COLOR FACIAL IMAGE DENOISING BASED ON RPCA AND NOISY PIXEL DETECTION

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ABSTRACT

In this paper, a novel approach for color facial-image denoising based on robust principal component analysis (RPCA) [1] in the $L^*a^*b^*$ color space and noisy pixel detection is proposed. Firstly, RPCA is employed for color facial-image recovery in the $L^*a^*b^*$ space. Then, the reconstructed image is used for noisy pixel detection. Finally, the denoised facial-image can be obtained. Experiments are conducted based on the AR database, where our proposed method is compared with several state-of-the-art image-denoising methods. Experimental results show that our method can achieve a better performance in terms of both quantitatively evaluation and visual quality.

Index Terms— Image denoising, color facial-image, RPCA, noisy pixel detection

1. INTRODUCTION

Images contain a great amount of information and provide great intuitions which are with incomparable superiority over written characters and voices. For these reasons, images are of great importance and significance to us in terms of information. Nowadays, human-computer interaction and computer-vision techniques have been extensively and widely applied. Therefore, there is a higher demand for image quality, especially with color facial-images, which play an important role in high-tech applications such as videophones, video conferencing, digital cameras, etc. Obtaining a color facial-image of high quality is crucial, and has a great influence on applications such as object detection, image encoding, face recognition, image segmentation, and edge detection. Therefore, color image denoising is an essential step in image processing and seeking an effective denoising method is a significant task.

Over the past decades, facial-image denoising has been widely studied in the field of computer vision and image processing, with the aim of removing noises while preserving the useful information in images. Thierry and Florian [2] presented a denoising method which reformulates the denoising problem as a search for the denoising process. It can be expressed as a linear combination of elementary denoising processes, which are based on the image-domain minimization of an estimate in terms of mean squared errors. Kostadin et al.[3] proposed the BM3D method, which divides an image into blocks of a certain size, assembles those 2D blocks with a similar structure to form a 3D array, processes the 3D array by means of joint filtering, and finally obtain a denoised image using an inverse 3D transformation. Wang et al.[4] used the Gabor-feature-based nonlocal means (GFNLM) filter for textured image denoising. Noise-corrupted images are recovered by replacing each pixel value with a weighted sum of pixel values within its search window, where each weight is defined based on the Gabor-based texture similarity measure. Aharon et al.[5] presented a KSVD method for training an over-complete dictionary containing prototype signal-atoms. Denoised images are obtained by using a sparse, linear combinations of the atoms under strict sparsity constraints.

Although all of the above-mentioned methods can achieve a good performance, severe blurring occurs in the denoised images when noise power increases, and these methods depend largely on the noise-distribution parameters, which become complicated in practical applications. In this paper, the strong clustering characteristics of facial images is utilized, and noise is considered as a local distortion. A novel color facial-image denoising approach based on RPCA recovery in the $L^*a^*b^*$ space and noisy pixel detection is proposed. Experimental results show that our proposed method can effectively remove noises without requiring any prior knowledge of the noise, and can effectively preserve the facial features.

2. ALGORITHM

2.1. Facial-image reconstruction based on RPCA in $L^*a^*b^*$ space

Our object is to denoise a color facial-image. A color image has three channels, i.e. R, G and B. However, considering the heterogeneity of the RGB color space [6], it is desirable to have a color space which is perceptually more uniform for image denoising so as to produce images with a better visual quality. An ideal candidate is the $L^*a^*b^*$ color space, where L^* represents luminance, ranging from 0 to 100, and color is described by a^* and b^*. It is the most complete color model for describing all of the visible colors, and is independent of display devices. We can adjust luminance contrast through

L^*, and balance color effect by changing a^* and b^* separately, which is very difficult to achieve using the RGB space. What is even more attractive about using this color space is that a change in the values in this space will produce almost the same change in the visual effect [7]. Therefore the $L^*a^*b^*$ model is used for our color facial-image denoising algorithm.

