Cluster Comput (2019) 22:S827–S834
https://doi.org/10.1007/s10586-017-1330-5

Distributed SVM face recognition based on Hadoop

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Received: 5 August 2017 / Revised: 23 October 2017 / Accepted: 3 November 2017 / Published online: 9 November 2017

Abstract In the work, we analyzed the face recognition method under the cloud computing platform. Based on the distributed support vector machine classification model, face recognition method was established on Hadoop platform to develop parallel computing advantage of MapReduce, thus improving recognition efficiency. With different functions in face feature recognition, conventional and depth LBP operators were integrated by weighted approach to play their respective advantages. Finally, face recognition method under cloud computing platform was conducted with example analysis by Yale B, ORL and FERET face databases, which were most widely used in face recognition field. Under the same cloud computing platform, the classifier was established by BP and RBF neural networks to compare with the research method in the work. The results showed that the SVM classifier has better face recognition effect than BP and RBF neural network classifier under cloud computing platform. The research method in the work has higher recognition accuracy than traditional method.

Keywords Cloud computing · Hadoop platform · Face recognition · Support vector machine · Neural network

1 Introduction

With the continuous development of information technology, face recognition has been widely used in authentication, security verification, screen monitoring and human-computer interaction. Face recognition becomes one of the key research topics in pattern recognition, machine learning and artificial intelligence [1–4]. Cloud computing is one of the products derived from the continuous development of internet technology. With limited computing power and room for improvement, traditional data processing platform cannot successfully cope with mass data for internet statistics and analysis. Cloud computing platform can efficiently use the computing resources in the network to integrate available resources, thus efficiently completing the calculation task with high quality. As a hot topic in the internet nowadays, cloud computing platform has been widely and deeply discussed.

Neural network is a widely used classification and recognition algorithm. Now there are BP and RBF neural network algorithms. Massive matrix operations are required to establish face recognition method by BP neural network algorithm. Cloud computing platform MapReduce can realize matrix operation. However, the multi-layer structure of neural network requires multiple cycles and trainings to get the best algorithm parameters, thus restricting the application under the cloud computing platform. MapReduce can complete the task of neural network algorithm only by multiple repetition of read-write operation. The establishment of neural network recognition and classification model under cloud computing platform may not increase, but reduce computational efficiency. Therefore, the neural network algorithm is not suitable for the MapReduce model [5–7].

In the work, face recognition method under the cloud computing platform is established by support vector machine (SVM) algorithm which is more suitable for MapReduce model. At present, scholars have analyzed face image recognition based on the Hadoop cloud platform. Sweeney et al. [8] established image data format of HIPI to store small graphs into a large file. The HIPI format consists of a file that contains all images and an index file, improving the

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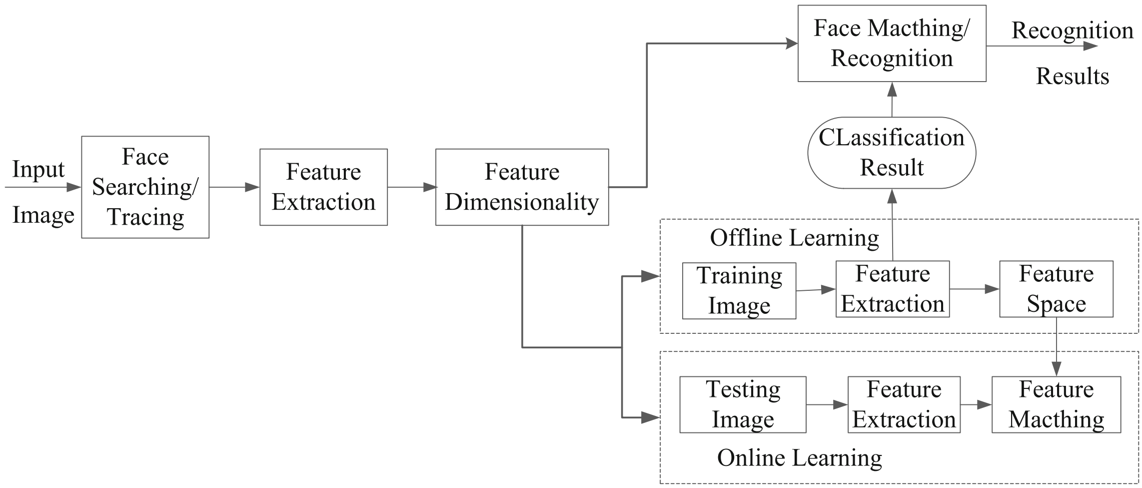


