

Novel Image Recognition Based on Subspace and SIFT

Tongfeng Sun, Shifei Ding

School of Computer Science and Technology, China University of Mining and Technology, Xuzhou, China

Email: stfok@126.com dingsf@cumt.edu.cn

Zihui Ren

School of Information and Electrical Engineering, China University of Mining and Technology, Xuzhou, China

Email: ren_zicumt@126.com

Abstract—In the light of the deep analyses of subspace recognition and SIFT recognition, a novel image recognition based on subspace and SIFT is proposed to provide a recognition from global features to minutiae features. First, subspace is used to implement coarse image recognition, gaining one or more candidate samples with different identities. Then, a special SIFT recognition environment is designed, in which the approach takes all the images as objects, builds a multi-object sample image with its size limited below a certain size, detects SIFT points based on object regions and recognizes the test image through SIFT point registration statistical vote. The experiments show that the designed SIFT recognition environment can increase SIFT recognition accuracy and the method based on subspace and SIFT can provide accurate recognitions in a mass of images. Under some special environments, recognition accuracy tends to 100%.

Index Terms—subspace recognition, SIFT recognition, region features, registration statistical vote

I. INTRODUCTION

Image recognition is composed of two parts: feature extraction and pattern recognition. Image features include gray/color, texture, edges, transform coefficients or filter coefficients, etc[1]. Pattern recognition as the application on features is mainly to obtain the identities of test data through a classifier. For high-dimensional images, feature extraction is more critical while the classifier is relatively easy to implement, adopting either the nearest-neighbor rule or some pattern recognition algorithms, such as neural network, support vector machines, fuzzy clustering, etc. Human's image recognition is a gradual process: the initial coarse recognition is made to get a brief perception based on global features; the final accurate recognition is further drawn based on minutiae features, which provides a reference for us to use computers to implement image recognition.

Subspace as a global feature extraction method can achieve dimensionality reduction and off-line batch feature extraction, widely applied in various fields, such as computer vision, data mining and pattern recognition[2-5]. Common subspace methods include principal component analysis (PCA), independent

component analysis (ICA), singular value decomposition (SVD), linear discriminant analysis (LDA), non-negative matrix factorization (NMF), etc., whose vital characteristic is to map high-dimensional data to low-dimensional data. In recent years, subspace has been constantly evolving to solve practical problems, such as: tensor subspace, nonlinear kernel subspace, incremental subspace. We take PCA as an example: 2DPCA is proposed to extract features from covariance matrixes instead of on-dimensional image matrixes, which achieves better recognition results in [6-7]; kernel PCA is proposed to map sample data to higher-dimensional space to resolve nonlinear problems in [8-9]; incremental PCA is proposed to implement an approximate update of prime components with low computational complexity instead of relearning all the samples when samples change in [10-11]. In image recognition, subspace can reduce the complexities of computation and storage memory, but doesn't work well in some cases: there are not enough samples; images are shot from different angles; images are partially occluded or deformed. For an instance, in face recognition, we usually get the images with similar poses or dresses, such as two side face images, two glasses-wearing images. Although the complex classifier of neural network [12], vector machine [13], etc., can increase recognition accuracy, its effects are yet unideal and it is also difficult to implement, because it needs search for training samples and establish a training library which can't be achieved in many cases.

Image minutiae are mainly represented as keypoints, edges, etc., among which keypoints have been more extensively studied. SIFT (scale invariant feature transform) is a kind of keypoint detection, proposed by Lowe in 2004[14]. Studies in [15-16] have shown that SIFT, with accurate location and the insensitivity to scale, rotation and illumination invariance, etc., is superior to other local keypoint detections, such as Moravec[17], Susan[18], Harris[19]. Because keypoint registrations are consistent with image recognition in some degree, reflecting common features of two images, Lowe proposed that at least 3 SIFT keypoints be correctly matched from each object for reliable identification. In

fact, SIFT is mainly used in image registration instead of image recognition because of its unideal recognition accuracy[20-22].

In view of the superiority and deficiency of subspace recognition and SIFT recognition, a novel image recognition based on subspace and SIFT is proposed. First, subspace is used to implement coarse recognition, choosing one or more candidate samples (candidate identities). Then the paper designs a SIFT recognition environment, in which we take the test image and the candidate images as objects, build a multi-object image object, detect SIFT points and carry out SIFT registration vote to achieve accurate registration. The method is essentially different from PCA+SIFT proposed by Ke, et al. in [16]. The latter realizes dimensionality reduction of SIFT descriptor through subspace technology to reduce computation complexity and space complexity, while this new method is a combination of subspace and SIFT for different stages in image recognition.