It is well known that the images of a convex, Lambertian surface under varying illuminations span a low-dimensional subspace [8]. Noises can be seen as local distortions in facial images, and we know that facial images have a very strong clustering characteristic. Therefore, if we have a sequence of facial images, a denoised image can be obtained using R-PCA, whose basic idea is to recover a low-rank matrix L_0 (representing a denoised image) and a sparse matrix S_0 (representing the noise) from a highly corrupted measurement M (representing a noisy image), i.e. $M = L_0 + S_0$ [1]. In this paper, RPCA is applied to derive a reconstructed image, which can then be used for noisy pixel detection and elimination. Figs. 1(b) and 1(c) illustrate that RPCA in the $L^*a^*b^*$ space can perfectly supplement that in the RGB space. The reconstructed images in the $L^*a^*b^*$ space (i.e. the images shown in Fig. 1(c)) have better visual effects, without additional colors in the canthus and hair, which occur in the images recovered in the RGB space (i.e. the images shown in Fig. 1(b)).

Fig. 1. (a) Gaussian noise $\sigma^2 = 25$ and $\sigma^2 = 225$ is added to the images in the first and the second row, respectively; (b) images obtained using RPCA recovery in the RGB space; (c) images obtained using RPCA recovery in the $L^*a^*b^*$ s-pace; and (d) the denoised images obtained using our proposed method.

2.2. Noisy pixel detection and image denoising

Gaussian noise is added into the testing image to form a noisy image, and RPCA is then performed in the $L^*a^*b^*$ space to reconstruct a denoised image. It can be seen that RPCA recovery can remove the noise effectively. However, blurred edges and face morphing may occur simultaneously in the reconstructed images, as shown in Fig. 1(c). There may be two reasons for this. The first is that the aim of RPCA is to produce a low-rank matrix. This will remove noises and redundancies, as well as some useful high-frequency information that results in image blurring. The second reason is that only the common features of the images in the training set, rather than the whole information in the testing image, are contained in the reconstructed image. In other words, face morphing will unavoidably occur. Therefore, a noisy pixel detection and elimination procedure is performed to preserve as much of the information in the testing image as possible.

The idea of our algorithm is to determine whether a point under consideration is a noisy pixel, based on a certain criterion. Each pixel in the the $L^*a^*b^*$ color space can be represented as a 3D vector. Then, the Euclidean distance and the intersection angle between two 3D vectors are used to measure their similarity. Therefore, in order to make an effective determination, we propose two measurements [9], namely pixel-distance standard deviation (denoted as PDSD) and pixel-angle standard deviation (denoted as PASD), which are defined as follows:

$$\begin{aligned} PDSD_{i,j} &= \left(\frac{1}{N}\sum_{n=1}^{N}\left(D(v_{n,i,j},\overline{v_{i,j}}) - \overline{D(v_{n,i,j},\overline{v_{i,j}})}\right)^2\right)^{\frac{1}{2}} \\ PASD_{i,j} &= \left(\frac{1}{N}\sum_{n=1}^{N}\left(\theta(v_{n,i,j},\overline{v_{i,j}}) - \overline{\theta(v_{n,i,j},\overline{v_{i,j}})}\right)^2\right)^{\frac{1}{2}} \end{aligned} \tag{1}$$

$$\begin{aligned} D(\overrightarrow{x},\overrightarrow{y}) &= \left(\sum_{p=1}^{m}(x_p - y_p)^2\right)^{\frac{1}{2}} \\ \theta(\overrightarrow{x},\overrightarrow{y}) &= arccos\left(\frac{\overrightarrow{x}\cdot\overrightarrow{y}^T}{|\overrightarrow{x}||\overrightarrow{y}|}\right) \end{aligned} \tag{2}$$

where N is the number of images in the training set; $\overline{v_{i,j}}$ is the mean pixel vector of the training set at pixel position (i,j); $D(\overrightarrow{x},\overrightarrow{y})$ is the Euclidean distance between the two vectors; $\theta(\overrightarrow{x},\overrightarrow{y})$ is the intersection angle between the two vectors; and p is the dimensions of the pixel vector (i.e. $p = 3$).

