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Face Recognition Robust to Occlusion via Dual Sparse Representation

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Purpose In face reocognition area, estimating occlusion in face images is on the rise. In this paper, we propose a new face recognition algorithm based on dual sparse representation to solve this problem.
Method Each face image is partitioned into several pieces and sparse representation is implemented in each part. Then, some parts that have large sparse concentration index are combined and sparse representation is performed one more time. Each test sample is classified by using the final sparse coefficient where correlation between the test sample and training sample is applied.
Results The recognition rate of the proposed algorithm is higher than that of the basic sparse representation classification.
Conclusion The proposed method can be applied in real life which needs to identify someone exactly whether the person disguises his face or not.

Key Words Face recognition · Occlusion · Sparse representation · Correlation · Sparsity concentration index (SCI).

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Introduction

These days, many researches about sparse representation classification (SRC) have been presented. Among the researches, Allen Y. Yang showed various face recognition experiments based on SRC. (1) In that paper, it is turned that SRC has generally superior performance, compared with nearest neighborhood (NN) (2), nearest subspace (NS) (3), support vector machine (SVM) (4, 5), etc. Especially, SRC is robust to occlusion and disguise like sunglasses or scarves.

In this paper, the solutions to some issues in face recognition are suggested.

1) In case of basic SRC (1), the whole image equally influences classification. That is, everywhere of the image, even occluded part, does not affect classification differently, so the recognition rate decreases. Therefore, we propose the algorithm robust to occlusion by differentiating the influences between the normal part and occluded part.

2) Basic SRC (1) decides the class of the test sample that has minimum residual (the difference between training set subject to sparse coefficient and a test sample). Here, if we add another parameter that can represent the distance between training image and test sample, not only sparse coefficient, the performance would increase.

Materials and Methods

We suggest a new sparse representation-based face recognition algorithm using both parts and the whole of the image. Fig. 1 shows the flow chart of the proposed algorithm.

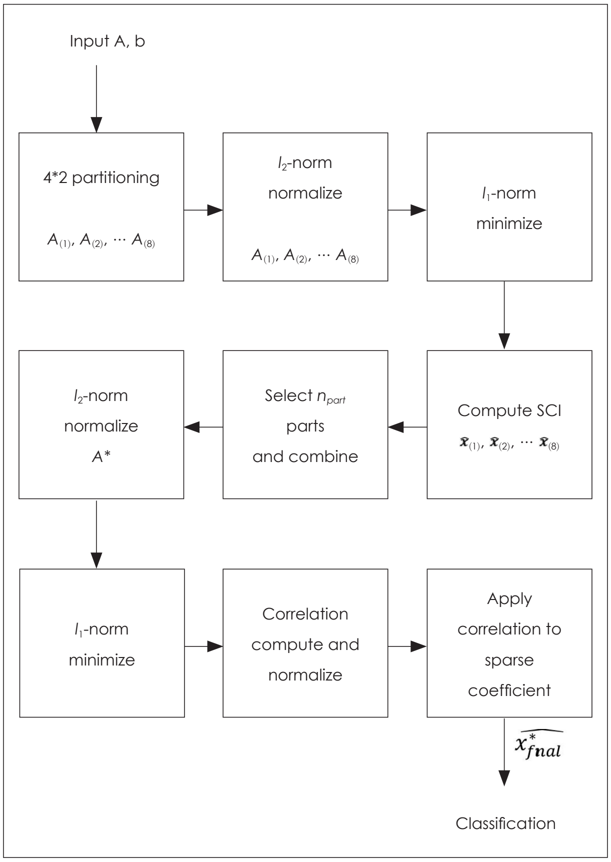

Fig. 1. Flow chart.

Partition Selection Using Sparse Concentraion Index (SCI)

After partitioning each face image, we compute SCI (1, 6) of sparse coefficient.

$$\mathrm{SCI}(\hat{x}_{(1)}) \doteq \frac{k \cdot \frac{max_i \|\delta_i(\hat{x}_{(1)})\|_1}{\|\hat{x}_{(1)}\|_1} - 1}{k-1}$$
$$\mathrm{SCI}(\hat{x}_{(2)}) \doteq \frac{k \cdot \frac{max_i \|\delta_i(\hat{x}_{(2)})\|_1}{\|\hat{x}_{(2)}\|_1} - 1}{k-1}$$
$$\cdots$$
$$\mathrm{SCI}(\hat{x}_{(8)}) \doteq \frac{k \cdot \frac{max_i \|\delta_i(\hat{x}_{(8)})\|_1}{\|\hat{x}_{(8)}\|_1} - 1}{k-1} \tag{1}$$

Large SCI means sparse coefficient distirbutes densely in the specific classes. The larger SCI becomes, the more advantageous information to classify exists. Hence, if we only use the partitions of large SCI, classification becomes robust to image occlusion, so the recognition performance increases.

