International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol. 6, No. 3, June, 2013

Face Recognition Based on Image Latent Semantic Analysis Model and SVM

Jucheng Yang [1, 2], Min Luo[3] and Yanbin Jiao[4]

[1]*Ahead Software Company Limited, Nanchang, 330041, China*
[2]*College of Computer Science and Information Engineering, Tianjin University of Science and Technology, Tianjin, China*
[3]*Jiangxi Institute of Computing Technology, Nanchang, China*
[4]*School of Information Technology, Jiangxi University of Finance and Economics, Nanchang, China*

yangjucheng@hotmail.com

Abstract

In this paper, we propose a novel and effective image model—Image Latent Semantic Analysis (ILSA) for extracting latent semantic features of face image, and recognizing face with Support Vector Machine (SVM). The novel feature extraction by the ILSA model can be better overcome the impact of some negative factors, such as the image quality fuzzy, illumination changes effect. The main contribution of the paper is that the ILSA features can obtain a wealth of information than the conventional image semantic features and has a stronger expression and classification abilities than the low-level features. The experimental results on the ORL and large-scale FERET databases show that the proposed algorithm significantly outperforms other well-known algorithms.

Keywords: *face recognition; LSA; image latent semantic analysis; SVM*

1. Introduction

With many applications in various fields, face recognition technology has received a great deal of attention over the decades in the field of image analysis and computer vision. One of the key challenges for face recognition is to explore efficient and discriminative appearance descriptors that are resistant to large variations in illumination, pose, facial expression, aging, partial occlusions and other changes [1]. Most current face recognition systems use the holistic and local features methods [1]. Popular representation holistic methods for face recognition which consider the whole attribute of the image model include Principal Component Analysis (PCA), Kernel PCA (KPCA), Hidden Markov Model (HMM) and Fisher Linear Discriminant Analysis (FLDA) [2]. These methods based on the whole face not only retain the topological relationship between the different components of the face, but also retain the information of the components themselves. However, the holistic methods extract the global properties which are influenced constantly by the light, noise and pose change. Local characteristics are insensitive to the illumination, expression and shelter which are more and more used to face recognition. The popular and successful local appearance descriptors include the Gabor Wavelets [3], Local Binary Pattern (LBP) [4], Local Non-negative Matrix Factorization (LNMF) and Local Gabor Binary Pattern (LGBP) [6] and so on. To sum up, the holistic and local features methods have been widely used in recent years. Physiology and psychology researchers show that both of the two methods are necessary for face recognition [7]. So many researchers proposed to use the global and local features to represent face [5]. Such as the Elastic Bunch Graph Matching (EBGM) [14], Local Feature Analysis (LFA) [13] achieves good effect. There are some semantic features between the fusion features which are more conforming to the human understanding of the image content. Therefore, it is need to explore some novel features of the face image from the fusion features.

In recent years, contents based image analysis attracts the attentions of the researchers. The most important step is the semantic analysis. The semantic features which are obtained through the semantic analysis reflect the essential characteristics of image [8]. In additional, face expression, illumination, shelter can be regarded as the face semantic features for the human face. And these semantic features obtained from the texture or shape of the low-level. So the face semantic features can be extracted by mapping from the low-feature of the face image to improve the face recognition accuracy. However, there are some defects for face image because the low-feature and the semantic feature are not always one-to-one relationship. In order to avoid this kind of defects, researchers introduce the Latent Semantic Analysis (LSA) into this mapping mode to fill the gap between low-feature and high-level semantic feature [9]. Similarly, LSA also attracts some researchers' attentions in the image analysis field [10-11]. The LSA can solve some of the biometric image that does not contain obvious semantic features. Although these studies have made some achievements, there are obvious shortcomings in the LSA-based image extraction. (1) Only use single low-level features to represent the image are difficult to get accurate latent semantic features. (2) The feature-image matrix is a two-dimensional matrix, if we use the 1D-PCA, 1D-NMF (1D-Nonnegative Matrix Factorization), or SVD (Singular Vector Decomposition) method for feature reduction, large amounts of the structure information of the feature-image will be lost.