At each pixel position, the mean pixel vector is first calculated. Then, the Euclidean distance variance and intersection-angle variance are computed to describe the pixel-distribution range. After that, the Euclidean distance and intersection angle between the testing image and the corresponding RPCA reconstructed image are calculated, and are denoted as $D_{i,j}$ and $\theta_{i,j}$, respectively. The images in the training set, which are obtained from a standard color face database, are considered noiseless. Our detection criterion is based on the Chebyshev Inequality [10]. That is, if both the Euclidean distance and the intersection angle between a testing image and its reconstructed image are within a certain range of the mean Euclidean distance and mean intersection angle, then that pixel can be considered noiseless; otherwise, it is a noisy pixel.

The detection criterion, therefore, is as follows:

$$\begin{aligned} |D_{i,j} - \overline{D(v_{n,i,j},\overline{v_{i,j}})}| &< kPDSD_{i,j} \\ |\theta_{i,j} - \overline{\theta(v_{n,i,j},\overline{v_{i,j}})}| &< kPASD_{i,j} \end{aligned} \tag{3}$$

where $\overline{D(v_{n,i,j}, \overline{v_{i,j}})}$ is the mean Euclidean distance and $\overline{\theta(v_{n,i,j}, \overline{v_{i,j}})}$ is the mean intersection angle of the training images at pixel position (i, j), and *k* is an empirical constant. The detection criterion will be applied to all pixels one by one. Then, the final reconstructed, denoised color facial image is obtained as follows:

$$X_{FINAL,i,j} = \begin{cases} c_1 \cdot X_{test,i,j} + c_2 \cdot X_{RPCA\_rec,i,j} & \text{noisy} \\ c_2 \cdot X_{test,i,j} + c_1 \cdot X_{RPCA\_rec,i,j} & \text{if not} \end{cases} \quad (4)$$

where c_1, c_2 are the blending coefficients whose function is to reduce errors of judgement, and $c_1 + c_2 = 1$.

All of the procedures of our algorithm are illustrated in Fig. 2.

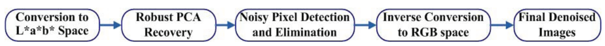

Fig. 2. The procedures of our algorithm

From Fig. 1(d), it can be found that more information about the testing image is preserved in the final, denoised image. The problems of edge blurring and face morphing are resolved by introducing a slight noise.

3. EXPERIMENTAL RESULTS

In our experiments, color facial images from the AR database [11] are selected as the training set. All images are cropped to a size of 64×64 and are normalized to align the two eyes and the vertical position of the mouth. 282 images are selected as our training set, which contains 47 persons, and for each person there are 6 samples with different expressions and poses. The other 10 persons not included in the training set are selected to form the test set. The images in the training set and the test set are all without occlusions. Gaussian noise, salt-and-pepper noise, blocky noise, and mixed noise (a combination of the other three kinds of noise) are added to the test images. For our proposed method, RPCA recovery in the $L^*a^*b^*$ space is first carried out, and the noisy pixel detection and elimination method is then performed. The value of *k* in (3) is set at 0.2 and in (4), c_1 and c_2 are set at 0.1 and 0.9, respectively. The BM3D [3], KSVD-DCT, KSVD-Global and KSVD-Adaptive [5]methods are compared to our algorithm. PSNR is adopted to evaluate the performances of the different algorithms. The corresponding results are illustrated in Fig. 3 and Fig. 4, where we also show the results based on RPCA recovery only.

