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An efficient face recognition algorithm based on multi-kernel regularization learning

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Abstract. A novel face recognition algorithm based on multi-kernel regularization learning is proposed. Firstly, we present three types of visual features to describe human faces, including: 1) Local Gabor Gradient Pattern (LGGP), 2) Histogram of Gabor Ordinal Ratio Measures (HGORM) and 3) Densely Sampled Local Binary Pattern (DSLBP). Secondly, we integrate the multiple kernel based method and the manifold regularization together to solve the face recognition issue. Particularly, the face recognition problem is solved by minimizing an optimization problem based on manifold regularization calculation using the graph Laplacian. Finally, three typical human face databases are used to test the performance of our proposed algorithm. Experimental results show that the proposed algorithm can achieve high recognition accuracy even when occlusion happens.

Key words. Face recognition, multi-kernel regularization learning, manifold regularization, loss function.

1. Introduction

With the development of information science, biometric technology has become a key mode for personal identification or authentication technology [1]. ID authentication refers to a crucial issue in human's daily life. We need to prove our own ID in many occasions, such as electronic business, bank online, public security. However, existing ID authenticating methods can no longer satisfy our requirements [2], [3]. In particular, face recognition refers to an important branch of biometrics, which is more easily accepted for the most intuitive means of identification. Face features of humans will not be changed with age varying [4]. Different from other biometric identification methods (such as fingerprint, retina, iris, and so on), face recognition is a more humanitarian approach, which is more direct and friendly [5].

However, due to the issues of face recognition (e.g. illumination, angle, and occlusion) which have not been tackled well, the accuracy of face recognition still cannot be satisfied. Face recognition is made up of two steps: 1) face detection

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and 2) face identification [6], [7]. Face detection aims to obtain the location and size of faces in the host image. On the other hand, face identification analyzes and extracts visual feature vector from the target image [8]. In general, face recognition has significant theoretical research values and wide application values [9].

The main idea of this paper is to introduce regularization learning to solve the human face recognition problem. To tackle an ill-posed issue and avoid overfitting, regularization learning has been proposed, and it is hot topic in machine learning and computer science. In the following, we introduce related works about applications of regularization learning, such as Real-time visual tracking [10], high dimensional classification [11], MRI reconstruction [12], image classification [13], Multiple task learning [14], object tracking [15], human face-based age estimation [16], Text categorization [17], Learning Gene Expression Programs [18], image noise reduction [19], Image Understanding [20].

2. Feature description for human face recognition

For the face recognition task, effective feature description is a crucial problem. Therefore, in this section, we explain what visual features are chosen to describe human faces. Particularly, in this paper, we assume that a human face image is represented as $I \in R^{128 \cdot 128}$.

2.1. Feature type 1: Local Gabor Gradient Pattern (denoted as LGGP)

In order to code Gabor magnitude responses, we exploit a gradient descriptor which is defined as follows.

$$\xi\left(x_c\right) = \arctan\left(\beta \cdot \frac{N_{\mathrm{v}}}{N_{\mathrm{h}} + \lambda}\right), \tag{1}$$

where N_{v} and N_{h} denote the gradients, which should be calculated in both vertical direction v and horizontal directions h. The parameters β and λ are used to stabilize the gradient descriptor. Function arctan () and parameters β, λ are exploited to avoid the output from increasing or decreasing too fast. Then, the gradients are calculated as follows.

$$N_{\mathrm{v}} = \gamma_{\mathrm{mod}(i+4,R)} - \gamma_i\,, \tag{2}$$

$$N_{\mathrm{h}} = \gamma_{\mathrm{mod}(i+6,R)} - \gamma_{\mathrm{mod}(i+2,R)}\,, \tag{3}$$

where the function mod () means the modulo operator, and symbol i denotes the index of the neighbor pixel. Then, in order to obtain Local Gabor Gradient Pattern features, each gradient-encoded Gabor image is separated to several non-overlapping patches, and then histogram of these patches is constructed.