Considering the above analysis, this paper proposes a novel and effective model for face recognition which is called Image Latent Semantic Analysis (ILSA). First of all, some feature extraction methods such as Gabor Wavelets [3], Hu invariant moment [17] and Local Ternary Pattern (LTP) [12] are used to extract the low-features. Then, construct the Feature-Image matrix and decompose the matrix with the 2D-PCA [16]. The last results are the Image Latent Semantic Features (ILSF) which are trained and tested by the Support Vector Machine (SVM). The experiment results show that this new method can improve the accuracy of face recognition, especially for the face image in complex environment.

The organization of the rest of the paper is as below. Section 2 briefly introduces the theory of LSA. In Section 3, the proposed method is explained in details. In Section 4, the experimental results are analyzed. At the last, conclusions are drawn in Section 5.

2. Related Theory

2.1. Latent Semantic Analysis

Latent semantic concept was firstly proposed in the text information retrieval and K.L. Tomas *et al.*, [9] proposed the Latent Semantic Analysis (LSA) method. LSA can be regarded as a kind of extended vector space analysis model which decomposes the Term-Document matrix through the Singular Value Decomposition (SVD).

First of all, we may get a Term-Document matrix $M_{m\times n}$ according to the analyzed document data when we analyze the document, where m is the number of word in the analyzed document and n is the number of document. The Term-Document matrix is shown in Figure 1.

Terms	Document								
	C1	C2	C3	C4	C5	M1	M2	M3	M4
Human	1	0	0	1	0	0	0	0	0
Interface	1	0	1	0	0	0	0	0	0
Computer	1	1	0	0	0	0	0	0	0
User	0	1	1	0	10	0	0	0	0
System	0	1	1	2	0	0	0	0	0
Response	0	1	0	0	1	0	0	0	0
Time	0	1	0	0	1	0	0	0	0
EPS	0	0	1	1	0	0	0	0	0
Survey	0	1	0	0	0	0	0	0	1
Trees	0	0	0	0	0	1	1	1	0
Graph	0	0	0	0	0	0	1	1	1
Minors	0	0	0	0	0	0	0	1	1

Figure 1. Term-Document Matrix

The main principle of the method is to decompose the Term-Document matrix $M_{m\times n}$ through SVD to map the high dimension of vector space model into low dimensional latent semantic space. SVD decomposes the matrix $M_{m\times n}$ by the formula: $M = WSD^T$, where matrix W is the feature vector matrix, which is derived by the relationship MM^T matrix constituted between term and term, and matrix D^T is the feature vector matrix, which is derived by the transposed $M^T M$ constituted between document and document. Matrix S is a singular value diagonal matrix r×r, and $r = \min(m,n)$,which is the rank of matrix M.