Fig. 1 Face recognition process

efficiency of small file processing by Hadoop. Soyata et al. [9] proposed MOCHA, a cell phone-based face recognition cloud processing algorithm. The images are collected by local cell phone for cloud processing, achieving real-time recognition. RedHadoop recently exhibits a video of Hadoop-based face detection system, which quickly detects human faces from moving characters. In addition, some companies have done some jobs based on other cloud platforms. E.g., Shanghai Haolong Intelligent Technology Company developed a human face cloud computing platform which can complete face search and contrast within one second [10].

2 Face recognition

A common face recognition process consists of face detection, tracking, feature extraction, dimensionality reduction, matching recognition (See Fig. 1).

As the first step in achieving face recognition, face detection aims at automatically finding the face area in the image. If there is a face in the image, it is necessary to find the specific location and scope of human face. Face detection is divided into image-based and video-based face detections. If the input is a still image, then each image will be detected. If the input is a video, then face detection will be required in the entire video sequence.

Feature extraction is established based on face detection, with the input of detected face image. Common features are LBP, HOG and Gabor. HOG [11] is good at description of edge features. It is insensitive to changes in light and small displacements, thus better describing the overall and local face information. LBP [12] is a feature that describes the local texture changes of image, with brightness invariance. Gabo [13] can capture the local structures of spatial location, direction selectivity and spatial frequency, which is suitable for human face description.

Feature dimensionality reduction is the third step of face recognition. Face feature is generally a high-dimensional feature vector. Direct application of high-dimensional feature vector increases the time and spatial complexity, failing to make effective judgment on the description ability of high-dimensional face features. The high-dimensional face feature vector can be projected into low-dimensional subspace, where the information makes the computer complete face feature identification. It is necessary to filter the original features after the feature extraction, thus reducing the dimension of face feature vector.

After the previous links, we compare the face to be identified with the present face database based on a certain matching strategy to finally make a decision. Matching recognition can be expressed as offline learning and online matching models.

3 Face recognition model in cloud computing environment

3.1 Hadoop

Hadoop is distributed system architecture. If Hadoop is used to develop distributed program, we can make full use of cluster storage and computing resources without discussing the details of distributed bottom [14]. Hadoop has become a de facto standard for large data storage and massive data processing. There are many subprojects including Hive, Pig, HBase, Zookeeper, Mahout and Tez. Figure 2 shows a complete ecosystem.

Hadoop contains a Hadoop Distributed File System (HDFS). With the emergence of YARN explorer, Hadoop

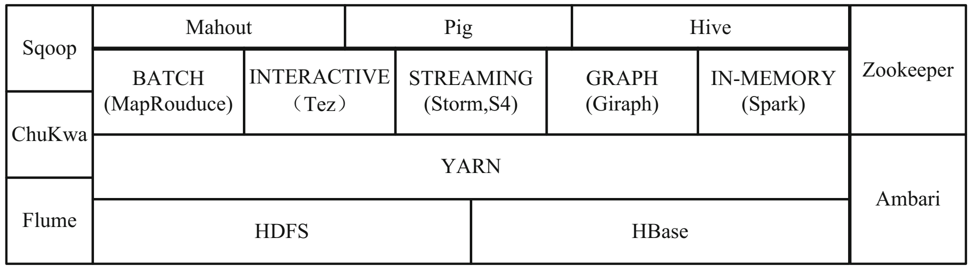


Fig. 2 Hadoop ecosystem

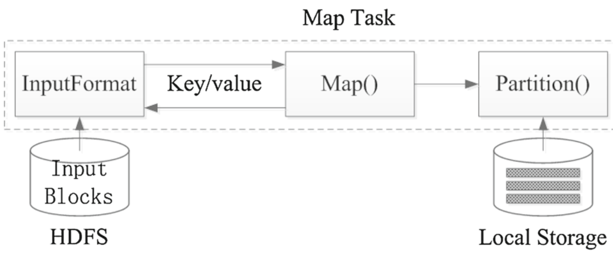


Fig. 3 Map phase

becomes a "cloud operating system" to weaken the dispute of computing framework. Therefore, multiple computing models coexist in the Hadoop platform. MapReduce is a batch offline computing framework; Tez a directed graph computing framework; Spark a memory computing model; Storm a real-time computing framework developed by Twitter; HBase a column family-oriented distributed non-relational database; Hivea a data warehouse suitable for large data set processing.

