[36] Y. L. Xie, X. F. Li, J. W. Lu, and Y. B. Gao, "Underwater images real-time registration method based on SURF," *Journal of Computer-Aided Design & Computer Graphics*, vol. 22, no. 12, pp. 2215–2220, 2010.

[37] K. Velmurugan and S. S. Baboo, "Content-based image retrieval using SURF and colour moments," *Global Journal of Computer Science and Technology*, vol. 11, no. 10, pp. 1–5, 2011.

[38] K. Chen and J. Hennebert, "Content-based image retrieval with LIRe and SURF on a smartphone-based product image database," in *Pattern Recognition*, J. F. Martínez-Trinidad, J. A. Carrasco-Ochoa, J. A. Olvera-Lopez, J. Salas-Rodríguez, and C. Y. Suen, Eds., vol. 8495 of *Lecture Notes in Computer Science*, pp. 231–240, Springer, Berlin, Germany, 2014.

[39] M. Vel Murugan and M. Sam Mathews, "2D and 3D active shape model with SURF algorithm for object retrieval: Content based image retrieval," in *Proceedings of the International Conference on Advanced Computing and Communication Systems: Bringing to the Table, Futuristic Technologies from Around the Globe*, pp. 1–7, IEEE, Coimbatore, India, 2014.

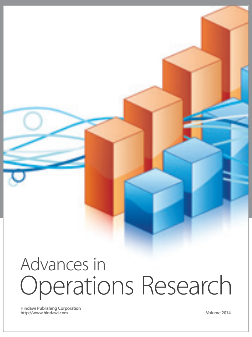
[40] Q. B. Dang, V. P. Le, M. M. Luqman, M. Coustaty, C. D. Tran, and J. M. Ogier, "Camera-based document image retrieval system using local features—comparing SRIF with LLAH, SIFT, SURF and ORB," in *Proceedings of the 13th International Conference on Document Analysis and Recognition (ICDAR '15)*, pp. 1211–1215, IEEE, Tunis, Tunisia, August 2015.

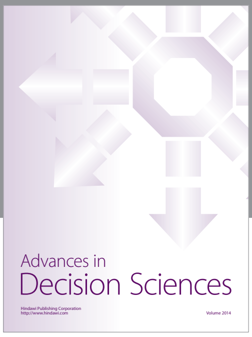
[41] F. Xue, J. Gu, G. Cui, S. Xu, and J. Xu, "ROI selection and image retrieval method based on contribution matrix of SURF features," *Journal of Computer-Aided Design and Computer Graphics*, vol. 27, no. 7, pp. 1271–1277, 2015.

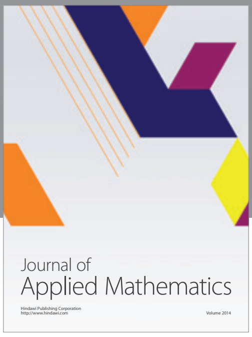
[42] Y.-H. Lee and Y. Kim, "Efficient image retrieval using advanced SURF and DCD on mobile platform," *Multimedia Tools and Applications*, vol. 74, no. 7, pp. 2289–2299, 2015.

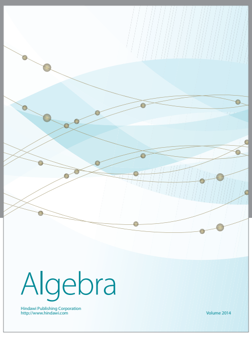
[43] H. A. Elnemr, "Combining SURF and MSER along with color features for image retrieval system based on bag of visual words," *Journal of Computer Science*, vol. 12, no. 4, pp. 213–222, 2016.

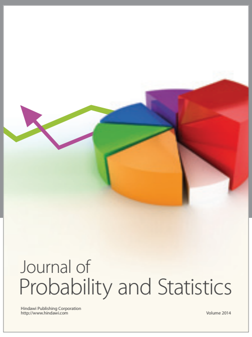
[44] A. Goller, I. Glendinning, and D. Bachmann, "Parallel and distributed processing," in *Digital Image Analysis*, pp. 135–153, Springer, Berlin, Germany, 2001.


Advances in
Operations Research

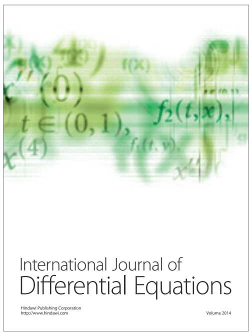

Advances in
Decision Sciences


Journal of
Applied Mathematics

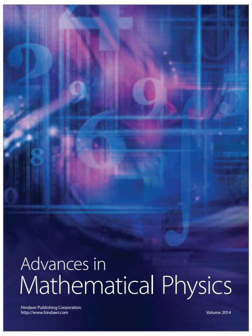

Algebra

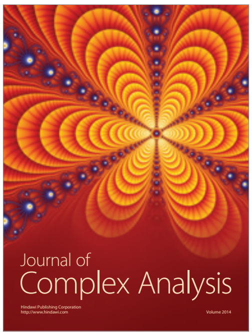

Journal of
Probability and Statistics

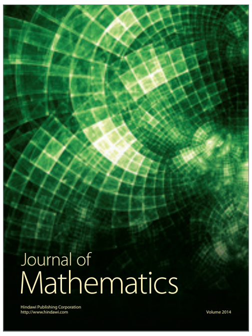
The Scientific
World Journal

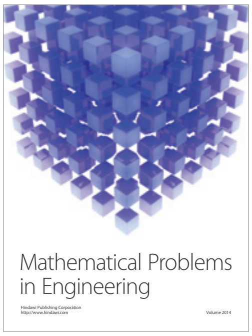

International Journal of
Differential Equations

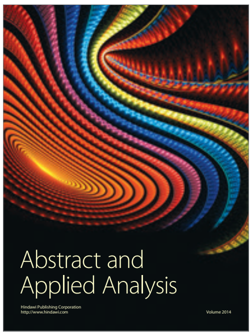
International Journal of
Combinatorics

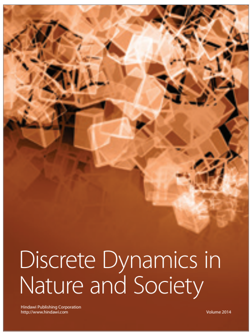

Advances in
Mathematical Physics

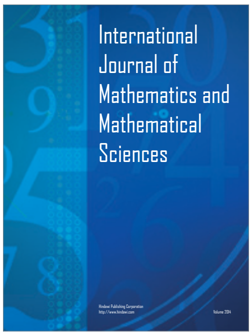

Journal of
Complex Analysis


Journal of
Mathematics


Mathematical Problems
in Engineering

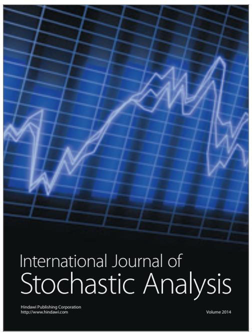

Abstract and
Applied Analysis


Discrete Dynamics in
Nature and Society


International
Journal of
Mathematics and
Mathematical
Sciences

Journal of
Discrete Mathematics

Journal of
Function Spaces


International Journal of
Stochastic Analysis

Journal of
Optimization