2.2. Feature type 2: Histogram of Gabor Ordinal Ratio Measures (denoted as HGORM)

In order to effectively describe Gabor phase responses, we utilize the Ordinal Measure to compares two various regions to make a decision which region has a higher value. We establish a horizontal ordinal filter, and we use this ordinal filtering to generate the output of Gabor phase responses. Afterwards, a ratio measure is exploited to calculate the features as follows.

$$OF = \arctan\left(\beta \cdot \frac{O_{\mathrm{v}}}{O_{\mathrm{h}} + \lambda}\right), \tag{4}$$

where symbols O_{h} and O_{v} refer to the convolution of horizontal and vertical ordinal filter with the Gabor phase response respectively. Furthermore, parameters β and λ refer to two constants which are exploited to ensure the function to be stable.

Then, HGORM feature is regarded as an updated version of the LGGP feature. The ratio measure utilized in HGORM is weighted through Gaussian kernel, and image is separated to several non-overlapping patches as well. The number of patches of an image is set to 64 with the patch size is $16 \cdot 16$, and the number of histogram bins is set to 16.

2.3. Feature type 3: Densely Sampled Local Binary Pattern (denoted as DS-LBP)

We use uniform LBP patterns which are obtained from the image, and then a 59-bin histogram feature vector is constructed. Furthermore, Uniform LBP patterns represent all binary patterns which have at most two bitwise transitions in the range $[0, 1]$. Next, to construct the DS-LBP feature vector, each image coded by LBP is separated to several overlapping patches, and then a histogram is extracted from image patch. Particularly, in this work we set the number of patches for in each image to 256 with the patch size is $16 \cdot 16$. Afterwards, feature vector of DS-LBP is represented as follows.

$$V_{\mathrm{DS-LBP}}(I) = (s_1, s_2, \cdots, s_N), \tag{5}$$

where N refers to the total number of patches in an image, and s refers to the histogram features.

Integrating all the above three feature types, overview of the feature descriptors used in this work is given in Table 1.

3. The proposed face recognition algorithm based on multi-kernel regularization learning

In this section, we discuss how to solve the face recognition problem by image classification, and the manifold regularized multiple kernel learning (denoted as

MKL) is used to design classifier. Multiple kernel learning is defined as follows.

$$\arg\min_{f\in H} C\sum_{i=1}^{K} L\left(x_i, y_i, f\right) + \gamma \left\|f\right\|_H^2 \ , \tag{6}$$

where total K pairs of training data $\left(x_i, y_i\right),\ i\in\{1,2,\cdots,K\}$, $L\left(x_i, y_i, f\right)$ refer to a loss function, $\left\|f\right\|_H^2$ denotes a norm restriction with the space H.

Table 1. Overview of the feature descriptors used in this work

Feature category	LGGP	HGORM	DS-LBP
Size of patch	16×16	16×16	16×16
Patch number	2560	2560	256
Number of bins for each patch	16	16	59
Patch organization mode	Non overlapping	Non overlapping	Overlapping

In terms of the Representer theory, to minimize the optimization problem in (8), the following equation should be solved in advance.

Considering that it is of great importance to integrate multiple kernel based policy and the manifold regularization. Therefore, the formation of the manifold regularized multiple kernel learning is given as follows

$$\arg\min_{f\in H} C\sum_{i=1}^{K} L\left(x_i, y_i, f\right) + \gamma_h \left\|f\right\|_H^2 + \gamma_p \left\|f\right\|_P^2 \ , \tag{7}$$

where $\left\|f\right\|_P^2$ is used to represent the internal structure of data and parameter γ_{h} is able to control the penalty of manifold.

In order to calculate the manifold regularization, graph Laplacian (denoted as L) is used as follows.

$$\gamma_{\mathrm{P}} \left\|f\right\|_{\mathrm{P}}^2 = \frac{\gamma_{\mathrm{P}}}{\ell^2} f^{\mathrm{T}} L f \, , \tag{8}$$

where $L = D - W$, among which W is the data adjacency graph weight and D refers to a diagonal matrix. Furthermore, the following condition is satisfied.

$$D_{ij} = \sum_{j=1}^{n} W_{ij} \, . \tag{9}$$

Afterwards, the loss function is used as the hinge loss function and it is suitable to be utilized in classifier, such as support vector machine.

$$C \cdot \sum_{i=1}^{K} L\left(x_i, y_i, f\right) = C \cdot \sum_{i=1}^{K} \max\left(0, 1 - y_i f\left(x_i\right)\right) . \tag{10}$$

Next, to estimate the error of hinge loss function, feature function is modified as follows.

$$f^*\left(x\right) = \arg\min_{f \in H} C \sum_{i=1}^{K} \max\left(0, 1 - y_i f\left(x_i\right)\right) + \gamma_{\mathrm{h}} \left\|f\right\|_H^2 + \frac{\gamma_{\mathrm{p}}}{\ell^2} f^{\mathrm{T}} L f . \tag{11}$$

Therefore, the face recognition problem can be tackled by minimizing the optimization problem in (11).

