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Research on Human Face Difference Imaging Based on Sparse Representation

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Abstract

To make sure human face can be more accurately identified in various poses, an identification method based on the characteristics human face image have been proposed in the thesis. First, it is a design for the optimal sampling matrix to acquire compressed measurement data; then it adopts iterative method based on the close loops of l_2 and l_1 in normal form to get an estimate on human face images, since the method based on norm l_2 can measure the relevancy of human face images in the space and time of the continuous time point, and the method based on norm l_1 mainly uses the modified total variation method and basis pursuit noise-reduction method. The simulation design has suggested that the method adopted in the thesis can achieve a higher human face identification rate and a remarkable promotion effect.

***Keywords**: Compressed sensing; Difference imaging; Human face identification*

1.Introduction

At present, human face identification has achieved a rapid development under local limited conditions, while in actual operation, the identification rate of the human faces collected remain subjected to a big influence from the uncontrollable factors like the sunlight and facial expression. Therefore, it is a question in urgent need of settlement how to improve human face identification under complex conditions [1]. In reference [2], the method of sparse representation classification (MSRC) has proposed based on monogenic characteristic, which, compared with Habor characteristics, can be used to extract the phase information of the images. Since the phase information is not allergic to the sunlight, so MSRC can improve the robustness of the sunlight. What's more, compared with the multi-dimension and multi-direction characters of GABOR, monogenic characteristic can reduce the time for process. it has been proved by the experiment results that the method mentioned in this the thesis has some use value, and can enhance identification rate and speed to certain extent. Lagrangian algorithm is used in reference [3] to solve the inverse deduction thought for matrix. It is a simplified pseudo-inverse calculation method to replace the calculation for l_1 norm, and turns matrix inversion calculation with higher calculation burden to lightweight vector matrix operations. The experiment based on AR human face base, the identification rate under a high dimension can reach up to 97%, meanwhile calculation complexity and expense can reduce by 95% from SRC calculation. Human face identification calculation under shade is come up with in reference [4]. First, it uses image decomposition algorithm to decompose the training image set into common portion, and the portions of low-rank condition and sparse error; then it respectively uses PCA to structure two projection matrixes, construct them to the final project matrix, then project the previous training set and test sample; in the end, it uses block sparse representation in the projection space to classify and identify the test

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samples. The experiment has proved that the method can achieve a high identification rate in low-dimension space and has a strong robustness. In reference [5], there has raised the sparse representation algorithm based on symmetric Gabor characters which has successfully been applied in human face identification. It first makes mirror transformation of human face images for the mirror image and decomposes human face to odd-even symmetry. Then, it respectively extracts Gabor characters from odd-even symmetry face to get Gabor odd-even symmetry characters. The odd-even character can be fused into some new characters by a weighing factor. In the end, the new characters will form an ultra-complete dictionary for human face identification based on sparse representation. Another identification method has been given in reference [6] based on even LBP (Local Binary Pattern) operator and sparse code. It uses a few key characters to replace the dimension reduction process and solve the problem of sparse training sample. The test on Stirling human face base has proved the effectiveness of algorithm by achieving a high identification rate and robustness.

Based on the research above, the thesis has first designed the optimal sampling matrix to acquire compressed measurement data; then it adopts iterative method based on the close loops of l_2 and l_1 in normal form to get an estimate on human face images, since the method based on norm l_2 can measure the relevancy of human face images in the space and time of the continuous time point, and the method based on norm l_1 mainly uses the modified total variation method and basis pursuit noise-reduction method. The simulation design has suggested that the method adopted in the thesis can achieve a higher human face identification rate and a remarkable promotion effect.