II. IMAGE RECOGNITION BASED ON SUBSPACE

To extract subspace features, images are treated as one-dimensional vectors. Supposing there are N sample gray images, whose sizes are all $p \times q$, each image is converted to a $L \times 1$ row vector ($L = p \times q$), noted as x_i . So, N images constitute a matrix $X = [x_1, x_2, \dots, x_N] \in R^{L \times N}$. Subspace is to find M ($M \ll L$) feature axe vectors constituting a subspace $W = [w_1, w_2, \dots, w_M] \in R^{L \times M}$ by which each sample image and an arbitrary input image can be approximately represented. The projection coefficients of X are their locations in the subspace. So $L - dimension$ vectors are transformed down to $M - dimension$ vectors, which we can be used to achieve further image recognition.

Assuming that recognition applies a nearest-neighbor classifier, subspace recognition is as follows:

(1) to calculate subspace feature axis vectors in accordance with subspace technology;

(2) to project sample images to the subspace as $X' = [x'_1, x'_2, \dots, x'_N] \in R^{M \times N}$;

(3) to input a test image and project it to the subspace as a vector x' ;

(4) according to the distance d between x' and each elements of X' , to match x' with X' . If $d_{\min} < t$ (t is a preset threshold), the identity of the test image can be determined based on its matching sample, namely:

$$\begin{aligned} g(x) &= g(x') = g(x'_k) \\ &= g(\operatorname{argmin}(d(x', X'))) \quad \& \quad d_{\min} < t \quad (1) \end{aligned}$$

where $x'_k \in X'$.

Subspace has been widely used in image recognition, especially for face recognition. It reduces memory

storage and increases running speed. But a large number of experiments have shown that subspace recognition is sensitive to pose, occlusion, background, etc. And when samples are insufficient, recognition rate is unideal.

III. IMAGE RECOGNITION BASED ON SIFT

SIFT recognition includes keypoint detection, keypoint description keypoint registration and object recognition, detailedly discussed in [14]. To efficiently detect stable keypoints in scale space, Lowe proposed scale-space extrema in difference-of-Gaussian scale space, which can be computed from the difference of two adjacent Gaussian-scale images separated by a multiplicative constant factor. Following are the major stages of computation:

(1) to built a Gaussian pyramid and a difference-of-Gaussian pyramid, consisting of some octaves each of which is further composed of some levels;

(2) to detect keypoints. In the stage, SIFT searches over all scales and image locations to identify potential interest points that are extrema at the current and adjacent scales;

(3) to localize, orient and describe keypoints. The method further determines the locations and scales of candidate keypoints and selects keypoints according to their stability. Then one or more orientations are assigned to each keypoint based on local image gradient directions. All following operations are based on image data that has been transformed relative to the assigned orientation, scale, and location for each feature. The keypoint descriptions are acquired on a local image gradients at the selected scale in the region around each keypoint allowing for significant levels of local shape distortion and change in illumination;

(4) to register keypoints. To keep one keypoint distinct from other keypoints, they are registered by the feature ratio between the nearest neighbor distance and the second-nearest neighbor distance;

(5) to recognize the test image. At least 3 features should be correctly registered from each object for reliable identification. Then, each registration cluster is further checked by performing a detailed geometric transform.

A complex image can be segmented into one or more independent some different parts each of which consists of nearby pixels with some practical significance, called an object in this paper (background can also be seen as an object). SIFT recognition is a kind of statistical matching based on keypoint registration, in which accurate keypoint registration is the premise of object recognition. It often takes place in two cases. In one case, the known image is a single-object image while the test image is a multi-object image. Our task is to find a object from the test image, which has the same identity with the known image. In another case, the known image is a multi-object image while the test object is a single-object image. Our task is to find the best matching object from the known image, which has the same identity with the test image. This paper focuses on the second case. Although SIFT point registration is superior to Susan, Moravec, Harris,

etc., SIFT can't be used for a great number of images and will lead to some recognition failures, including false registration or registration-missing. The reasons for the failure are mainly reflected in the following four aspects:

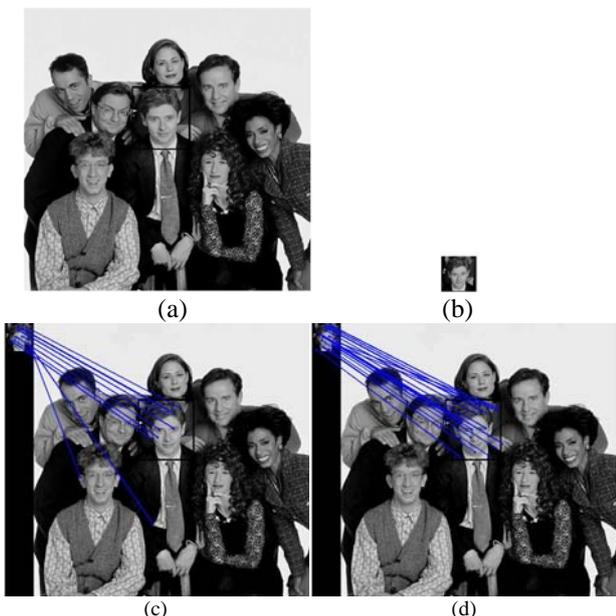


Fig.1 Registration based on global feature and object-region feature respectively