4. Experiment

In this section, we choose three typical human face databases (named as D1: Extended Yale B dataset, D2: FERET dataset, and D3: CMU PIE) to test the performance of our proposed algorithm. D1 is made up of 2414 frontal human face images of 38 persons, and nearly 64 images are taken from one person. The original images in D1 are organized as 192×168 pixels. In order to test the adaptive capacity of our test algorithm, D1 dataset is designed based on different illumination conditions. D2 includes 1199 subjects more than 14000 images. Particularly, face images in D2 are taken under various lighting conditions, facial expressions, and pose angles. For simplicity, only face images which are taken from the front view are chosen. D3 dataset contains 68 subjects with 41386 human face images, and images in this dataset are taken under different illuminations and expressions.

To make performance comparison, Multiple Kernel Learning based face recognition (denoted as MKL) [21] and SVM based face recognition [22] are used to compared with ours method. The overall performance of MKL, SVM and our proposed method is shown in Table 2.

Table 2. Face recognition accuracy for different methods

Dataset	MKL (%)	SVM (%)	Our proposed method (%)
D1	85.69	88.95	91.64
D2	82.47	84.12	87.93
D3	84.61	86.08	89.37

Table 2 shows that our proposed method is able to achieve higher face recognition accuracy than other two methods for all three datasets. Afterwards, we illustrate ROC curves for all above datasets under different methods (shown in Figs. 1–3).

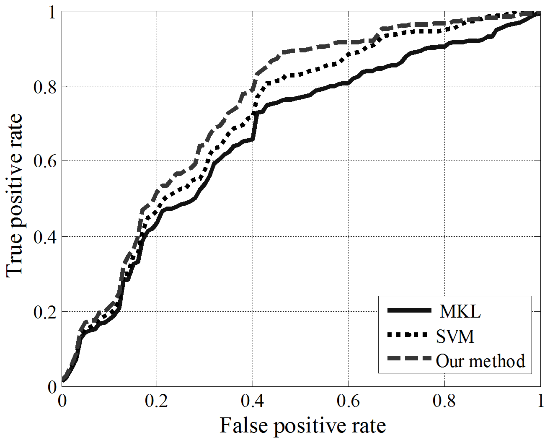

Fig. 1. ROC curve for dataset D1

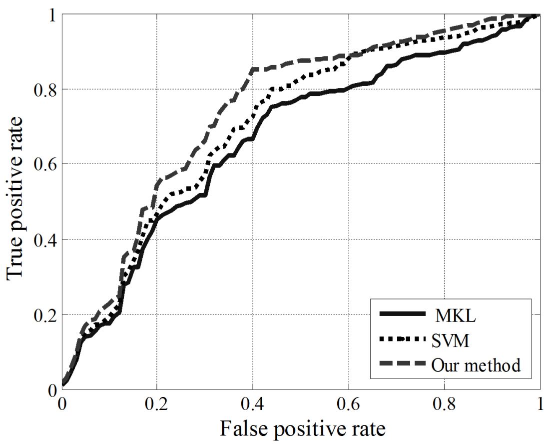

Fig. 2. ROC curve for dataset D2

To further test the performance of our proposed method when part of human face image is occluded, and experimental results are given in Figs. 4–6.

It can be observed that compared with MKL and SVM based face recognition methods, our proposed method can achieve higher recognition accuracy than other methods. When occlusion rate increasing, recognition accuracy of all methods decreases. However, we find that even when occlusion happens, our method still performs better than other methods.

