Zone-based Inpainting of Damaged Face Image

Sixun Liu, Kesen Li, You Yang, Yi Deng and Ling Luo

School of Computer and Information Science, Chongqing Normal University, Chongqing 401331, China.

Abstract

Image inpainting is benefit in document management system or document utility system. Large amount of damaged face images existed in the document manufactory procedure. These damage zones could be categorized to big/small plaque, big/small slender line breakage. First, correct algorithms were selected by experiment verification. Five traditional methods include BSCB, TV, CDD, Criminisi and GSR, compared to five deep learning-based methods include GMCC, PIC, Gated CNN, PConv and Shift-net. Performance best algorithm was adopted to fill the damaged part. Then, these correct algorithms were combined together to accomplish the whole image inpainting. Simulation experiments shows the zone-based image inpainting algorithm is effective. It could improve human visual heavily, including fine detailed textures and global semantic structure.

Keywords

Image Inpainting, Face Image, Human Visual.

1. Introduction

Image inpainting is a task that use the prior information of known regions to estimate and complete the missing part, which makes observers can hardly find handling traces and ensure global semantic structure. Furthermore, it is necessary to satisfy the visual continuity and blend with the background. Except for filling the missing part, image inpainting have many application scenarios such as removing redundant objects, text, etc. Specially, such image inpainting tasks make document management system or document utility system more valuable and useful.

Traditional methods that address the missing-filling problem fall into three groups. The first group of approaches fill in the missing part by diffusing the pixels next to the boundary into the missing area, which can complete small missing regions. It contains BSCB[1], Total Variation(TV) model[2] and Curvature Driven Diffusions(CDD) model[3]. The second group of approach [4-5] can complete bigger missing regions by means of combining texture synthesis with structure diffusion. Since people use sparse prior to restore incomplete images, the sparse matrix based method has been used for image inpainting. Guleryuz et al. first proposed analysis dictionary-based iterative inpainting algorithm [6]. On this basis, Zhang et al. Proposed a Group-based Sparse Representation (GSR) algorithm [7].

Since autoencoder (AE) [8] work, deep CNNs are widely used in image inpainting. Phatak et al. [10] trained the Context Encoders (CE) with reconstruction and adversarial loss [9] to predict the missing part directly. Although the results are encouraging, sometime it creates visible artifacts around the border. Iizuka et al. [11] designed a Global and Local (GL) discriminator network And Yu et al. [12] introduced Contextual Attention (CA) to address the problem. [13] used a Generative Multi-column Convolutional Neural Networks (GMCC) to extract different dimension information that can guarantee better coherence and clarity. On this basic, Yu et al. [15] suggested that using gated convolution can achieve better output than vanilla convolution when completing random missing regions. In order to generate multiple reliable results, Pluralistic Image Completion (PIC) [14] tried to update the network with Variational Auto-Encoder (VAE) and get encouraging success.

2. Zone-based Framework

Our idea come from the theory of "no free lunch" that no single method can be applied to all missing types directly. There are many kinds of missing types in a damaged face image, as shown in Figure 1. Rectangular box represents such zones with slender line breakage, triangle box represents such zones with small plaque damage, and the circular box represents such zones with semantic missing. therefore, zone-based image inpainting aims to use the advantages of each method and select the best inpainting method for each different damaged type.

Fig. 1 Different missing types

2.1 The Experimental Process

The process of our experiment is shown in Figure 2. First, we select four representative damaged images for test that (a)-(d) represent respectively large crease damage, scattered small plague damage, crease and large plaque damage, slender line damage. Second, we use single method to restore each image respectively, then select the best inpainting method for each different damaged type according to the image quality assessment. Third, we evaluate the zone-based image inpainting on these images and demonstrate its advantage over single inpainting method.