3.2 MapReduce parallel computing model

MapRedcue is the parallel programming model of Hadoop [15]. The model can take full advantage of the computing resources of cluster to efficiently process the stored data. There are MRv1 and MRv2 in MapReduce architecture. MRv1 is responsible for model calculation, resource and application program management, while MRv2 is only a calculation model. In Hadoop2.0, YARN is responsible for resource management; ApplicationMaster for application program management.

As data processing engine, MapReduce is consistent in MRv2 and MRv1. MapReduce parallel computing model mainly consists of Map and Reduce stages. The local calculation is completed in Map stage where each Split is resolved into multiple key-value pairs by InputFormat. After that, the user-defined Function Map () is called to complete the local calculation. In Map stage, the intermediate results are stored in the local disk, and divided into multiple partitions. Figure 3 shows the execution process of Map stage.

Figure 4 shows Reduce stage which consists of three sub-stages.

(1) In the shuffle stage, intermediate key/value generated from Map stage is read remotely.
(2) In the sort stage, the intermediate keys/values are sorted as the key increases from small to large.
(3) In the function reduce() processing stage, $<$ keylist $<$ value $>>$ is read to deliver Function reduce() for processing, and the results are written to HDFS at last.

The MapReduce model for cloud computing mainly improves the efficiency of calculation by allocating the massive data tasks completed by traditional single computer to multiple computers in the network. Figure 5 shows MapReduce model structure.

4 Face recognition method based on distributed SVM

4.1 SVM algorithm

SVM algorithm is a machine learning method based on the statistical theory. Figure 6 shows the network structure [16]. SVM algorithm can be regarded as a three-layer feedforward neural network with a hidden layer. Firstly, the input vector is mapped from the low-dimensional input to the high-dimensional feature space through the nonlinear mapping. Then, the optimal hyperplane with the largest interval is constructed in the high-dimensional feature space.

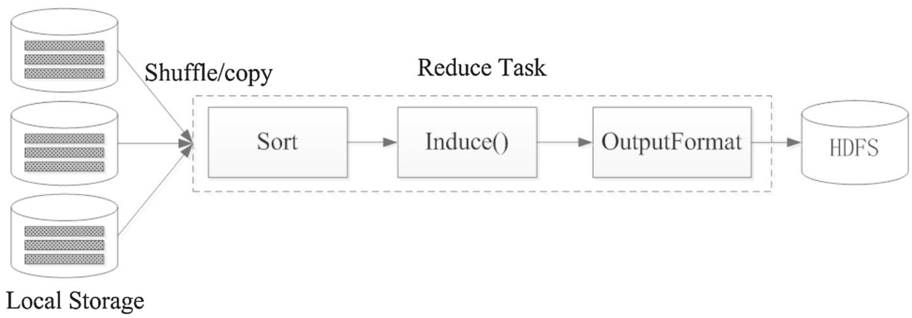
It is assumed that the input vector of SVM $\mathrm{x} = (x_1, x_2, \ldots, x_\mathrm{n})$. The network output of x in output layer is expressed as Eq. (1).

$$\mathrm{y}\,(\mathrm{x}) = \mathrm{sgn}\left(\sum_{i=1}^{N_{train}} y_i \partial_i^* \mathrm{K}\left(x^i, \mathrm{x}\right) + b^*\right) \tag{1}$$

where the inner product function $\mathrm{K}(\mathrm{x}^{(\mathrm{i})}, \mathrm{x})$ satisfying the Mercer condition is a kernel function. The common kernel functions consist of polynomial, Gauss and Aigmoid kernel functions. The Gauss kernel function $\mathrm{K}\,(\mathrm{x}, \mathrm{z}) = e^{\frac{||x-z||^2}{2\sigma^2}}$, where σ is the width function.