Fig. 2 Optimal SIFT image registration

(1) SIFT points possesses both regional features and global features, among which global features result in recognition failures. When detecting keypoints, scale space is built by image smoothing and downsampling. So, the larger the scale is, the more obvious the global feature is. For different images, their global features are different. In Fig. 1, Fig. 1(a) is a multi-object image, chosen from CMU face database [23]. An object in the rectangle box from Fig. 1(a) is picked out and transformed by an affine transform $H = [0.45 \ 0 \ 0; -0.05 \ 0.45 \ 0; 0 \ 0 \ 1]$ to gain Fig. 1(b) as a test object. Because Fig. 1(a) is divided into two parts: region (i) in the rectangle box and region (ii) outside the rectangle box, SIFT points in Fig. 1(a) can be detected in two ways: on the combined image of region (i) and (ii) (global feature extraction); on region (i) and (ii) respectively (object-region feature extraction). Fig. 1(c) and Fig. 1(d) are the registration results of Fig. 1(b), (a) according to global features and object-region features respectively. It can be seen that global feature registration gets 9 pairs of keypoints (three pairs are false) while object-region feature registration gets 19 pairs (only one

pair is false). It is clear that object features are much better than global features. The appropriate uses of object-region feature extraction in image recognition will help to improve recognition effects.

(2) SIFT registration is an optimal matching, supposing that there is a statistical matching object in the multi-object image for the test object. If there is no matching object in the multi-object image, it will produce some false registrations. As in Fig. 2, although there is no matching object for the test object in the multi-object image, the method gets some keypoint registrations according feature ratio between the nearest distance and the second-nearest distance, leading to some false registrations.

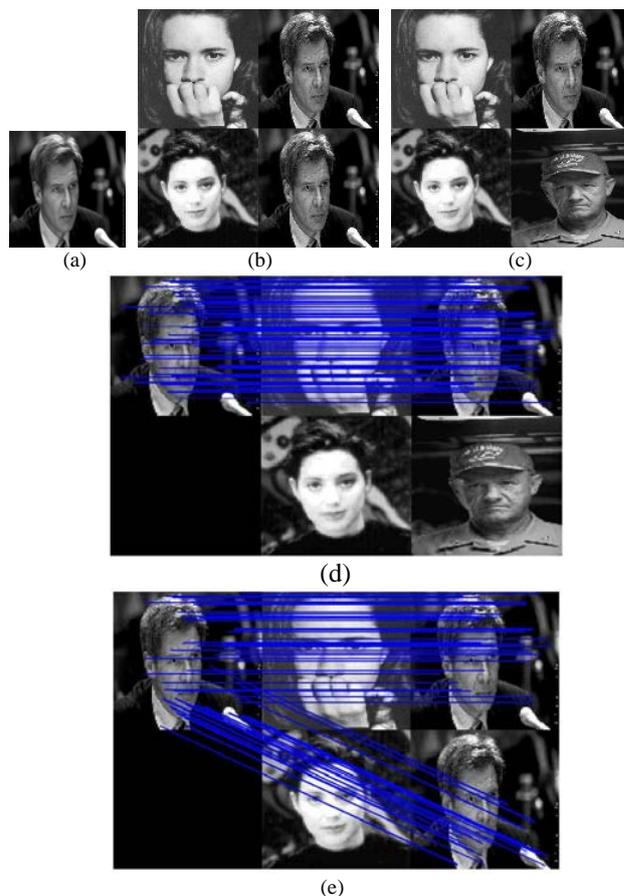


Fig. 3 Registration when the sample image contains more of the same statistical matching objects

(3) For the multi-object image with more of the same statistical matching objects, the rule of ratio between the nearest distance and the second-nearest distance will lead to registration failure. As shown in Fig. 3, Fig. 3(a) is a test image and Fig. 3(b), (c) are two artificial multi-object images containing four sample objects. Fig. 3(b) contains one matching object for Fig. 3(a) while Fig. 3(c) contains two matching objects for Fig. 3(a). Fig. 3(d) is the registration results between Fig. 3(a) and (b), getting 84 pairs of registered keypoints while Fig. 3(e) is the registration results between Fig. 3(a) and (c), getting 64 pairs of registered keypoints. It can be seen that when the sample image contains more than one of the same objects,

registration effect will degrade.