Terms	Document								
	C1	C2	C3	C4	C5	M1	M2	M3	M4
Human	**0.1621**	**0.4005**	**0.3790**	**0.4676**	**0.1760**	**-0.0527**	**-0.1151**	**-0.1591**	**-0.0918**
Interface	**0.1406**	**0.3698**	**0.3290**	**0.4004**	**0.1650**	**-0.0328**	**-0.0706**	**-0.0968**	**-0.0430**
Computer	**0.1524**	**0.5050**	**0.3579**	**0.4101**	**0.2362**	**0.0242**	**0.0598**	**0.0869**	**0.1240**
User	**0.2580**	**0.8411**	**0.6057**	**0.6974**	**0.3923**	**0.0331**	**0.0832**	**0.1218**	**0.1874**
System	**0.4488**	**1.2344**	**1.0509**	**1.2658**	**0.5563**	**-0.0738**	**-0.1547**	**-0.2096**	**-0.0489**
Response	**0.1596**	**0.5817**	**0.3752**	**0.4169**	**0.2765**	**0.0559**	**0.1322**	**0.1889**	**0.2169**
Time	**0.1596**	**0.5817**	**0.3752**	**0.4169**	**0.2765**	**0.0559**	**0.1322**	**0.1889**	**0.2169**
EPS	**0.2185**	**0.5496**	**0.5110**	**0.6281**	**0.2425**	**-0.0654**	**-0.1425**	**-0.1966**	**-0.1079**
Survey	**0.0969**	**0.5321**	**0.2299**	**0.2118**	**0.2665**	**0.1368**	**0.3146**	**0.4444**	**0.4250**
Trees	**-0.0613**	**0.2321**	**-0.1389**	**-0.2656**	**0.1449**	**0.2404**	**0.5461**	**0.7674**	**0.6637**
Graph	**-0.0647**	**0.3353**	**-0.1456**	**-0.3014**	**0.2028**	**0.3057**	**0.6949**	**0.9766**	**0.8487**
Minors	**-0.0431**	**0.2539**	**-0.0967**	**-0.2079**	**0.1519**	**0.2212**	**0.5029**	**0.7069**	**0.6155**

Figure 2. New Term-Document Matrix

Assume that the k biggest singular values of the matrix S are consistent with the corresponding column of the matrix W and matrix D^T . If the other singular values are moved, then the final matrix is M_k , whose rank is k. The matrix M_k is completely similarity with initial matrix $M_{m\times n}$ in some aspects. So the matrix can be written as $M_k = W_k S_k D_k^T$, where *k* is the dimension of the semantic space. The parameter *k* is the key index which is determined by experiments. When the value of k is 2, the new Term-Document matrix M_k is shown in Figure 2.

From the Figure 2, we can see that the term 'Human' in the Document 'C2' and 'C3' are zero in the matrix M, while they are non-zero in the new matrix M_k. That means that it has a litter appearance in document 'C2' and 'C3'. And the same, the term "User" is non-zero in 'C1' in the new matrix. And terms "Human" and "User" represent the same meaning of "people". So this may due to the latent semantic between the two terms.

The relationship between any two documents in the k dimension reduction space can be obtained by:

$$M_k^T M_k = (W_k S_k D_k^T)^T W_k S_k D_k^T = D_k S_k W_k^T W_k S_k D_k^T \tag{2.1}$$

$$= D_k S_k S_k D_k^T = D_k S_k (D_k S_k)^T \tag{2.2}$$

In the above matrix, the element (i, j) determines the document relationship between document d_i and d_j.

2.2. Support Vector Machine

For a two-class pattern recognition problem, Support Vector Machine (SVM) is committed to find an Optimal Separating Hyperplane which can most separate the largest fraction of two categories training samples. The most requirements are that it must maximize the distance or the margin between each class and the hyperplane.

SVM is successful applied in many pattern recognition, numerous researchers use it in the face recognition [16]. However, the two-class problem of SVM needs to be transformed when it applied in face recognition with multi-class problem. In this paper, the multi-class problem is unified into a two-class problem. Two new classes will be set with the difference between the face sample belong to the inter-class difference image sets C1 and the face sample belong to the intra-class difference image sets C2. They are defined as follows:

$$C_1 = \{t_i - t_j \mid t_i \neq t_j\} \tag{2.3}$$

Where t_i is the *i*th face image, the sign of $\neq$ means t_i and t_j is not the same person sample. The intra-class difference image sets characterize the difference between the same individual samples. It is defined as follow:

$$C_2 = \{t_i - t_j \mid t_i \equiv t_j\} \tag{2.4}$$

Where the sign of $\equiv$ means t_i and t_j is the same person image. The Class C1 and C2 were trained in SVM. The image difference between the unknown image P and the entire known image are evaluated in order. Then the SVM is used to classify all the difference images.

$$\delta_j = \sum_{i=1}^{N_s} \alpha_i y_i K(s_i, P - t_j) + b \tag{2.5}$$

Where α_i and b are defined in [16]. The image t_j corresponding to the minimum δ_j is the most matching to the image P.