2. Sparse Difference Images

Difference images refer to the images formed by the target scene subtracting the images at the continuous time point. Assume x_k and x_{k+1} are respectively the images of the target scene at the time of t_k and t_{k+1}, the difference image k can be defined like this:

$$\Delta x_k = x_{k+1} - x_k \tag{1}$$

Difference images in the broad sense ,means the difference of the images formed by the target scene at the time of t_k and t_{k+1}:

$$\Delta x_{kL} = x_{k+L} - x_k \tag{2}$$

Compared with the traditional method, the compression measurement can reduce the dimension of sampling data and separate the imaging scenes into the units with δ_r resolution ratio, then form the separated data to the vector of $N \times 1$. The compressed measurement value requires $M \times N$ random projection matrix to project the high-order data to the low-dimension data space, so that the compressed measurement value can include all the information required for restoration of the previous images.

Assume x_1 and x_2 are the target scenes at the continuous time points of t_1 and t_2. The target scenes at the two time points are both separated into vector, assume Φ_1 and Φ_2 are the corresponding random sampling matrix $M \times N (M < N)$, the compressed measurement data can be expressed as below:

$$y_1 = \Phi_1 x_1 + n_1 \tag{3}$$

$$y_2 = \Phi_2 x_2 + n_2 \tag{4}$$

Among， n_1 and n_2 means 0 average Gaussian noise at δ^2 variance

3. Optimal Method Description of the Two Norms

3.1. l_2 Norm Optimization Method

The optimization method based on norm l_2 is to use the compressed measurement values y_1 and y_2 to get difference image Δx_1 in the method of optimization, to make sure the minimum Δx_1 and norm l_2 of the actual difference value of the difference images.

The difference images can be directly acquired by the compressed measurement values y_1 and y_2. The method cannot only use the spatial relevancy of the pixel and also the time relevancy at different time points. Therefore, it can get a more accurate difference images. Assume the estimated difference images is

$$\Delta x_1 = W_1 y_1 + W_2 y_2 \tag{5}$$

Among， W_1 and W_2 are joint optimized estimation function. We call the method the direct difference image estimation method (DDIE)

In the method of DDIE, we assume that the scene is confirmed at the time of the earliest sampling, so we can assume the matrix Φ_1 as the unit matrix at the time t_1， and use the method of compression to acquire the measurement data after the time t_2. In this case, the formula (3) and (4) can be expressed as below：

$$y_1 = I x_1 + n_1 \tag{6}$$

$$y_2 = \Phi_2 x_2 + n_2 \tag{7}$$

Use Bayes estimation method, the target function can be：

$$J\left(W_1, W_2\right) = E\left[\left\|\Delta x - \Delta x\right\|_2^2\right] \tag{8}$$

The solution (8) is corresponded to the differential W_1 and W_2， and make it equal to 0， it can be acquired：

$$W_1 = \left(\left(R_{21} - R_{11}\right) - \left(R_\alpha - R_\beta\right)\Phi_2{}^T \times \left(\Phi_2 R_\alpha \Phi_2{}^T + R_{n_2}\right)^{-1} \Phi_2 R_{21}\right)\left(R_{11} - R_{n_1}\right)^{-1} \tag{9}$$

$$W_2 = \left(R_\alpha - R_\beta\right)\Phi_2{}^T \left(\Phi_2 R_\alpha \Phi_2{}^T + R_{n_2}\right)^{-1} \tag{10}$$

Among：

$$R_\alpha = R_{22} - R_{21}\left(R_{11} + R_{n_1}\right)^{-1} R_{12}$$

$$R_\beta = R_{12} - R_{11}\left(R_{11} + R_{n_1}\right)^{-1} R_{12}$$

Matrix R_β has reflected the loss of related information in presence of noise. In case of

0 noise, R_β will also be 0. However, noise can hardly be avoided in actual application and the loss of information is also inevitable. R_β happens to reflect the degree of information loss. So it is impractical to seek the optimal sampling matrix in noise, that is why some inferior sampling matrix are often adopted, like the sampling matrix (PC) formed by principal component (PC), the sampling matrix (DPU) formed by the principal component of the difference imaging, and the sampling matrix (WPC and WDPC) formed by the weighted principal component.