(4) Due to the high space complexity and computation complexity of SIFT, we will be confronted with computation and memory disasters with image size increasing. We take Fig. 1(a) as an example and implement image zooming by linear interpolation. When image size changes from 100×100 to 1100×1100 , we record required memory and running time, as shown in Fig. 4. It can be seen that running time and required memory are proportional to with the square of image's side. When the image size reaches 1000×1000 , the required memory exceeds 400MB and the running time is over 20 seconds. If the size increases more, PC will not normally run.

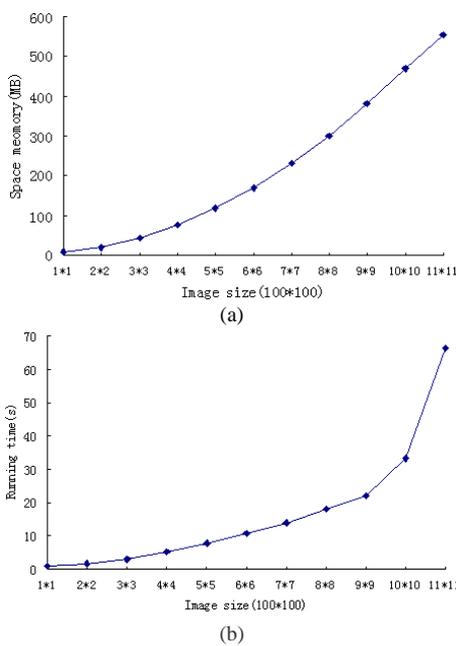


Figure 4. Relationship between image size and memory/ computation time

IV IMAGE RECOGNITION BASED ON SUBSPACE AND SIFT

A. Improved SIFT Recognition in A Special Recognition Environment

In improved SIFT recognition, the main task is to designed a special recognition environment to improve its accuracy. We assume that each sample has a definite identity and multiple samples may have the same identity. N sample images constitute a matrix $X = [x_1, x_2, \dots, x_N] \in R^{L \times N}$, identified as $G = [g_1, g_2, \dots, g_N]$. The test image and the sample images are projected to a subspace, getting x' and $X' = [x'_1, x'_2, \dots, x'_N] \in R^{M \times N}$. According to the distances between x' and $X' = [x'_1, x'_2, \dots, x'_N] \in R^{M \times N}$, the samples are ordered from minimum to maximum, getting $X'' = [x''_1, x''_2, \dots, x''_N]$ with the identities

$G'' = [g''_1, g''_2, \dots, g''_N]$. Based on the nearest-distance principle, V samples $X''' = [x'''_1, x'''_2, \dots, x'''_V]$ having different identities are selected for further recognition. Multiple candidate samples can increase the probability of subsequent accurate image recognition. For simplicity, $X''' = [x'''_1, x'''_2, \dots, x'''_V]$ is noted as $X = [x_1, x_2, \dots, x_V]$ with the corresponding identities as $G = [g_1, g_2, \dots, g_V]$ in the later chapters.

Both the test image and the candidate samples are all called as objects. The goal of SIFT recognition is to find an object with the same identity with the test object from the multi-object sample image. SIFT image recognition can be effectively improved by setting specific recognition environment. The environment is as follows:

- (1) to resize the candidate samples to the same size and build a multi-object images $I = [x_1, x_2, \dots, x_V]$ mosaicked along image column or row by subspace distance order;
- (2) to detect SIFT keypoints in the test object x and each sample object x_1, x_2, \dots, x_V ;
- (3) to zoom in/out the image x and I through a unified interpolation, keeping image size (mainly referring to I) less than 1000×1000 ;
- (4) Each candidate object has an exclusive identity;
- (5) to recognize the test object by SIFT keypoint registration statistical vote.

Above restrictions can effectively improve SIFT registration effects, overcoming registration failure: reducing the influences of global features; ensuring that the multi-object sample image contains a statistical matching object with high probability; ensuring that the multi-object sample image doesn't include multiple identical objects; keeping image size within a certain scope.

After the detection of the keypoints based on each object, all the objects are replace by keypoints descriptors. Then the test object and the multi-object image are expressed as s and $S = [s_1, s_2, \dots, s_V]$ respectively. Each descriptor vector of a keypoint in s is registered in S according to the ratio between the nearest distance and the second-nearest distance. The amounts of registered keypoints in each sample object are noted as r_1, r_2, \dots, r_V , called keypoint registration statistical vote in this paper. The sample object with the registration maximum is chosen as the final matching object, whose identity is the identity of the test object, described as:

$$g(x) = g(x_k) = g(\arg \max(r)) \quad (2)$$

where $x_k \in X$.

