Sparse representation algorithm for fusion error

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Abstract. In recent years, face recognition technology has been widely used in security, finance, media data retrieval and other fields due to its convenience, concealment, and stability, and has become a popular research field in various scientific research institutions. Among them, face recognition under complex conditions under different lighting, different expressions, and partial occlusion has become a research hotspot. Sparse representation algorithm, as the mainstream algorithm to solve the problem of face recognition under complex conditions, although it improves the recognition accuracy compared with other algorithms, there is still room for improvement. Aiming at the partial occlusion problem in face recognition, this paper conducted many experiments under different training samples through the sparse representation algorithm of fusion error. The experimental results show that the algorithm improves the recognition rate and provides a new solution for the problem of face recognition under partial occlusion.

1. Introduction

In recent years, due to the increasingly perfect image vision technology, face recognition has become the mainstream of the global image intelligence field. The market demand for face recognition continues to increase. As early as many years ago, many stations and airports have used face recognition to complete customs clearance security inspection systems. In the financial field, face recognition systems have been applied to reduce security risks. In recent years, face recognition has also begun to play an increasingly important role in security, education, and medical treatment, showing significant application value.

The technical research on face recognition began in the mid-1960s. Through the unremitting efforts of many scholars in various countries, many breakthroughs have been made in technology. In the field of occlusion face recognition, various algorithms are also emerging. There are currently three mainstream algorithms, subspace regression, robust error coding, and robust feature extraction.

The subspace regression algorithm assumes that the face image is a superposition of "clean face" and "occluded face". For this algorithm, it is more difficult to construct an occlusion subspace. The robust error coding algorithm assumes that the face image is a composite of "clean face" and "occluded face", and is divided into two composite models, "additive synthesis" and "multiplicative synthesis". The robust feature extraction algorithm converts high-dimensional face data into low-level data through some conversion, but in the process of feature extraction, local errors will spread to a certain extent.

Sparse representation algorithm is currently the mainstream face recognition algorithm under complex conditions. Although it has better recognition effect than other algorithms, it still has the problem of low recognition accuracy. This paper proposes a sparse representation algorithm for fusion...
errors, and conducts many experiments under different training samples. The experimental results show that the algorithm improves the recognition rate and provides a new solution to the problem of face recognition under occlusion.

2. Sparse representation algorithm for fusion error

In order to be able to better adapt to the situation of partial occlusion, the error is coded in the algorithm to better express the image information. Using the idea of maximum likelihood estimation to organize the formulas, an algorithm that performs well under occlusion conditions is obtained.

Suppose the image to be tested is $y$, the training sample matrix is $D$, error coding for the image is $e$, $e_i$ is the $i$-th element of $e$. Then let the error code be $e = y - Dx = [e_1; e_2; ...; e_i; ...; e_m]$. For error coding $e$, assuming it obeys independent identity distribution, the probability density function is $h(e_i)$, the likelihood function is $L(e) = \prod_{i=1}^{m} h(e_i)$, the maximum likelihood estimation function is $\max L(e) = \max \prod_{i=1}^{m} h(e_i)$. Take the logarithm of the probability density function $h(e_i)$, we can get $p(e_i) = -\ln(h(e_i))$. Then, the above formula can be written as $H(e) = \sum_{i=1}^{m} p(e_i)$. The above formula is expanded with a first-order Taylor, which is approximately:

$$H(e) = \sum_{i} \left[ p(|e_i'|) + p'(|e_i'|) \left( |e_i| - |e_i'| \right) \right]$$

(1)

In order to simplify the above formula, the Laplace mixture function is used to describe the probability density function to obtain $h(e_i) = \alpha(\exp(-|e_i|/b) + c)$. Taking the derivation of the above equation and bringing it into equation (1), omitting the constant term, we can get:

$$H(e) = \sum \frac{e_i' \exp(-|e_i'|/b) + c}{e_i' \exp(-|e_i'|/b) + c}$$

(2)