3. Proposed Method: Image Latent Semantic Analysis

This section describes the components of our face recognition algorithm based on ILSA and SVM in detail.

Similar with the application of LSA in the Term-Document, we introduce the LSA into the image recognition so-called image LSA (ILSA). When LSA applied in image analysis, the "term" is replaced by the image low-level features and the "document" is replaced by the "image", and the Feature-Image matrix replaces the Term-Document matrix. The main purpose of the ILSA is to explore the semantic features between the features and the images.

Due to these semantic features are mapping from the low-level features through the LSA, so more information of face image are reserved and they show stronger ability of expression and classification ability. And these features extraction by LSA can be a unique feature applied to the face recognition.

The ILSA for face recognition with SVM mainly contains five steps as illustrated in Figure 3, namely, they are pre-processing, low-level features extraction for image, multi-features fusion, building features-image matrix, image latent semantic analysis and classifying with SVM. The main steps are explained in details as below.

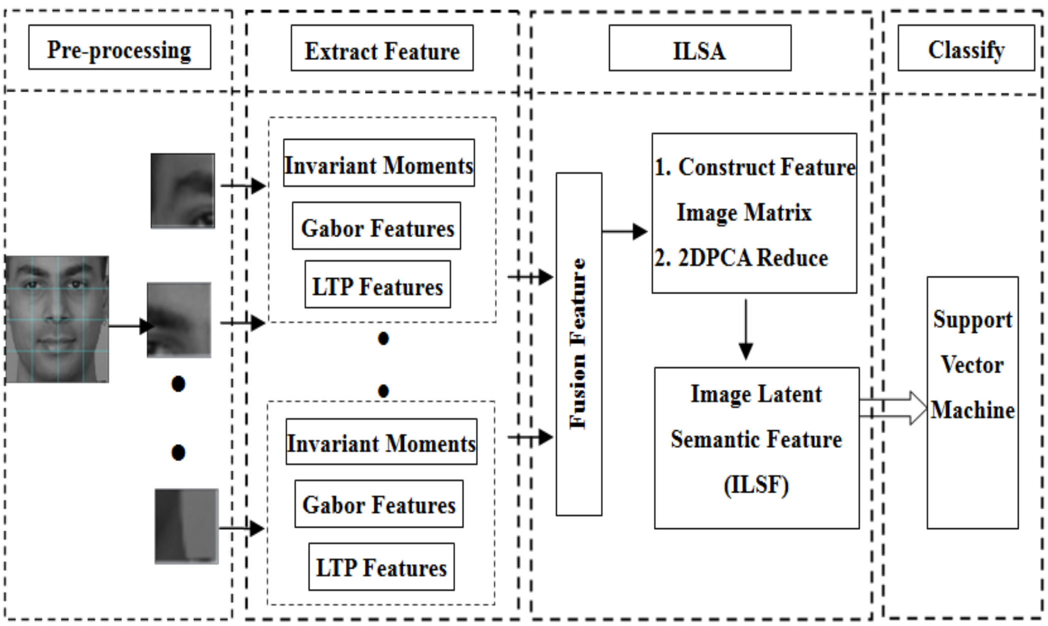


Figure 3. The Steps of the Whole Processing

1) Pre-processing.

We preprocess the face image before feature extraction. Firstly, we enhance and normalize the face image [12], and then each face image is divided into m×n=p sub-images.

2) Extraction the low-level features.

For each sub-image, we extract the local features. Some typical low-level features are obtained, such as Hu invariant moments, Gabor filter, and LTP features. These three low-level descriptors are selected due to their good region representation abilities. Invariant moments features widely used in image processing because of its properties of invariance to scale, position and rotation. The Gabor wavelets have been widely used in face recognition. And the LTP extends LBP to 3-valued a code which is more resistant to noise.