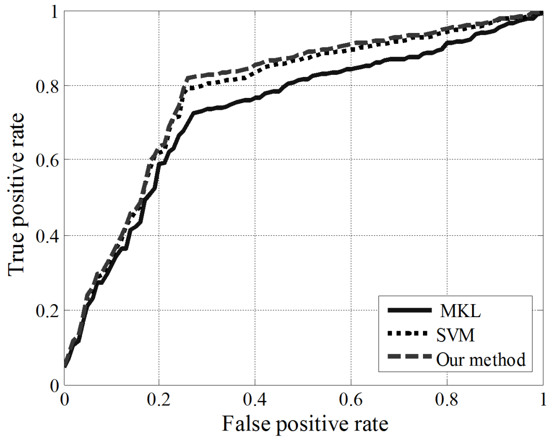

Fig. 3. ROC curve for dataset D3

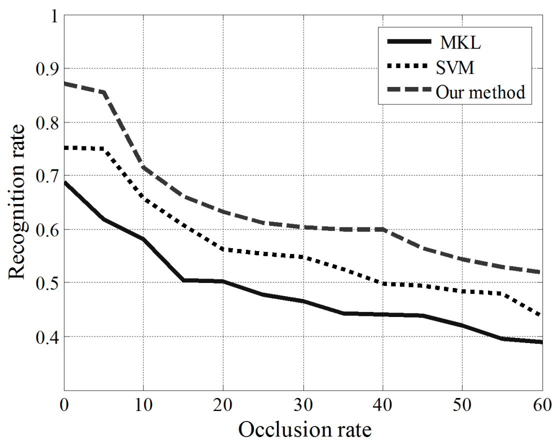

Fig. 4. Face recognition rate for different occlusion rate using dataset D1

5. Conclusion

This paper aims to present an efficient face recognition algorithm based on multi-kernel regularization learning. Three types of visual features are exploited to describe human faces, which are 1) Local Gabor Gradient Pattern, 2) Histogram of Gabor Ordinal Ratio Measures and 3) Densely Sampled Local Binary Pattern. Then, the multiple kernel and the manifold regularization are used to solve the human face recognition problem. Afterwards, the face recognition problem is solved by minimizing an optimization problem with manifold regularization calculation. In the end, experimental results demonstrate that that the proposed algorithm can achieve high

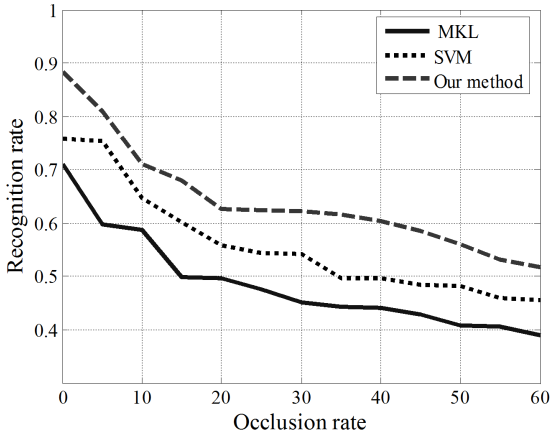

Fig. 5. Face recognition rate for different occlusion rate using dataset D2

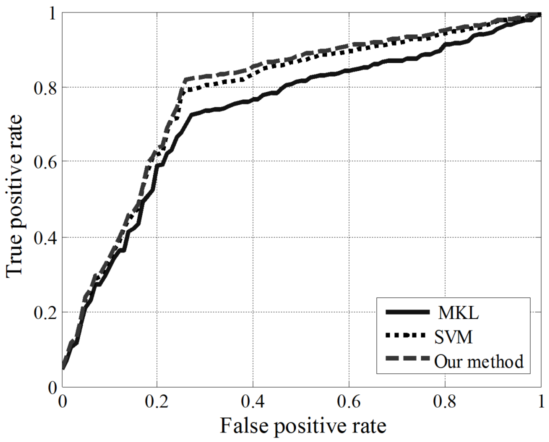

Fig. 6. Face recognition rate for different occlusion rate using dataset D3

recognition accuracy for various human face databases.

References

[1] H. Li, C. Y. Suen: *Robust face recognition based on dynamic rank representation.* Pattern Recognition *60* (2016), 13–24.