Among them, $\|ze\|_1$ is constrained by $l_1$ paradigm. And we consider preventing overfitting, adding regular items $\|x\|_1$. The final objective function is:

$$\min_{x} \|ze\|_1 + \lambda \|x\|_1 \quad \text{s.t.} \quad y - Dx = e$$

(3)

After the sparse representation obtained according to the objective function, for the training sample, the picture contained in each face is called a class. Let $\delta_i : R^n \rightarrow R^n$, the effect is to select coefficients that are only associated with the category. First, verify the test sample to verify whether the test sample belongs to one of the training samples. Calculation:

$$\text{sci} = \frac{k \times \max_{i} \| \delta_i(x) \|_1}{\| x \|_1} - 1$$

(4)

If $\text{sci} = 1$, the test sample is only represented by images from only one class. If $\text{sci} = 0$, the sparsity coefficient is evenly distributed in all classes. Therefore, the picture can be judged by the value of sci. If the picture belongs to a class of the training sample, the residual is calculated to obtain the classification of the test sample. Let the residuals be:

$$\min_{i} r_i(y) = \| y - D\delta_i(x) \|_2$$

(5)

According to the above formula, for each category, the category with the smallest residual value is the category of the test sample.
3. Experiment and analysis

3.1. Recognition on AR face dataset
There are 126 people in the AR face database, with a total of more than 4000 face images. These images all have different expressions, lighting, and occlusion, which can effectively test the algorithm. In this experiment, an image with shades of sunglasses and a scarf was selected for experimentation. Among them, sunglasses account for about 20% of the human face, and scarves account for about 40% of the human face. Select each group of seven unoccluded faces and three pictures that are blocked by sunglasses or scarves for experiments. The results are as follows:

![Examples of pictures blocked by sunglasses and scarves in AR.](image)

| Table 1. Recognition of Sunglasses and Scarf Occlusion on AR Face Data Set |
|----------------------------------------------|
| Sunglasses | Scarf |
| SRC        | 0.9023 | 0.6374 |
| CRC        | 0.8563 | 0.7749 |
| LRC        | 0.8375 | 0.5028 |
| Algorithm of this paper                     | 0.9257 | 0.9032 |

It can be seen from Table 1 that the algorithm in this paper can still identify well under the occlusion of sunglasses and scarves that are common in life. Although the large-area scarf occlusion has a certain impact on the recognition accuracy, the reduction ratio is not large. Compared with other algorithms, the sparse representation algorithm of fusion error in this paper still has better robustness.

3.2. Recognition on Extended Yale B face dataset
The Extended Yale B face dataset contains a total of 2412 face images, divided into 38 categories, each with 64 faces. The data set contains images in different poses and lighting conditions. The experimental plan is to add black blocks to the image to verify the effectiveness of the algorithm under occlusion. For the test image, add black patches of different proportions at random locations and then identify them. The results obtained are as follows:

| Table 2. Recognition of black color block occlusion on Extended Yale B face dataset |
|---------------------------------------------|
| 20% | 40% |
| SRC  | 0.8289 | 0.5038 |
| CRC  | 0.7637 | 0.5624 |
| LRC  | 0.8246 | 0.5022 |
| Algorithm of this paper  | 0.9716 | 0.9635 |

It can be seen from Table 2 that for simple random color block occlusion, the algorithm in this paper still has a good recognition effect. Although the proportion of occluded blocks increased from...
20% to 40%, the recognition rate only decreased by 1%. The traditional algorithm is reduced by about one-third, obviously not well adapted to large-area random occlusion.

4. Conclusion
In order to solve the problem of low accuracy of face recognition in the case of partial occlusion, this paper proposes a sparse representation algorithm for fusion errors based on the idea of maximum likelihood estimation from the perspective of errors in training samples and test samples. On the AR and Extended Yale B face data sets, we select the occluded pictures, or use different proportions of color blocks to simulate occlusion, and compare with the SRC, CRC, and LRC algorithms to verify the algorithm in this paper. Compared with other algorithms, the higher recognition accuracy proves that this algorithm has better robustness in the case of partial occlusion.

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