(1) Hu invariant moments. Invariant moments features widely used in image processing because of its properties of invariance to scale, position and rotation. We use the Hu invariant moments [17] to extract seven invariant moment features. The rotation invariant pattern identification as below:

$$
\begin{aligned}
&M_1 = \eta_{20} + \eta_{02} \\
&M_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11} \\
&M_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \\
&M_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\
&M_5 = (\eta_{03} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + 3\eta_{12})^2 - 3(\eta_{21} + 3\eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\
&M_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \\
&M_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]
\end{aligned}
\tag{3.1}
$$

(2) Gabor filters. Gabor wavelets are in many ways like Fourier transform but have a limited spatial scope. 2D Gabor wavelets most commonly used in face recognition have the formula [3]

$$\varphi_{\mu\nu}(z) = \frac{\|k_{\mu\nu}\|^2}{\sigma^2} e^{-\frac{\|k_{\mu\nu}\|^2 \|z\|^2}{\sigma^2}} [e^{ik_{\mu\nu}z} - e^{\frac{-\sigma^2}{2}}] \tag{3.2}$$

Where $k_{\mu\nu} = k_\nu e^{i\phi_\mu}, k_\nu = k_{\max} / f^\nu$ gives the frequency, $\phi_\mu = \mu\pi / 8, \phi_\mu \in [0, \pi)$ gives the orientation.

(3) LTP features. Local Ternary Patterns extends LBP to 3-valued codes[12], in which gray-levels in a zone of width $\pm t$ around i_c are quantized to zero, ones above this are quantized to $+1$ and ones below it to -1. The indicator $s(m)$ is replaced with a 3-valued function.

$$s(m, i_c, t) = \begin{cases} 1, & m \geq i_c + t \\ 0 & |m - i_c| < t \\ -1 & m \leq i_c - t \end{cases} \tag{3.3}$$

The LTP encoding procedure is illustrated in Figure 4. It shows that the threshold t was set to 7 and the tolerance interval is [50, 64].

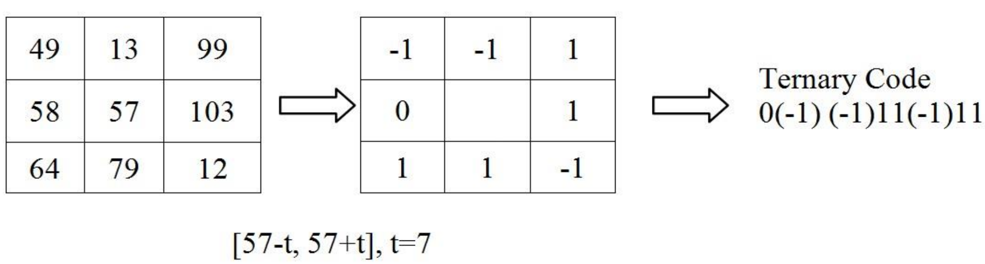


Figure 4. The Basic LTP Operators

3) Constructing the Feature-Image Matrix.

The constructing of the Feature-Image Matrix is summarized as below. Firstly, we directly use the feature level fusion of these low-level features to extract the most discriminant features, which describe the image from the different aspects. The number of the sub-images is P. The dimension of fusion features is Q. Then, the Feature-Image Matrix is constructed by sub-image and their corresponding fusion features. The number of the sub-images is taken as the row of the Matrix, and the dimension of the fusion features is taken as the column of the Matrix. And the element of the Feature-Image Matrix is the fusion features of the corresponding sub-image. So, the size of the Feature-Image Matrix is P×Q.

4) Image Latent Semantic Feature (ILSA).

After construct the Feature-Image matrix, we may decompose the matrix to dig out the image latent semantic feature. Because the Feature-Image matrix is two-dimensional matrix, in order to guarantee matrix content and structure integrity, we use 2D-PCA (Principle Component Analysis) method [16]. After the decomposition of matrix, we obtain the semantic-space which is spanned by the semantic basis vectors. Then, we can project the input face image into this semantic-space to get the image latent semantic features.