Experimental data are chosen from Indian female face database[24] to verify the improved SIFT recognition. Each experiment chooses 4 images, as the simulation of subspace recognition result. Among them, two images belong to one individual as a test object and a sample

object respectively, and other two images belong to different individuals as sample objects. Three sample objects compose a multi-object image. Keypoints are detected based on each object and then the keypoints of the test object is registered with the keypoints of sample objects. In Fig. 5 (a), the test image is a positive face image whose matching object is a nearly 30 degree profile image. The amounts of registered keypoints between the test object and each sample object are as follows: 3, 0, 19. According to statistical vote, we can draw a conclusion that the test object is matched with the third sample object. In Fig. 5(b), the test object is a 30-

degree-left profile image whose matching object is a right-side profile object. The method can realize accurate recognition, especially for symmetric images, such as face images. Even for two face images with the same identity swinging 45 degrees left and right respectively, the method is still able to correctly recognize. 100 experiments are carried out on Indian Female face database, whose accuracy rate approximately tends to 100%. In the designed environment of this chapter, we can deem that the improved SIFT recognition can achieve fully accurate image recognition.

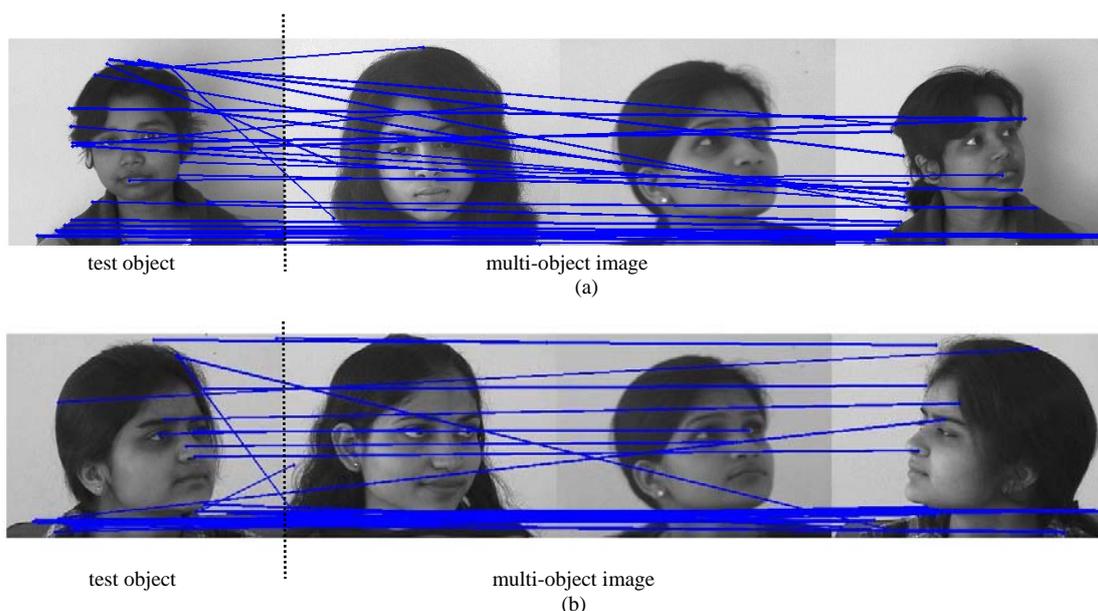


Figure 5. SIFT registration vote recognition

B. Image Recognition Based on Subspace and SIFT

Image recognition based on subspace and SIFT can resolve image recognition among a mass of images, including two steps: the subspace coarse recognition choosing candidate sample objects; SIFT precise recognition getting the matching object of the test image. According to the nearest-neighbor principle, subspace recognition selects candidate images with different identities from a sample gallery. Based upon subspace results, SIFT recognition searches for the best matching sample by SIFT keypoint registration statistical vote in a designed environment. The detailed steps are as follows:

- (1) to extract feature vectors in accordance with selected subspace technology;
- (2) to project the test object and the sample objects to the subspace. Then get candidate sample objects with different identities by the nearest neighbor classifier;
- (3) to build a candidate multi-object image, detect keypoints in test object and each sample object, and register keypoints in accordance with the feature ratio between the nearest distance and the second-nearest distance;
- (4) to count registered keypoints in every sample object and choose the object with registration maximum

as the final matched object whose identity is the test object's identity according to voting principle.

V. EXPERIMENTS

The method is implemented through MATLAB language. Due to the abundance of face images, experimental data are chosen from face images selected from ORL[25] and Indian Female face databases. Experiments are carried out to compare subspace+SIFT (PCA+SIFT, PCA+ICA and PCA+LDA) with subspace (PCA, ICA, IDA) to verify the performances of subspace+SIFT recognition in a mass of images.

