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Low Resolution Face Recognition using Super-resolution

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***Abstract*— With the increasing demand of surveillance camera-based applications, the low resolution face recognition algorithms need in many face application system. Recognition performance will be dramatically degraded under the low resolution. In order to overcome this problem, face super-resolution methods can be employed to enhance the resolution of the images. In this paper low resolution face recognition algorithm using new super-resolution is introduced in which the resolution of the face image to be recognized is 16×16. Experiments of super-resolution image reconstruction were performed with the L2 error norm for data-fidelity and proposed weighted gradient constraint were used as regularization terms. Additionally, the eigenface and fisherface were employed for face recognition. Experimental results show that the proposed SR algorithm outperforms the existing algorithms in public face databases.**

Keywords*— *super-resolution, regularization technique, low resolution face recognition, bilateral filter

I. Introduction

Over the last ten years or so, face recognition has become a popular area of research in computer vision and one of the most successful applications of image analysis and understanding. However, in surveillance system, the regions of interests are often impoverished or blurred due to the large distance between the camera and the objects, or the low spatial resolution of devices when the input face images are degraded seriously, such as low-resolution (LR). This is because the LR face image contains very limited information and many image details have been lost [1].

In order to overcome these problems, several algorithms to recover the missed details of the face image such as super-resolution (SR) image reconstruction [2]. The SR image reconstruction method creates high-resolution image from one or more observed low-resolution images. In general, the SR image reconstruction approach is an ill-posed problem, which means that an infinite number of solutions exist due to an insufficient number of LR images, and an ill-conditioned problem, which means that small amounts of noise in measurements will result in large perturbations in the final solution. Sever approaches to the SR image reconstruction problem have been developed [3].

Due to the self-similarity of the face images, a specific SR has been designed to enhance the size of the face region and this SR is referred to as facial SR or face hallucination. By contrast with traditional SR technology, most facial SR algorithms are machine learning based. Although machine learning based techniques can also e used in traditional SR, machine learning based techniques are more effective for face images due to the characteristics of human faces.

In this paper, a new facial SR image reconstruction algorithm is introduced; an initial HR image using sparse representation [6] is obtained, and then edge enhancement pre-process is applied using a bilateral filter [7]. Next, HR image is obtained using the proposed weighted gradient constraint. Additionally, proposed facial SR image reconstruction algorithm was applied to LR face recognition using eigenfaces and fisherfaces [4,5].

II. Super-resolution

A. Basic Concepts of Super-resolution

The goal of the super-resolution (SR) algorithm is to recover a high-resolution (HR) image from one or more low-resolution (LR) input images. In SR image reconstruction, it is assumed that toe observed LR image Y is a blurred and down-sampled version of the HR image X:

$$Y = DHX\ . \tag{1}$$

Here, H represents a blurring filter and D is the down-sampling operator. This problem can be rewritten as the following minimization problem:

$$X^* = Argmin_X \rho_d(Y, DHX)\ . \tag{2}$$

Here, ρ is the error norm measuring the "distance" between the model and the measurements.

B. Regularized SR approach

The regularized SR reconstruction approach is very useful as a method for identifying a stable solution. Moreover, regularization can assist the algorithm to remove artifacts from the final answer and improve the rate of convergence. Regularized SR approach occurs using of two terms; the data-fidelity term and the regularization term, which is defined as follows:

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$$X^* = Argmin_X [\rho(Y, DHX) + \lambda\Gamma(X)] . \quad (3)$$

Here, λ, which is the regularization parameter, is scalar for appropriately weighting the first term against the second term and Γ is the regularization cost function.

The regularization term can compensate the missing measurement information with some general prior information about the desirable HR solution, and it is usually implemented as a penalty factor in the generalized minimization cost function in (2). One of the most widely referenced regularization cost functions is the total variation (TV), which penalizes the total amount of change in the image as measured by the L1 norm of the magnitude of the gradient. The TV method is a successful regularization technique for denoising and deblurring, and it tends to preserve the edges as well. Another popular regularization cost function is the bilateral total variation (BTV), which is based on the TV criterion and a bilateral filter [8].

The solution to the optimization problem in (3) can be efficiently computed using a gradient descent. Therefore, the equation for this iterative method is:

$$X_{t+1} = X_t + \beta\left[\frac{\partial\rho(Y, DHX_t)}{\partial X_t} - \lambda\frac{\partial\Gamma(X_t)}{\partial X_t}\right]. \quad (4)$$

Here, the parameter β is scalar and determines the step size in the direction of the gradient.