The quadratic function optimization problem in Eq. (2) is solved to obtain the optimal parameter vector $\partial^* =$

Fig. 4 Reduce phase



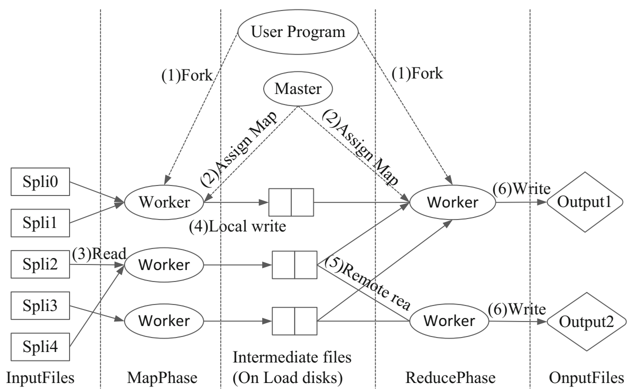


Fig. 5 MapReduce model model structure

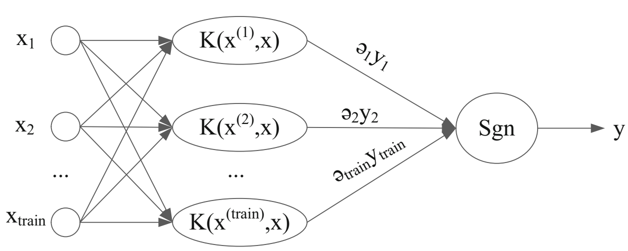


Fig. 6 The network structure of distributed SVM

$(\partial_1^*, \partial_2^*, \ldots, \partial_{N_{train}}^*)^T$ in the discriminant function.

$$\min \frac{1}{2}\left(\sum_{i=1}^{N_{train}}\sum_{i=1}^{N_{train}} \partial_i \partial_j y^i y^j K\left(x^i, x^j\right) - \sum_{i=1}^{N_{train}} \partial_i\right)$$

$$s.t. \sum_{i=1}^{N_{train}} \partial_i y^i \quad i = 1, 2, \ldots, N_{train}$$

$$0 \le \partial_i \le C \tag{2}$$

The training sample x^i corresponding to $\partial^i > 0$ becomes the support vector, and the optimization parameter b^* can be calculated by Eq. (3).

$$b^* = \frac{1}{N_{sv}} \sum_{i \in SV} \left(y^i - \sum_{j \in SV} \partial_j^* K\left(x^i, x^j\right)\right) \tag{3}$$

The research of distributed SVM based on MapReduce model has made some progress. Caruana [17] proposed a SVM spam filtering algorithm based on MapReduce. Alam [18] proposed an image SVM multi-classification algorithm MRSMO based on MapReduce, which obtains high recognition accuracy in solving binary classification and multi-classification problems. Catak [19] proposed a SVM training algorithm based on MapReduce, which obtains the global optimal classifier under finite iteration conditions. Ma [20] proposed an MR-SVM algorithm. Only when all samples at Map end satisfy the KKT condition, the sample can reach global optimization. The global optimal classifier is obtained by multiple iterations. Based on MapReduce calculation model, Alham [21] proposed MRESVM algorithm to shorten the training time, thus maintaining high prediction accuracy.

4.2 LBP feature extraction

4.2.1 Conventional LBP

LBP operator has been widely used in image and face recognition. In the window 3×3, LBP operator calculates the central and neighborhood pixels of window image by the threshold, deriving the binary code of neighborhood and the gray level of new pixel. The LBP coding is calculated as follows [22]:

$$\text{LBP}_{P,R}(x_c, y_c) = \sum_{i=0}^{p-1} S(g_i - g_c) \times 2^i \tag{4}$$

$$S(x) = \begin{cases} 1, x \ge 0 \\ 0, x < 0 \end{cases} \tag{5}$$

$$S(g_i - g_c) = \begin{cases} 1, g_i - g_c \ge 0 \\ 0, g_i - g_c < 0 \end{cases} \tag{6}$$

where g_i is neighborhood pixel value of; g_c the center pixel value; $S(g_i - g_c)$ the threshold; (x_c, y_c) the neighborhood center pixel coordinate; P the number of pixels on the circle with the center of g_c and radius of R.