3.2. l_1 Norm Optimization Method

The advantages of the estimation method based on l_2 norm is that it can provide a close-loop linear estimation method to get a minimal MSE of the target scene, but the estimation method based on l_2 never uses the sparse characters of the difference images. In addition, although the time and space-related matrix used in l_2 norm estimation method fails to achieve a satisfactory estimation result, it is unrealistic to assume the images are static. Therefore, the estimation method based on l_1 norm can be adopted, which can make full use of the sparse characters of the difference images. In addition, total variation method based on l_1 norm can also effectively estimate the margin characters of the difference images.

The difference image estimation method based on l_1 norm can be seen as the linear inverse problem as expressed in formula (11):

$$y = Ds + n \tag{11}$$

Among, D represents linear transformation. Linear inverse problem aims to estimate s from noise measurement value y. Formula (11) is the typical signal reconstruction issue based on l_1 norm, but the issue is different from those in the formulas of (3) and (4). To use the method based on l_1 norm, the formulas (3) and (4) can be changed to:

$$y = \Phi_D x + n \tag{12}$$

Among:

$$\Phi_D = \begin{bmatrix} I & \mathbf{0} \\ \mathbf{0} & \Phi \end{bmatrix}, y = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}, x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, n = \begin{bmatrix} n_1 \\ n_2 \end{bmatrix} \tag{13}$$

Assume x can be expressed as below on the sparse matrix Ψ:

$$x = \Psi s \tag{14}$$

Formula (12) can be represented like:

$$y = \Phi_D \Psi s + n \tag{15}$$

Formula (15) can be expressed through the formula (16):

$$\arg\min_{\mathbf{s}} \|y - \Phi_D \Psi s\|_2^2 + \xi R(s) \tag{16}$$

Among, $R(\mathbf{s})$ regularization component

$$R(\Delta x_1) = \|x_2 - x_1\|_{l_1} = \|\Delta x_1\|_{l_1}$$

To make full use of the sparse characters of the difference images, the regularization component in the formula (16) can be defined as below:

In case the method of total variation is adopted to solve the formula (16), the regularization component can be defined as：

$$\begin{aligned} R_{iso}(\Delta x_1) &= \sum_i \sqrt{\left(\Delta_i^h \Delta x_1\right)^2 + \left(\Delta_i^v \Delta x_1\right)^2} \\ R_{niso}(\Delta x_1) &= \sum_i \Delta_i^h \Delta x_1 \Big| + \Big| \Delta_i^v \Delta x_1 \end{aligned} \tag{17}$$

Among, R_{iso} and R_{niso} respectively represent homo-components and hetero-components. Δ_i^h and Δ_i^v are the difference operator in horizontal and vertical directions.

Sparse representation method based on the ultra-complete dictionary can also be adopted for the estimation of the difference images. Assume the sparse representation dictionary is Ψ and Ψ is symmetric orthogonal wavelet transform matrix，the regularization component will be $\|\mathbf{s}\|_{l_1}$. The method can be solved by use of basis pursuit method (BPDN).

4. Simulation Experiment

On the platform Windows 7, Matlab 2012 has been used in the thesis for simulation. To verify the algorithm introduced in the thesis on human face identification function, PCA algorithm, and the algorithms in other previous thesis have been used for comparative experiment, with identification rate and time as the performance evaluation indicators.

4.1. Human Face Base

（1）Yale B human face base

Yale B human face base is composed of 10 people, with each showing 9 poses. As shown specifically in Fig.1, human faces under the direct sunlight are chosen in 4 subsets, because the thesis mainly focuses on human face identification under the sunlight:

(a) Subset 1

(b) Subset 2

(c) Subset 3

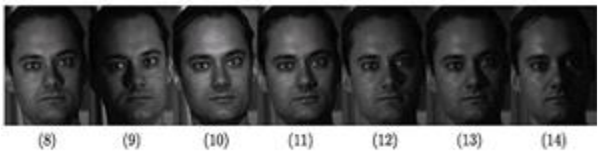
(d) Subset 4

Figure 1. YaleB Four Human Face Subsets Under Sunlight

(2) CMU-PIE human face base

65 human face images are randomly selected in the thesis, with each person having a image set under 21 sunlight conditions that can be divided into 3 subsets, as shown in Fig. 2