III. Proposed SR Algorithm

A. Sparse representation

In (4), a good initial approximation X_0 of the desired HR image is required. In many cases, a bilinearly interpolated LR image serves for the initial value X_0. However, it has a blurring effect and jaggy artifacts along the edges. Hence, the initial X_0 was set using a sparse representation.

Let D_l, and D_h be the dictionary that consists of the LR and HR image patches, respectively. These patches were taken starting from the upper-left corner with an overlap of 1 pixel in each direction. Sparse representation means that for each HR image patch x, a sparse vector α exists such that $x \approx D_h\alpha$ and $\|\alpha\|_0$ is sufficiently small. Also, an LR image patch y can be generated by multiplying D_l by the same sparse vector α. This problem can be formulated as follows:

$$\min_\alpha \|\alpha\|_1 \text{ such that } \|FD_l\alpha - Fy\|_2^2 \le \epsilon . \quad (5)$$

Here, F is a feature extraction operator. In this paper, four filters that perform first and second horizontal and vertical derivatives, respectively, are used. This problem can be efficiently solved using linear programming such as LASSO or OMP.

B. Proposed Regularization cost function

In section 2, the well-known regularization cost function, such as total variation, bilateral total variation, was introduced. These functions tend to reserve the edges. In this paper, a new regularization cost function is introduced that uses the initial HR image X_0, which is defined as follows:

$$\Gamma(X) = \| \omega\nabla X - (1-\omega)\nabla X_0 \|_2 . \quad (6)$$

The influence function of (6) is formulated as follows:

$$\frac{\partial\Gamma(X)}{\partial X} = \omega\nabla^2 X - (1-\omega)\nabla^2 X_0 . \quad (7)$$

Here, X_0 is the initial HR image, and $\nabla^2 X$ is the Laplace of X. The weight ω is scalar with values between 0 and 1, and it determines how the gradient of X follows the gradient of the initial SR image X_0.

Before regularized SR image reconstruction, as apply to edge enhancement pre-process, clearer image with visually sharp edges were obtained. In order to enhance the edges of X_0, bilateral filter, which is an edge-preserving and noise-reducing smoothing filter, is used.

IV. Experiments

A. Data base and settings

Public face database CMU-PIE is selected for the experiments [9]. Database consists of 41,368 images of 68 people, each person under 13 different poses, 43 different illumination conditions and with 4 different expressions. Since there is no general method for aligning images with different poses, a subset of frontal view images from 68 persons with 21 different illuminations is used in our experiments. All images are manually aligned by the position of the eyes and normalized to the resolutions of 64×64 (HR) and 16×16 (LR).

For each database, images are decided into two no-overlapped set according to their class label. Image from 10 different illuminations per one person are randomly selected as the training data, and the rest of images are randomly selected as the training data, and the rest of images are used as the testing set.

B. Facial SR image reconstruction

In SR face image reconstruction, a step size parameter β = 0.3, a regularization parameter λ = 0.05 from (4), and weight scalar ω = 0.7 in (6) was used. Fig. 1 shows some of the reconstructed images using the proposed and existing method on the CMU-PIE database. Fig. 1(a) and (d) show the input LR image and the original HR image, respectively. Fig. 1(b) is the reconstructed HR image using bicubic interpolation. It is shown that bicubic interpolation method give a relatively blurred image, and high-frequency details cannot be recovered. Fig. 1(c) shows the reconstructed HR image using the proposed method. It is shown that the proposed method removes the blurring effect and obtains visually clear, sharp edges.

Figure 1. SR results on the CMU-PIE database. (a) Input LR image, (b) Bicubic interpolation, (c) Proposed method, (d) Original HR image.

C. Face Recognition

In this experiment, we would like to evaluate the performance of the proposed facial SR image reconstruction algorithm in terms of recognition accuracy. In order to face recognition, we employ the widely used the eigenface and fisherface. Fig. 2 shows the recognition rate vs. the number of principal components on the CMU-PIE database with eigenfaces. In Fig. 2, the gap between the HR and bicubic interpolation method is around 6%. The proposed facial SR method improves the performance (around 3%) and outperforms bicubic interpolation method.