4.2.2 LBP depth LBP

In the extraction of face recognition feature, the conventional LBP operator has disadvantages including unstable algorithm and overlong image feature length. Therefore, the depth LBP operator is used to compensate for the shortcomings of the conventional LBP operator. The depth LBP takes 8 depth difference images in 8 directions from the LBP calculation image. The center pixel coordinate of each neighborhood is calculated using LBP coding. Center pixels of P depth differences are calculated by Equation (10).

$$\mathrm{D}_{p=0,1,2,\ldots,p-1}^{\mathrm{P,R},p} = \max((g_p - g_c, 7), -8) \quad (7)$$

where g_p is the depth of the circle with the radius of R around the center pixel; g_c i the center pixel depth; $\mathrm{D}_{p=0,1,2,\ldots,p-1}^{\mathrm{P,R},p}$ the image depth difference [23].

4.2.3 Combination of convention and depth LBP operators

Convention and depth LBP operators recognize different face features. Therefore, the weighted approach is used to combine two operators.

$$f = \lambda_1 \times LBP + \lambda_2 \times D - LBP \quad (8)$$

where λ_1 and λ_2 are the weighting coefficients of convention and depth LBP operators, respectively. λ_2 is set to be more than 0.5, which means the depth LBP operator dominates the combined operator [24].

In the work, the weighted approach is used to combine two operators to play their own advantages.

4.3 SVM face recognition processing flow

Traditionally, the face recognition model is established by SVM algorithm in a single computer, where all the computing tasks are completed. This brings high requirement and load to the computer [25–29]. The face recognition model is established by SVM algorithm based on the Hadoop cloud computing platform, which can effectively exploit the computational advantage of the MapReduce model. Figure 7 shows the specific flow. In the MapReduce model, the subsupport vector SVs of training data can be calculated by the Map operation, and then aggregated by the Reduce operation to establish the whole support vector AllSVs. The test process is described as follows. Firstly, the test result Rs of each test data subset can be calculated by the Map operation. After that, the test results are integrated by the Reduce operation to obtain the final recognition result [30].

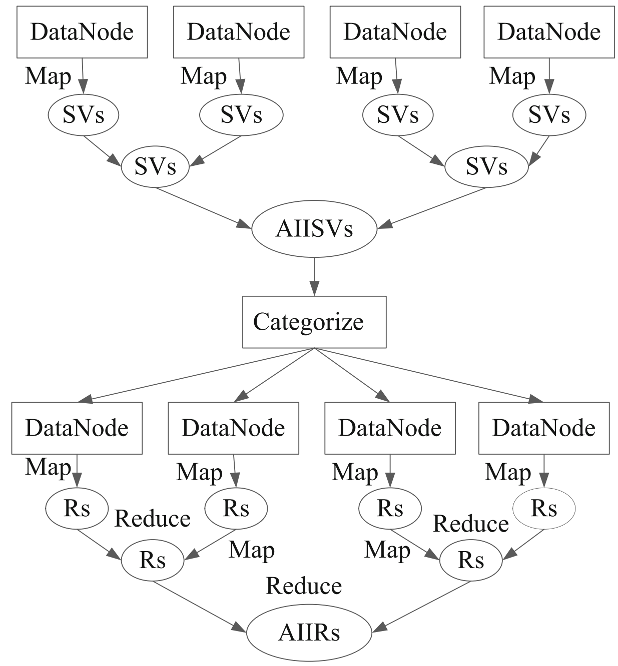


Fig. 7 The process of face recognition for distributed SVM based on Hadoop

5 Example analysis

Examples are used to test the performance of face recognition processing model based on the cloud computing platform including:

No. 1 Host NameNode (CPU: Intel I5 4950; RAM: 16 GB DDR3 1,333 MHz; HD 1 TB); No. 4 Data nodes DataNode (CPU: Intel I3 4170; RAM: 8 GBDDR3 1,333 MHz; HD 500 GB); software platform: Hadoop version 1.0.2.

In the work, the face recognition algorithm under the cloud computing platform is conducted with example analysis by Yale B, ORL and FERET face databases which are most used in face recognition field. The Yale B face database contains image subsets of 38 faces under 64 lights. Figure 8 shows partial samples of the Yale B face database [31,32].

The method in the work is compared with convention and depth LBP operator extraction features by tests. Table 1 shows recognition accuracies of the above three face databases. Figure 9 shows the average recognition rate of three algorithms with the increase of iterations.