A. Face Recognition in ORL Database

ORL Database contains a set of face images, in which there are ten different images of each of 40 distinct subjects. Images were taken at different time against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement), varying in the lighting, facial expressions (open/closed eyes, smiling/not smiling) and facial details (glasses/no glasses).

We randomly choose two images for 20 individuals and choose one image for the remaining 20 individuals,

totally gaining 60 sample objects. Then the test object is chosen from the remaining face database.

PCA, ICA, LDA select a sample object as matching result according to the nearest-distance principle. In subspace+SIFT, it first chooses multiple distinct candidate samples with different identities similarly to subspace recognition. Then it designs a special environment, in which we build a multi-object image, detect SIFT features based on object and determine final matching object by voting, whose identity is the identity of the test object. Here, we take PCA and PCA + SIFT as an example. As shown in Fig. 6(a), in which a multi-object image is built along the candidate objects' rows by subspace-distance order, PCA recognition gets a false result--the first object in the multi-object images, while PCA+SIFT gets a correct results with the test object

matched with the second candidate object. Similarly in Fig. 6(b), the test object is matched with the first object in PCA while matched with the third candidate in SIFT keypoint vote.

Experimental results are shown in Table I. It is clear that subspace+SIFT is superior to subspace, such as PCA, ICA and LDA. Its recognition accuracy can reach 95% and an appropriate increase in the amount of candidates can help improve recognition accuracy. When the candidate amount reaches 5, recognition accuracy is close to 100% in the designed experimental environment.

As concerning computation and space complexity, if subspace vectors have been gained in advance, the required running time and memory are mainly caused by SIFT, nearly needing 15M Bytes and 1.2s respectively, which can meet actual application needs.