(a) Subset 1



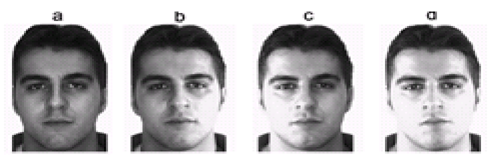
(b) Subset 2

(c) Subset 3

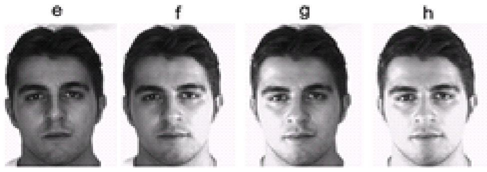
Figure 2. CMU-PIE the Images of the Same Person Under 21 Sunlight Conditions

(3) AR human face image base

AR human face base includes over 4000 colorful images and multiple facial expressions deviating from the ideal conditions. 8 facial expressions of the same people have been chosen in the thesis divided in 2 subsets, as shown in Fig. 3



(a) Subset 1

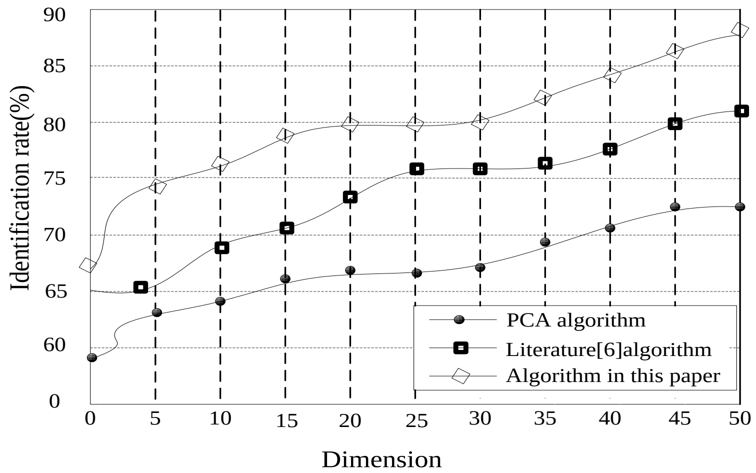


(b) Subset 2

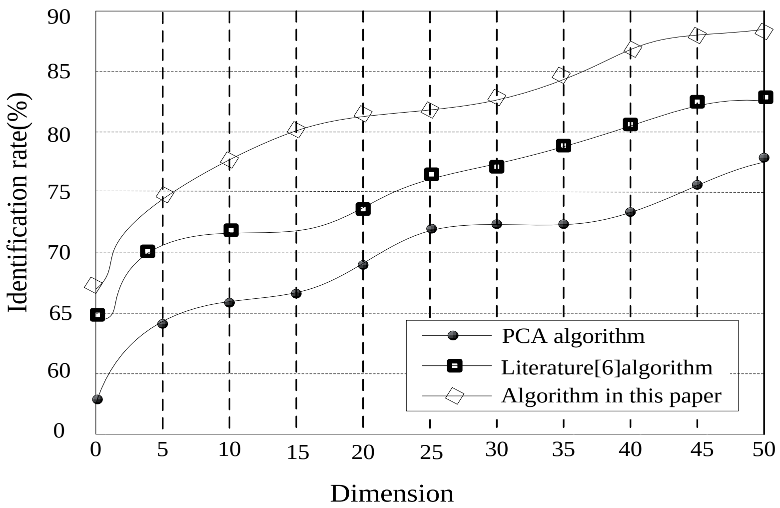
Figure 3. AR the Face Images of the Same Person under 8 Sunlight Conditions