5) Recognition with SVM.

After we get the latent semantic features, we may recognize them with a classifier. Statistical learning algorithm such as SVM [16] has stronger generalization ability as introduced in Section 2.2, so SVM is used to classify the latent semantic features with the training and test stages.

4. Experiments and Analysis

In order to test the performance of the proposed method, two well-known available public databases, ORL and FERET database [15], were used, which contains large illumination variations. Our experiments in ORL were performed using the first *k* image sample per subject for training, and the remaining images for testing.

In the image pre-processing step, we should divide the face image into n*n block. How to divide the image is an important factor which is affects the recognition feature keep degree. In order to study the block number how to affect the final recognition results, we choose the value of size n with 2,4,5,6,8,10 and 20. And the classifier is SVM. Some parameters of the SVM are the default parameter of LIBSVM [18].

The recognition results based on image latent semantic analysis and SVM classifier on ORL database are shown in Figure 5. From the figure, we can see that the accuracy is lowest with 62.5% when the face image is divided into 2*2 blocks.

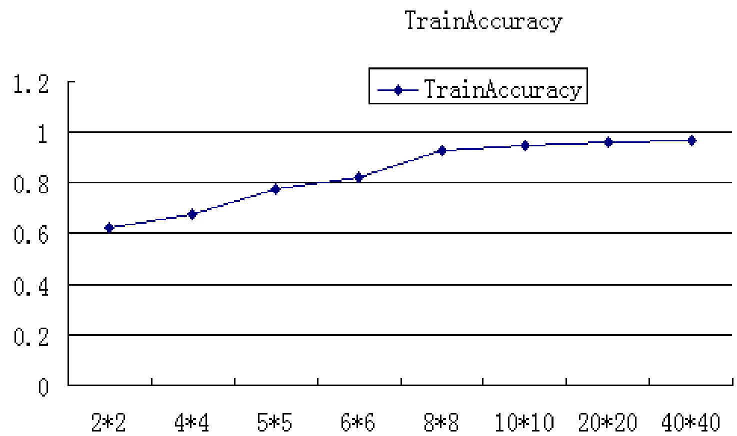


Figure 5. Performance of Different Blocks in ORL Face Database

And bigger block number, higher recognition accuracy. When n is 10 or bigger, the accuracy does not increase nearly, and when n is 40, the accuracy is 96.5%. However, as n increasing, the training cost of time also increases. So considering the two factors of the precision and time, we choose the value of n is 20 in our experiment and the number of training sample is 5. And if n is chosen by other value like 4, 5, 6, 8, 10, 20, the accuracies are 67.5%, 77.5%, 82.5%, 92.5%, 95%, 96%, respectively.

In order to prove the effectiveness of our proposed algorithm, the existed state-of-the-art methods and our method are compared. The recognition accuracy performances for Gabor, LBP, LGBHPS and our proposed method are as shown in Figure 6. From the figure, we can see that the recognition accuracy of all of the algorithms gradually rise with the increasing of the training samples.