From the results, we can see that, for facial images with Gaussian noise, when the noise power is small, the denoising performances of our method, BM3D, KSVD-DCT, KSVD-Global and KSVD-Adaptive are approximately the same and are better than using RPCA recovery only. However, when the noise power increases, our method performs better. A higher PSNR can be achieved, as well as better visual quality. For salt-and-pepper noise, blocky noise, and mixed noise, the visual qualities of the denoised images based on BM3D, KSVD-DCT, KSVD-Global and KSVD-Adaptive are all lower than that with our method, as illustrated in Fig. 4: severe blurring occurs, and a large amount of noise still remains. As the noise power increases, the denoising capabilities of these methods will become worse. For RPCA recovery, noises can be removed effectively, but edge blurring and face morphing occur. For our method, even when the noise power is large and several different kinds of noise exist, a good denoising performance can still be achieved. That is due to the fact that our method does not consider noise type, while the the other methods assume the noise type to be Gaussian, and their performances depend on the noise variance. Therefore, the denoising capability of these methods will drop significantly for non-Gaussian noises. Furthermore, even if the noise is Gaussian, when its power is large, severe blurring occurs in the denoised images, and useful information may be filtered out. RPCA recovery works based on the facial-feature clustering characteristic, and regards noises as local distortions. Therefore, RPCA recovery does not depend on any prior knowledge about the noise. However, some detailed information on input images may sometimes be eliminated in the denoising process. For our proposed method, the noisy-pixel detection method is included, which can effectively distinguish a noisy point from a noiseless point. Therefore, more information about the query image can be used in producing the final denoised image. Consequently, noises in the images can be further reduced, and only a slight blurring and relatively clear face profile will appear in the denoised images. This is of great significance to the tasks that follow, such as image segmentation, edge detection, and face recognition.

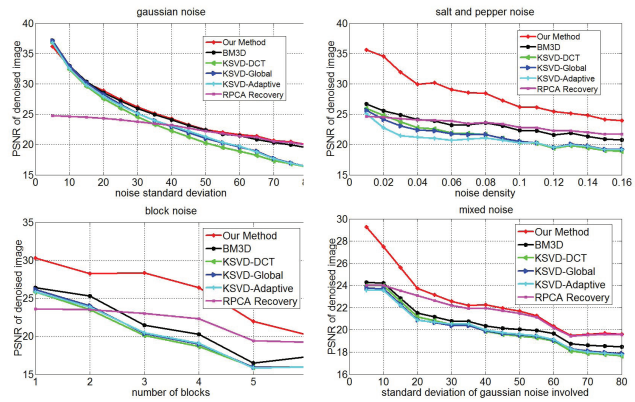

Fig. 3. Denoising performance comparison for different algorithms with different kinds of noise.

Fig. 4. Denoised color facial images using different denoising algorithms with different noise types and magnitudes. (a) the first row is with gaussian noise $\sigma = 10$; the second row is with pepper-and-salt noise $\rho = 0.03$; the third row is with blocky noise $n = 1$; the last row is with mixed noise; and the first column is the noise-corrupted images, denoised images with KSVD-DCT, KSVD-Global, KSVD-Adaptive, BM3D, RPCA recovery and our proposed method are listed respectively in the second to the last column. (b) is the same as what we say about (a) with $\sigma = 50$, $\rho = 0.1$ and $n = 3$.

4. CONCLUSIONS

In this paper, a novel color facial-image denoising algorithm based on RPCA recovery in the $L^*a^*b^*$ space and a noisy-pixel detection scheme is proposed. In our approach, RP-CA is firstly carried out in the $L^*a^*b^*$ space and a noisy-pixel detection and elimination method is applied to further remove the noises. Consequently, the noises in an image can be significantly reduced, while the blurring effect can also be minimized in the final, denoised image. Experimental result-s based on the AR database have proved that noises can be effectively removed and facial features can be preserved satisfactorily. Also, our proposed method is compared with four state-of-the-art denoising methods, including BM3D, KSVD-DCT, KSVD-Global and KSVD-Adaptive. From the results, it can be seen that our proposed method can achieve a much better performance when the noise power increases, and is effective to different kinds of noise. Our proposed method can achieve a better performance than the other methods in terms of both PSNR and visual quality.

5. ACKNOWLEDGEMENTS

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