4.2. Result and Analysis

Human face images at the angles of 10° and 50° are chosen for test in the thesis. 3 images are randomly selected as the test sample, and the test result can be shown in Fig. 4

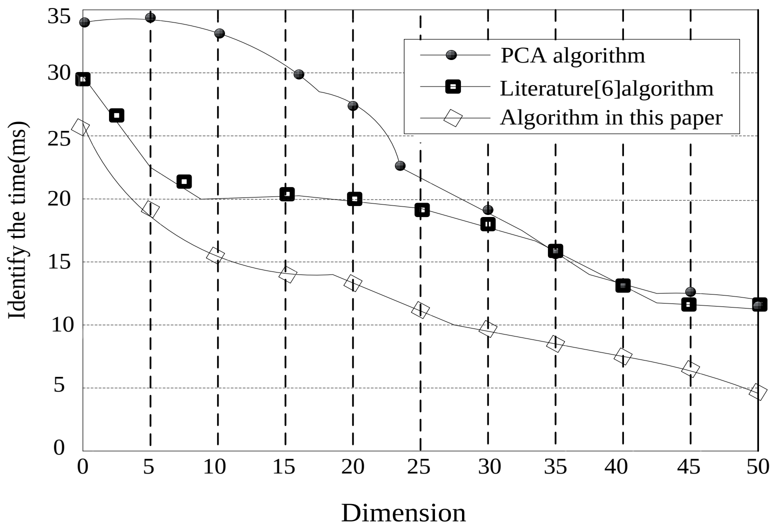


(a) θ=10°

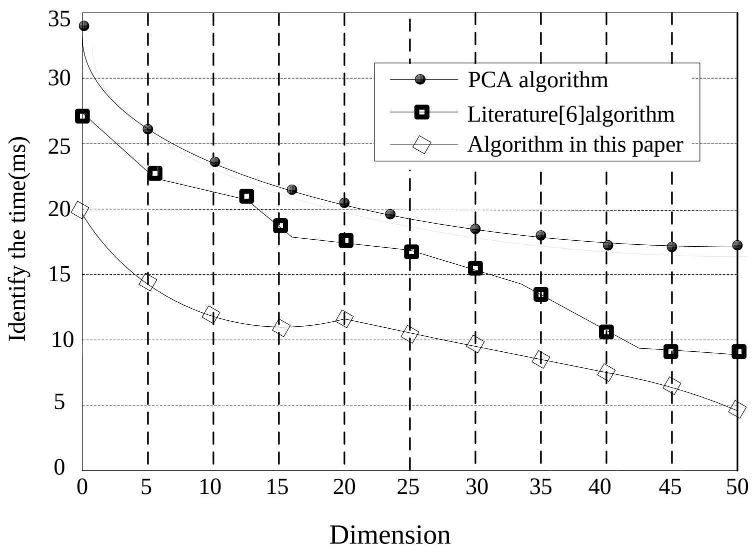


(b) θ=50°

Figure 4. Human Face Identification Rate Changing Curve in Different Poses



(a) θ=10°



(b) θ=50°

Figure 5. Human Face Identifcation Time Curve in Different Poses

It can be discoveed from Fig 4-5 that the idenftification rate by the algorothim introduced in the thesis is obviously higer than the otjer two algorithms, and it consumes much less time. that suggests that the algorithm introduced in tge thesis has a distinct superior.

5. Conclusion

The thesis mainly focuses on a method based on human face image characteristics, First, it is a design for the optimal sampling matrix to acquire compressed measurement data; then it adopts iterative method based on the close loops of l_2 and l_1 in normal form to get an estimate on human face images, since the method based on norm l_2 can measure the relevancy of human face images in the space and time of the continuous time point, and the method based on norm l_1 mainly uses the modified total variation method and basis pursuit noise-reduction method. The simulation design has suggested that the method adopted in the thesis can achieve a higher human face identification rate and a remarkable promotion effect.

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