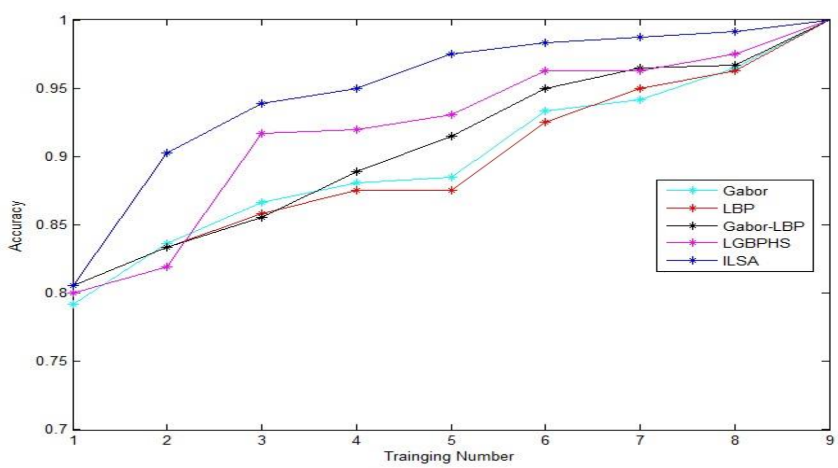


Figure 6. Performance of Different Methods in ORL Face Database

Though all the recognition accuracies are 100% when the number of training sample is 9, the whole recognition of ILSA is the highest. The average recognition of the ILSA is 98.75%, and the other methods such as Gabor, LBP, Gabor-LBP, LGBPHS are 94.5%, 94.25%, 95.93%, 96.4%. So the performance of our proposed method is better than those well-knows methods.

On the other hand, the average accuracies of Gabor, LBP, LGBHPS and our proposed method in the ORL and FERET face database are as shown in Table 1. From the table, we can see that all the methods in the FERET database also get high recognition accuracies, and the accuracy of the methods of ILSA is 98.47%, which is higher than that of the Gabor, the LBP and the LGBPHS. So the ILSA method can get higher accuracy in both two face databases, so the performance of the proposed method is better than the existed state-of-the-art results.

Table 1. Accuracy of Gabor, LBP, Gabor-LBP, LGBHPS, and ILSA in the ORL and FERET Face Database

Algorithm	Gabor	LBP	Gabor-LBP	LGBPHS	ILSA
ORL database	94.5%	94.25%	95.93%	96.4%	98.75%
FERET database	95.0%	97.0%	97.3%	98.0%	98.49%

5. Conclusion

In this paper, we propose a novel and effective image model--Image Latent Semantic Analysis for extracting the latent semantic features of face image, and classifying face image with SVM.

There are two main contributions. The first contribution of this paper is that a heterogeneous features fusion-based recognition framework that combines three popular feature sets-Gabor, Invariant moment and LTP. The second contribution of this paper is to extract the image latent semantic features which are obtained from a Feature-Image matrix; the unique feature extraction by the ILSA will be efficient to overcome the impact of some of the negative factors, such as the image quality fuzzy, illumination changes effect and so on.

Experiments on two public databases show that the proposed methods outperform than other traditional methods.

Acknowledgements

This work was supported in part by the National Natural Science Foundation of China under Grant 61063035, and was also supported by China Postdoctoral Science Foundation under the grant No.2012M510977, and supported by the advanced project of Jiangxi Provincial postdoctoral Science Foundation.

References

[1] X. Tan and B. Triggs, "Fusing Gabor and LBP Features Sets for Kernel-Based Face Recognition", Analysis and Modeling of Faces and Gestures Lecture Notes in Computer Science, vol. 4778, **(2007)**, pp. 235-249.

[2] S. Chen, Y. Zhu, D. Zhang and J. -Y. Yang, "Feature extraction approaches based on matrix pattern: MatPCA and MatFLDA", Pattern Recognition Letter., vol. 26, no. 8, **(2005)**, pp. 1157-1167.

[3] L. Shen and L. Bai, "A review on Gabor wavelets for face recognition", Pattern Analysis and Applications, vol. 9, **(2006)**, pp. 273-292.

[4] T. Ahonen and A. Hadid, "Face description with local binary patterns: Application to face recognition", IEEE TPAMI, vol. 28, **(2006)**, pp. 2037-2041.

[5] Y. Su, S. Shan, X. Chen and W. Gao, "Hierarchical ensemble of global and local classifiers for face recognition", IEEE Trans. Image Processing, vol. 18, **(2009)**, pp. 1885-1896.