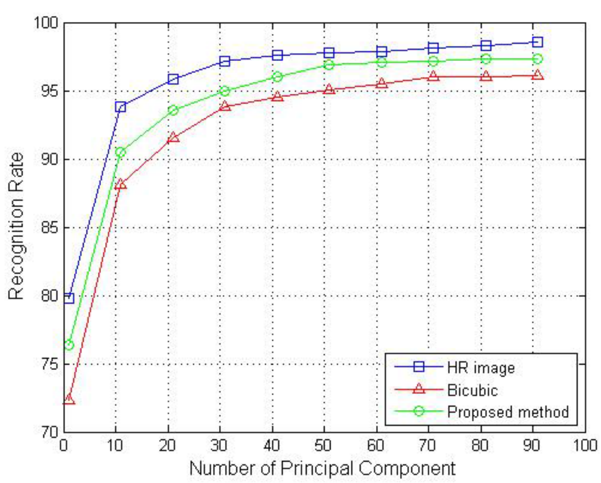

Figure 2. Recognition result on the CMU-PIE database from the eigenfaces.

In Fig. 3, the gap between the HR and bicubic interpolation method is around 25%. The proposed facial SR method improves the performance (around 13%) and outperforms bicubic interpolation method.

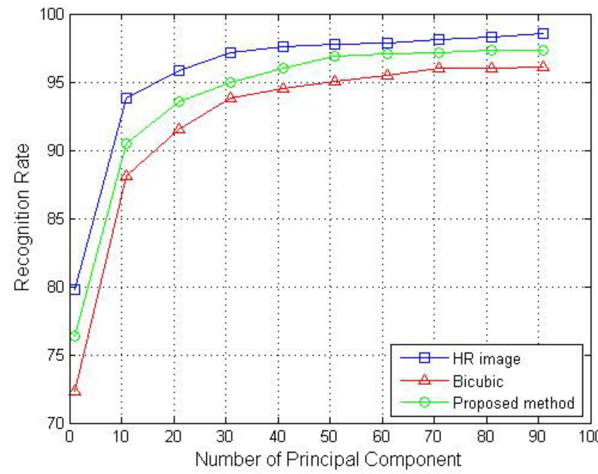

Figure 3. Recognition result on the CMU-PIE database from the fisherfaces.

V. CONCLUSION

In this work, LR face recognition algorithm using new SR image reconstruction is introduced in which the resolution of the face image to be recognized is 16×16, which consists of two steps: facial SR image reconstruction, a HR image was created from a single facial LR image using sparse representation and regularized SR image reconstruction. A new regularization cost function, which is called weighted gradient constraint, was introduced. As change weight scalar ω, how the gradient of the updated HR image follows the gradient of the initial HR image was determined. In the face recognition, the proposed SR method improves the performance and outperforms bicubic interpolation method.

REFERENCES

[1] Wilman W. W. Zou, Pong C. Yuen, "Very Low Resolution Face Recognition Problem", *IEEE Trans. on Image Processing*, vol. 21, no. 1, Jan. 2012.

[2] P. H. Hennings-Yeomans, S. Baker, and B. Kumar, "simultaneous super-resolution and feature extraction for recognition of low-resolution faces" in *Proc. IEEE Int. Conf. Comput. Vis. Pattern Recogni.*, pp. 1-8, 2008.

[3] S.C. Park, M.K. Park, and M.G. Kang, "Super-Resolution Image Reconstruction: A Technical Overview", *IEEE Signal Processing Magazine*, vol. 20, no 3, pp. 21-36, May 2003.

[4] M. Turk and A. Pentland, "Eigenfaces for recognition", *Journal of Cognitive Neurosci*, vol. 3, no. 1, pp. 71-86, 1991.

[5] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, "Eigenfaces vs. Fisherfaces: Recognition using class-specific linear projection", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, pp. 711-720, 1997.

[6] Y. Jianchao, W. John, and T. S. Huang, "Image Super-Resolution Via Sparse Representation", *IEEE Trans. Image Processing*, vol. 19, no. 11, pp. 2861-2873, Nov. 2010.

[7] C. Tomasi and R. Manduchi, "Bilateral Filtering for Gray and Color Images", *6th International Conference on Computer Vision*, Bombay, India, pp. 839-846, Jan. 1998.

[8] S. Farsiu, M. D. Robinson, and M. Elad, "Fast and Robust Multiframe Super Resolution", *IEEE Trans. on Image Processing*, vol. 13, no. 10, pp. 1327-1344, Oct. 2004.

[9] T. Sim, S. Baker, and M. Bsat, "The CMU pose, illumination, and expression database" *IEEE Trans. Pattern Anal. Mach*. Intell., vol. 25, no. 12, pp. 1615-1618, Dec. 2003.