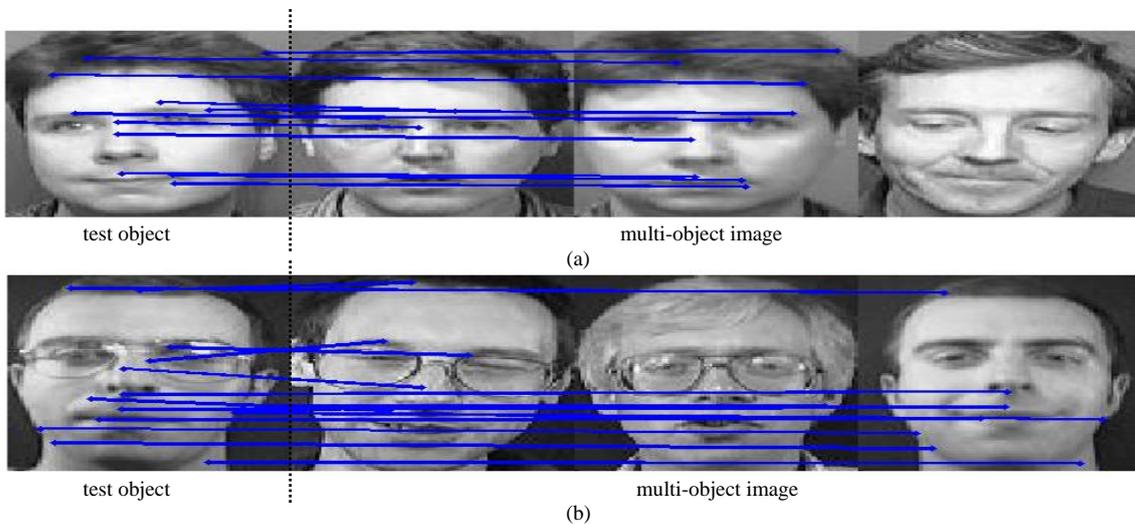


Figure 6. PCA+SIFT face Recognition in OR database

TABLE I. SUBSPACE AND SUBSPACE+SIFT FACE RECOGNITION ACCURACY IN ORL DATABASE

	PCA	ICA	LDA	PCA+SIFT	PCA+ICA	PCA+LDA
Recognition accuracy	75	78	78	95	95	95

B. Noise Face Recognition in Indian Female

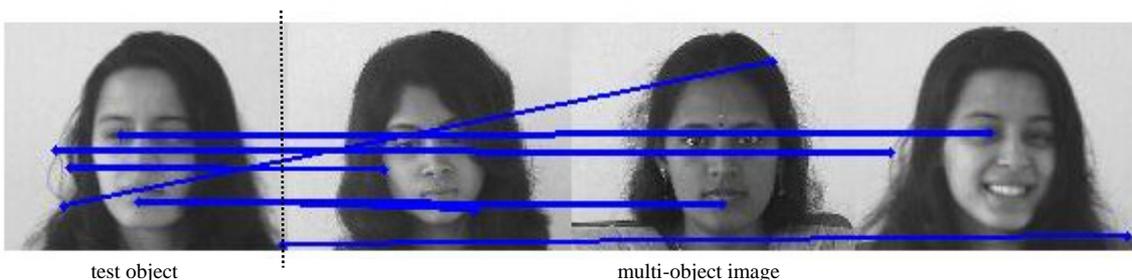


Figure 7. PCA+SIFT face Recognition in Indian female database

TABLE II. SUBSPACE AND SUBSPACE+SIFT FACE RECOGNITION ACCURACY IN INDIAN FEMALE DATABASE

	PCA	ICA	LDA	PCA+SIFT	PCA+ICA	PCA+LDA
Recognition accuracy	72	76	82	92	93	93

Indian female database contains images of 40 distinct subjects with nearly eleven different poses for each individual (some with a few additional images). For each individual, it includes the following poses: looking front, looking left, looking right, looking up, looking up towards left, looking up towards right, looking down. In addition to the variation in pose, images with four emotions - neutral, smile, laughter, sad/disgust - are also included for every individual. All the images are added Gaussian noise with its mean 0 and its variance 0.0001. Two images per individual are chosen as samples objects and the test image is randomly selected from the remaining database. Similarly to last section, we take PCA and PCA+SIFT as an example. As in Fig. 7, PCA gets a false result, matching the test object with the first object in the multi-object image, while SIFT keypoint vote gets a correct result, matching the test object with the third object. A large number of experimental results are shown in Table II. It can be seen that the method is not sensitive to noise and can significantly improve image recognition accuracy, reaching 92%. When the amount is 5 in the designed environment experiment, the recognition accuracy is close to 100%. And when all the images are resized to 320×240 , the method nearly needs 260MB storage and 13s running time.

VI. CONCLUSION

Subspace recognition is a kind of global feature recognition while SIFT recognition is a kind of minutiae registration recognition. The combination of above two recognitions is consistent with human recognition process from coarse to precise. Subspace can improve image processing speed through dimension reduction and filter out possible candidate images from database. SIFT recognition takes the test image and the candidate sample images as objects, build a multi-object image and match the test object with all candidates based on objects by keypoint registration vote. Experiments show that subspace+SIFT is superior to corresponding subspace.

The method still has some areas for further improvement, mainly in one aspect: the premise of correct recognition is that the candidate samples gained in subspace recognition should contain the matching object of the test object, otherwise SIFT recognition will fail. And the approximate increase of candidate sample objects can improve the final recognition accuracy, but it will increase calculation complexity and space complexity.

ACKNOWLEDGMENT

The authors would like to thank the editor and the anonymous reviewers for their valuable comments and constructive suggestions. This paper is jointly supported by the National Key Basic Research Program of China (No. 2013CB329502), the National Natural Science Foundation of China (No. 51104157, 41074003) and the Ph.D. Programs Foundation of Ministry of Education of China (No. 20110095120008).