[2] G. Zhang, H. Sun, Z. Ji, Y. H. Yuan, Q. Sun: *Cost-sensitive dictionary learning for face recognition.* Pattern Recognition *60* (2016), 613–629.

[3] C. Chen, A. Dantcheva, A. Ross: *An ensemble of patch-based subspaces for makeup-robust face recognition.* Information Fusion, Part B *32* (2016), 80–92.

[4] S. Huang, L. Zhuang: *Exponential discriminant locality preserving projection for face recognition.* Neurocomputing *208* (2016), 373–377.

[5] Z. M. Li, Z. H. Huang, K. Shang: *A customized sparse representation model with mixed norm for undersampled face recognition.* IEEE Trans. Information Forensics and Security *11* (2016), No. 10, 2203–2214.

[6] F. Shen, W. Yang, H. Li, H. Zhang, H. T. Shen: *Robust regression based face recognition with fast outlier removal.* Multimedia Tools and Applications *75* (2016) No. 20, 12535–12546.

[7] G. F. Lu, Y. Wang, J. Zou: *Graph maximum margin criterion for face recognition.* Neural Processing Letters *44* (2016), No. 2, 387–405.

[8] Z. Lei, D. Yi, S. Z. Li: *Learning stacked image descriptor for face recognition.* IEEE Trans. Circuits and Systems for Video Technology *26* (2016), No. 9, 1685–1696.

[9] L. Zhao, Y. Zhang, B. Yin, Y. Sun, Y. Hu, X. Piao, Q. Wu: *Fisher discrimination-based-norm sparse representation for face recognition.* The Visual Computer *32* (2016), No. 9, 1165–1178.

[10] P. Zhang, T. Zhuo, Y. N. Zhang, L. Xie, D. P. Tao: *Real-time tracking-by-learning with high-order regularization fusion for big video abstraction.* Signal Processing *124*, (2016), 246–258.

[11] Y. J. Wu, B. Y. Liu: *Spatial and anatomical regularization based on multiple kernel learning for neuroimaging classification.* IEICE Trans. Information and Systems *99* (2016), No. 4, 1272–1274.

[12] A. K. Tanc, E. M. Eksioglu: *MRI reconstruction with joint global regularization and transform learning.* Computerized Medical Imaging and Graphics *53* (2016), 1–8.

[13] F. M. Sun, Y. Xu, J. Zhou: *Active learning SVM with regularization path for image classification.* Multimedia Tools and Applications *75* (2016), No. 3, 1427–1442.

[14] J. Pu, J. Wang, Y. G. Jiang, X. Xue: *Multiple task learning with flexible structure regularization.* Neurocomputing *177* (2016), 242–256.

[15] S. Zhang, Y. Sui, S. Zhao, X. Yu, L. Zhang: *Multi-local-task learning with global regularization for object tracking.* Pattern Recognition *48* (2015), No. 12, 3881–3894.

[16] Q. Tian, S. Chen: *Cumulative attribute relation regularization learning for human age estimation.* Neurocomputing *165* (2015), 456–467.

[17] W. Zheng, Y. Qian, H. Lu: *Text categorization based on regularization extreme learning machine.* Neural Computing and Applications *22* (2013), No. 3, 447–456.

[18] G. Ye, M. Tang ,J. F. Cai, Q. Nie, X. Xie: *Low-rank regularization for learning gene expression programs.* Plos One *8* (2013), No. 12, paper 82146.

[19] S. Yang, L. Zhao, M. Wang, Y. Zhang, L. Jiao: *Dictionary learning and similarity regularization based image noise reduction.* J Visual Communication and Image Representation *24* (2013), No. 2, 181–186.

[20] L. Li, S. Q. Jiang, Q. M. Huang: *Learning hierarchical semantic description via mixed-norm regularization for image understanding.* IEEE Trans. Multimedia *14* (2012), No. 5, 1401–1413.

[21] X. Z. Liu, G. C. Feng: *Multiple kernel learning in Fisher discriminant analysis for face recognition.* SAGE journals, I. J. Advanced Robotic System *10* (2013), No. 2, paper 142.

[22] W. H. Li, L. J. Liu, W.,G. Gong: *Multi-objective uniform design as a SVM model selection tool for face recognition.* Expert Systems with Applications *38* (2011), No. 6, 6689–6695.

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