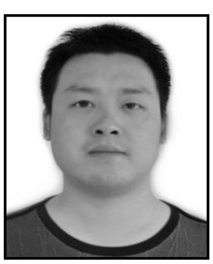
[6] W. Zhang, S. Shan, W. Gao, X. Chen and H. Zhang, "Local Gabor binary pattern histogram sequence (LGBPHS): A novel non-statistical model for face representation and recognition", Tenth IEEE International Conference on Computer Vision. ICCV2005, vol. 1, **(2005)**, pp. 786-791.

[7] B. Zhang, S. Shan, X. Chen and W. Gao, "Histogram of Gabor Phase Patterns (HGPP): A Novel Object Representation Approach for Face Recognition", IEEE Trans. Image Processing, vol. 16, **(2007)**, pp. 57-68.
[8] Y. Liu, D. Zhang, G. Lu and W.-Y. Ma, "A survey of content-based image retrieval with high-level semantics", Pattern Recognition, vol. 40, **(2007)**, pp. 262-282.
[9] T. K. Landauer, P. W. Foltz and D. Laham, "An Introduction to Latent Semantic Analysis", Discourse Processes, vol. 25, **(1998)**, pp. 259-284.
[10] S. Ghosh, "A general framework for reconciling multiple weak segmentations of an image", Workshop on Applications of Computer Vision, **(2009)**, pp. 1-8.
[11] Y. Xue, C. Sze Tong, W.-S. Chen, W. Zhang and Z. He, "A modified non-negative matrix factorization algorithm for face recognition", 18th International Conference on Pattern Recognition, vol. 3, **(2006)**, pp. 495-498.
[12] X. Tan and B. Triggs, "Enhanced Local Texture Feature Sets for Face Recognition under Difficult Lighting Conditions", IEEE Transactions on Image Processing, vol. 19, **(2010)**, pp. 1635-1650.
[13] P. S. Penev and J. J. Atick, "Local Feature Analysis: A general statistical theory for object representation", Network: Computation in Neural Systems, vol. 7, **(1996)**, pp. 477-500.
[14] L. Wiskott, J.-M. Fellous, N. Kuiger and C. vonder Malsbrug, "Face recognition by elastic bunch graph matching", IEEE Trains, On Pattern Analysis and Machine Intelligence, vol. 19, **(1997)**, pp. 775-779.
[15] P. Jonathon Phillips, H. Wechsler, J. Huang and P. J. Rauss, "The FERET database and evaluation procedure for face-recognition algorithms", Image and Vision Computing, vol. 16, **(1998)**, pp. 295-306.
[16] T. Hoang Le and L. Bui, "Face Recognition Based on SVM and 2DPCA", International Journal of Signal Processing, Image Processing and Pattern Recognition, vol. 4, **(2011)**, pp. 85-94.
[17] J. Yang and D. Park, "A fingerprint verification algorithm using tessellated invariant moment features", Neurocomputing, vol. 71, **(2008)**, pp. 1939-1946.
[18] C. -C. Chang and C. -J. Lin, "LIBSVM: A Library for Support Vector Machines", ACM Transactions on Intelligent Systems and Technology, vol. 2, (Http://www.csie.ntu.edu.tw/~cjlin/papers/libsvm.ps.gz), **(2011)**.

Authors

Jucheng Yang is a professor in College of Computer Science and Information Engineering, Tianjin University of Science and Technology, Tianjin, China. He is a post-doc in Ahead Software Company Limited, Nanchang, too. He received his B.S. degree from South-Central University for Nationalities, China, and M.S. and Ph.D. degree from Chonbuk National University, Republic of Korea. He has published over 50 papers in related international journals and conferences. His research interests include biometrics, image processing, pattern recognition and neural networks.

Min Luo is an associate researcher of Jiangxi Institute of Computing Technology, China. She got her master degree in Xidian University. She is the associate editor of the journal of Computer and Modernization. Her major is image processing, information security.



Yanbin Jiao is a master candidate in School of Information Technology, Jiangxi University of Finance and Economics, China. He received his B.S degree from Hubei Normal University. He has published several conference papers in face recognition field. His research area is image processing, face recognition.