Correlation Application to Sparse Coefficient

Assume that there is a training image $a_{train} \in \mathbb{R}^m$ and a test image $b_{test} \in \mathbb{R}^m$. Then, correlation between a_{train} and b_{test} is like below.

$$\mathrm{corr}(a_{train}, b_{test}) = \frac{cov(a_{train}, b_{test})}{\sigma_{a_{train}} \sigma_{b_{test}}} = \frac{E[(a_{train} - \mu_{a_{train}})(b_{test} - \mu_{b_{test}})]}{\sigma_{a_{train}} \sigma_{b_{test}}}$$

If corr (a_{train}, b_{test}) goes near to -1, the relationship between a_{train} and b_{test} is negative. On the other hand, if corr (a_{train}, b_{test}) approaches 1, their relationship is positive. That is to say, corr (a_{train}, b_{test}) near to 1 means the image features of a_{train} and b_{test} are similar, so the probability that a_{train} and b_{test} are the same class's image is high. Here, calculated corr (a_{train}, b_{test}) ranges from -1 to 1, so corr (a_{train}, b_{test}) is normalized to be in [0, 1]. Normalized corr (a_{train}, b_{test}) near to 0 means the distance between a_{train} and b_{test} is large and corr (a_{train}, b_{test}) near to 1 means a_{train} and b_{test} are similar each other. Therefore, if corr (a_{train}, b_{test}) is applied to sparse coefficient, classification becomes more reliable than before.

SCIs of correlation-applied sparse coefficient $\widehat{x^*_{final}}$ and the original sparse coefficient $\widehat{x^*}$ are as follows.

$$\mathrm{SCI}(\widehat{x^*_{final}}) \doteq \frac{k \cdot \frac{max_i \|\delta_i(\widehat{x^*_{final}})\|_1}{\|\widehat{x^*_{final}}\|_1} - 1}{k-1}$$
$$\mathrm{SCI}(\widehat{x^*}) \doteq \frac{k \cdot \frac{max_i \|\delta_i(\widehat{x^*})\|_1}{\|\widehat{x^*}\|_1} - 1}{k-1}$$

Because correlation ranges from 0 to 1, l_1-norm of $\widehat{x^*_{final}}$ is smaller than l_1-norm of $\widehat{x^*}$.

$$\|\widehat{x^*_{final}}\|_1 < \|\widehat{x^*}\|_1$$

In addition, maximum $\|\delta_i(\widehat{x^*_{final}})\|_1$ is also smaller than maximum $\|\delta_i(\widehat{x^*})\|_1$.

$$max_i \|\delta_i(\widehat{x^*_{final}})\|_1 \leq max_i \|\delta_i(\widehat{x^*})\|_1$$

However, in ideal condition, correlations of class i that has the maximum $\|\delta_i(\widehat{x^*})\|_1$ are almost near to 1.

$$max_i \|\delta_i(\widehat{x^*_{final}})\|_1 \approx max_i \|\delta_i(\widehat{x^*})\|_1$$

Therefore, $\widehat{x^*_{final}}$ is sparser than $\widehat{x^*}$.

$$\mathrm{SCI}(\widehat{x^*_{fnal}}) > \mathrm{SCI}(\widehat{x^*})$$

In the paper, we apply correlation after partition selection using SCI. It is because we can't get proper correlation when face images are awfully occluded. That is, occluded parts can influence correlation calculation, so we can get appropriate correlation when these parts are excepted.

Results

AR database consists of 4000 images of 126 subjects shot in varying expressions, illuminations, disguises, etc. during two sessions (7). In the paper, the images of 50 men and 50 women are chosen. Training images are composed of 7 images of each person from the first session and also 7 images of each person from the second session, only including illumination or expression variations. Because 27th woman's 14th image is not related wih face, we just except the image (1).

All images are cropped and resized to 83*60. In the experiment, two types of images are tested. The first type images wearing sunglasses occlude about 20% of faces and include 2 images of each person. The second type images wearing scarves occlude about 40% of faces and consist of 2 images of each person (1).

We apply the proposed algorithm to the two type of test images and also perform the extra three experiments.

1) Basic SRC (1, 8)

2) Voting after performing SRC in each partition (1, 8)

3) Proposed algorithm except for applying correlation to sparse coefficient

In the case of sunglasses test type, the recognition rate of the proposed algorithm is 98%. It is larger than those of the extra three experiments. Case 2 shows better performance (95%) than case 1 (87.5%), but there is a possibility to increase that performance. By using the definition of SCI, we can select the most useful partitions in the face and avoid from being disturbed by occlusion. Then, we can increase the performance a little bit to 98% by applying the correlation to sparse coefficient. On the other hand, the scarves' recognition rate of the proposed algorithm is, like the preceding, larger than those of the extra three experiments. By using the definition of SCI, we can get better performance (91.5%) than case 2 (89.5%). However, because the very large occlusion area means feature infromation is very insufficient, the correlation does not contribute to the clear increase in the recognition rate, but just gives reliability to decision. We can verify that because SCI increases after applying correlation (Table 1).

Table 1. The Recognition rate of each experiment

Algorithm	Recognition rate (%)	
	Sunglasses	Scarves
SRC (1,8) (Partitioned (1,8))	87.5 (95)	59 (89.5)
SCI selection	97.5	91.5
Proposed method	98	91.5

Discussion

In the paper, the proposed algorithm is demonstrated to be robust to both occlusion through AR database experiment. If some feature descriptors or extraction algorithm are applied to the algorithm, we can expect to get better performance.

Conclusion

In the paper, we proposed face recognition algorithm via dual sparse representation by using both SCI and correlation. The proposed algorithm uses SRC twice. The first SRC is performed in independent image partitions. The second SRC is implemented when the partitions with high SCI are selected and summed up. After that, we find the final sparse coefficient applied with correlation between each training image and a test sample. Then, a test sample is classified by usiing the final sparse coefficient.

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