REFERENCES

- [1] Yu D., Wei W., Zhang Y-H., "Mean Shift Tracking Algorithm Based on Multi-Feature Space. *Pattern Recognition and Artificial Intelligence*", 22(4), pp. 666-672, 2009.
- [2] Golub G. H., Van Loan C. F., "Matrix Computations", Johns Hopkins University Press, Baltimore, 1989.
- [3] Turk M. A., Pentland A., "Eigenfaces for Recognition", *Journal of Cognitive Neuroscience*, 3(1), pp. 71-86, 1991.
- [4] Men H., Zhang P., Zhang C., et al., "An electronic tongue system for recognition of mineral water based on principle component analysis and wavelet neural network", *Journal of Computers*, 6(12), pp. 2692-2699, 2011.
- [5] Lang L., Jing X., "Application of Non-negative Sparse Matrix Factorization in Occluded Face Recognition", *Journal of Computers*, 6(12), pp. 2675-2679, 2011.
- [6] Wang L., Wang X., Zhang X., et al. "The equivalence of two-dimensional PCA to line-based PCA", *Pattern Recognition Lett*, 26 (1), pp. 57-60, 2005.
- [7] Meng J., Zhang W., "Volume measure in 2DPCA-based face recognition", *Pattern Recognition Letters*, 28(10), pp. 1203-1208, 2007.
- [8] Kirby M., Sirovich L., "Application of the KL procedure for the characterization of human faces". *IEEE Transaction on Pattern Analysis Machine Intelligence*, 12 (1), pp. 103 - 108, 1990.
- [9] Debruyne M., Hubert M., Horebeek J. V., "Detecting influential observations in Kernel PCA". *Computational Statistics & Data Analysis*, 54(12), pp. 3007-3019, 2010.
- [10] Li Y., "On incremental and robust subspace learning", *Pattern Recognition*, 37(7), pp. 1509-1518, 2004.
- [11] Kim M., "Correlation-based incremental visual tracking". *Pattern Recognition*, 45(3), pp. 1050-1060, 2012.
- [12] He F., Ma C., "Modeling greenhouse air humidity by means of artificial neural network and principal component analysis". *Computers and Electronics in Agriculture*, 71(Supplement 1), S19-S23, 2010.
- [13] Chang C., Wang H., Li C., "Semantic analysis of real-world images using support vector machine Expert Systems with Applications", 36(7), pp. 10560-10569, 2009.
- [14] Lowe D. G., "Distinctive image features from scale-invariant keypoints", *International Journal of Computer Vision*, 60(2), pp. 91-110, 2004.
- [15] Mikolajczyk K., Tuytelaars T., Schmid C., et al., "A comparison of affine region detectors and descriptors", *International Journal of Computer Vision*, 65(1), pp. 43-72, 2005.
- [16] Ke Y., Sukthankar R., "PCA-sift: A more distinctive representation for local image descriptors", *Proceedings IEEE CVPR*, pp. 511-517, 2004.
- [17] Moravec H. P., "Towards automatic visual obstacle avoidance", *IEEE International Conference on Robotics and Automation C*, pp. 584-596, 1977.
- [18] Smith S M, Brady J M., "SUSAN-a new approach to low level image processing", *International Journal of Computer Vision*, 23(1), pp. 45-78, 1997.
- [19] Harris C., Stephens M., "A combined corner and edge detector", *Proceedings of the 4th Alvey Vision Conference*, Manchester, UK: Manchester, pp. 147-162, 1988.
- [20] Krish K., Heinrich S., Snyder W. E., et al. "Global registration of overlapping images using accumulative image features", *Pattern Recognition Letters*, 31(2), pp. 112-118, 2010.
- [21] González-Aguilera D., Rodríguez-González P., Hernández-López D., et al. "A robust and hierarchical approach for the automatic co-registration of intensity and

- visible images”, *Optics & Laser Technology*, 44(6), pp. 1915-1923, 2012.
- [22] Zeng L., Deng D., Chen X., “A Self-adaptive and Real-time Panoramic Video Mosaicing System”, *Journal of Computers*, 7(1), pp. 218-225, 2012.
- [23] Rowley H. A., Baluja S., Kanade T., “CMU image database: face”, http://vasc.ri.cmu.edu/idb/images/face/frontal_images/images.tar, 2012.
- [24] Jain V., Mukherjee A., “The Indian Face Database”, <http://vis-www.cs.umass.edu/~vidit/IndianFaceDatabase/>, 2012.
- [25] ORL, <http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html>, 2012.

Tongfeng Sun received the BS degree in industry automation from Northwestern Polytechnical University, the MS degree in Computer application technology in 2004 and the PhD degree in Detection technology and automation devices in 2012 from China University of Mining and Technology. He currently work as a teacher in the university. His research interests are in the areas of data mining, machine learning and information system.

Shifei Ding received his bachelor's degree and master's degree from Qufu Normal University in 1987 and 1998 respectively. He received his Ph.D degree from Shandong

University of Science and Technology in 2004. He received postdoctoral degree from Key Laboratory of Intelligent Information Processing, Institute of Computing Technology, Chinese Academy of Sciences in 2006. And now, he works in China University of Mining and Technology as a professor and Ph.D supervisor. His research interests include intelligent information processing, pattern recognition, machine learning, data mining, and granular computing et al. He has published 3 books, and more than 80 research papers in journals and international conferences.

Prof. Ding is a senior member of China Computer Federation (CCF), and China Association for Artificial Intelligence (CAAI). He is a member of professional committee of distributed intelligence and knowledge engineering, CAAI, professional committee of machine learning, CAAI, and professional committee of rough set and soft computing, CAAI. He acts as an editor for *Journal of Convergence Information Technology (JCIT)*, *International Journal of Digital Content Technology and its Applications (JDCTA)*. Meanwhile, he is a reviewer for *Journal of Information Science (JIS)*, *Information Sciences (INS)*, *Computational Statistics and Data Analysis (CSTA)*, *IEEE Transactions on Fuzzy Systems (IEEE TFS)*, *Applied Soft Computing (ASOC)*, *Computational Statistics and Data Analysis (CSDA)*, *International Journal of Pattern Recognition and Artificial Intelligence (IJPRAI)* et al.