The results show that the method in the work has higher recognition accuracy than the traditional method. The reason is that the face feature extraction method in the work can better solve the problems such as overlong face feature length and unstable encoding in convention LBP algorithm. In the work, the integrated algorithm of convention and depth LBP can represent the face feature information at multiple angles. Therefore, it has higher face recogni-

Fig. 8 partial samples of the Yale B face database

Table 1 Average recognition rate of the three database

Arithmetic	Yale B Face database	ORL Face database	FERET Face database
Conventional LBP + Cloud SVM	86.5	81.2	71.6
Deep LBP + Cloud SVM	91.2	88.6	79.2
Conventional LBP + Deep LBP + Cloud SVM	95.6	92.3	88.1

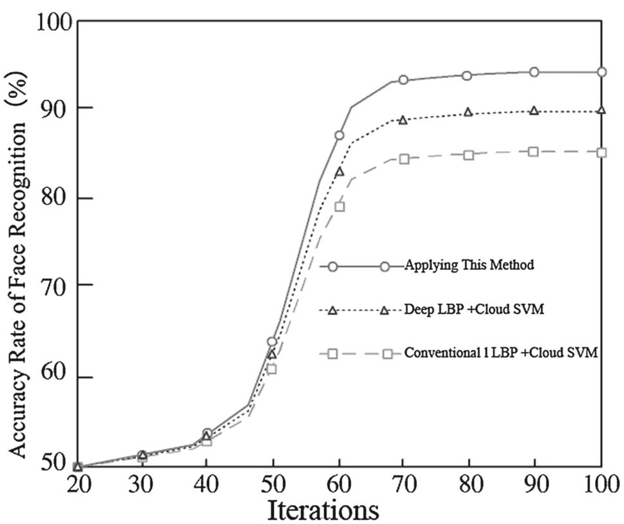


Fig. 9 Average recognition rate of the three method

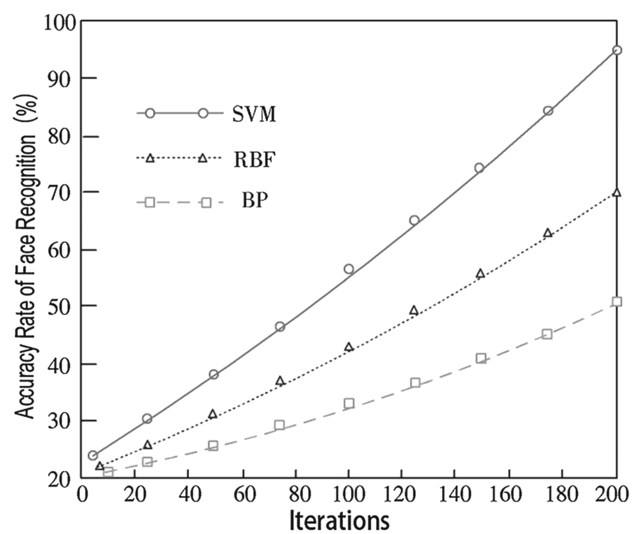


Fig. 10 The contrast of different categorize

tion accuracy than single feature recognition in traditional method.

Based on the same cloud computing platform, the classifier is established by BP and RBF neural networks to compare with face recognition method in the work. Figure 10 shows the average recognition rate of three face databases by three classifiers with the increase of iterations.

The results show that SVM classifier has better effect than that of BP and RBF neural network classifier in face recognition under cloud computing platform. It is illustrated that the multi-layer structure of neural network needs multiple trainings and circulations to obtain the optimal algorithm parameters, which limits its application under cloud computing platform. Under the cloud computing platform, the construction of neural network identification classification model may not increase, but decrease computational efficiency. Therefore, the neural network algorithm is not suitable for MapReduce model.

6 Conclusions

In the work, face recognition model was established based on popular cloud computing Hhadoop platform to improve the recognition efficiency of face recognition method. Then, the convention and depth LBP operators were integrated by weighting approach to play their respective advantages. Finally, the face recognition algorithm under the cloud computing platform was conducted with example analysis by Yale B, ORL and FERET face databases which are most used in face recognition field. Results showed that the method in the work has higher recognition accuracy than that of the traditional method. Based on the same cloud computing platform, the classifier was established by BP and RBF neural networks to compare with face recognition method in the work. Results showed that SVM classifier has better effect than BP and RBF neural network classifier in face recognition under cloud computing platform.

Acknowledgements The paper is subsidized by science and technology key project of Henan Province, NO. 172102210462.

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