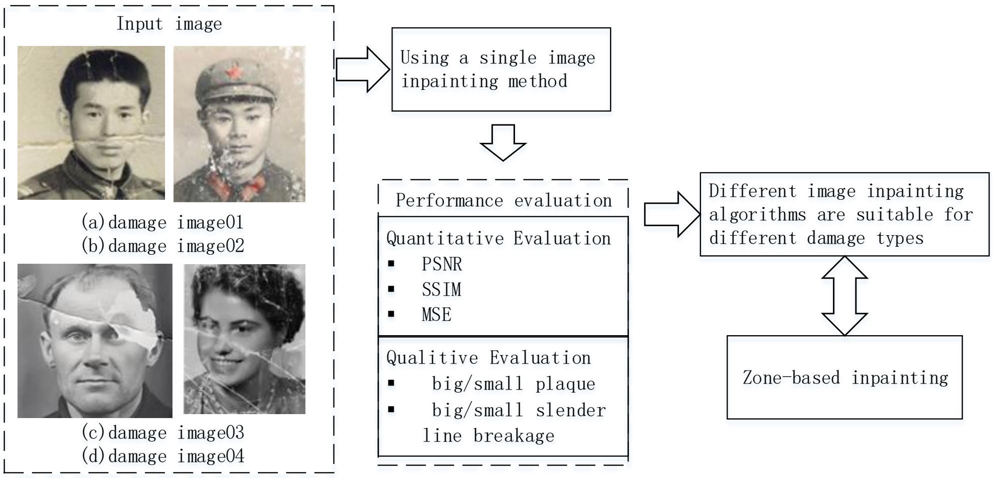


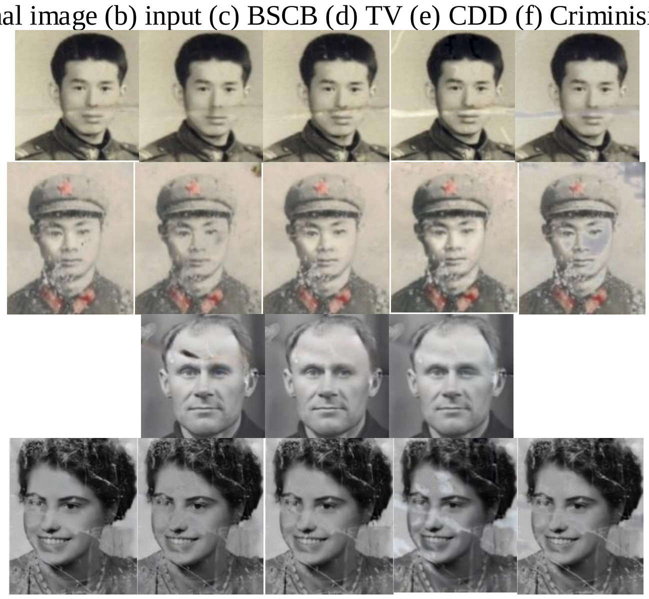
Fig. 2 Process of zone-based image inpainting

2.2 Image Quality Assessment

Image Inpainting is to get an image with reasonable and complete visual effects, but the inpainting result depends on the visual perception of the observer, and there is no unique correct result. Therefore, the qualitive evaluation method is mainly used to evaluate the restored face image. At the same time, it combines quantitative evaluation criteria such as mean-square error(MSE), peak signal-to-noise ratio (PSNR) and structure similarity (SSIM).

The results are using a single image inpainting algorithm, as shown in Figure 3. In the figure, (a) represent original image, (b) represent damaged image, (c)-(l) are restored by BSCB, TV, CDD, Criminisi, GSR, GMCC, PIC, Gated, Partial convolutions (PConv)[16],Deep feature rearrangement (Shift-Net)[17].

(a) original image (b) input (c) BSCB (d) TV (e) CDD (f) Criminisi (g) GSR



(h) GMCC (i) PIC (j) Gated (k) PConv (l) Shift-Net

Fig. 3 Damage figure inpainting results

2.2.1 Qualitive Evaluation

The inpainting results are shown in Figure 3, and the overall visual effect are inferior to the original image. Among which, using the BSCB and the Shift-Net are easy to generate blur effect during inpainting. When the Criminisi restored large area of damage, the confidence item may drop rapidly, leading to the appearance of randomly selected restore order, which makes the inpainting effect unable to satisfy the visual experience. Using PConv method inpainting, the image color is inconsistent and the original texture structure of the image is changed.

After damage image 01 is restored by GSR as a whole is more suitable for restored images with damaged creases because the color of the area after inpainting is similar to its background color. Use Gated to restore the damaged image 02 to make the image more coordinated from the overall visual perspective. Based on the existing information of the damage image 03, it can be inferred that the missing part should be an intact eye. When using traditional methods to inpainting the damaged area, only the texture structure is inpainting, while the deep learning methods can fill in the missing part of the eyes well after training data set. The image after PIC is better in terms of color coordination and overall vision. The TV and CDD are better to inpainting the damaged area in the damaged image 04. It can be seen that the slender line at the neck position is basically non-existent.

2.2.2 Quantitative Evaluation

The quantitative evaluation will be represented by line graphs, in which Figures 4, 5 and 6, are the PSNR, SSIM and MSE of the restored image.

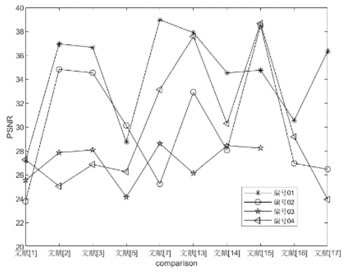


Fig. 4 Comparison of PSNR

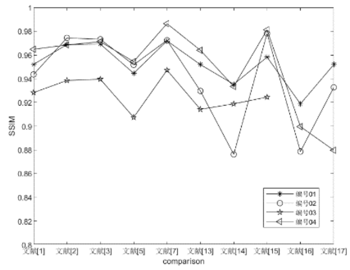


Fig. 5 Comparison of SSIM

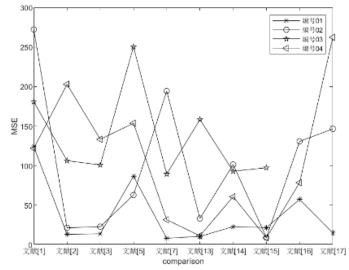


Fig.6 Comparison of MSE

Among the above 10 methods, the PSNR, SSIM and MSE values of the damaged image 01 inpainting by GSR are the best, Therefore, it can be seen from the combination of quantitative and qualitive evaluation that GSR is more suitable for damaged images with large crease damage. For damaged image 02, Gated is more suitable for the inpainting of small plaque damage than other algorithms mentioned above. There is a large area of broken image with missing semantics, and the value of GSR method is better. But from subject point of view, it is better to use the PIC to inpainting missing eye in damaged image 04. From qualitive evaluation, TV and CDD are better at inpainting damaged slender lines, but when combined with indicators, the CDD is more suitable for inpainting slender damaged lines.

Based on the above analysis results, it can be concluded that GSR is better for inpainting crease damaged zone, CDD is better for inpainting damaged traces of slender lines, Gated is better for inpainting small plaques damage, and PIC is better for inpainting semantic missing part.

3. Evaluation of Zone-based Inpainting

This is the verification of zone-based inpainting experiment. In Fig.7, (a) and (d) represent respectively zone inpainting results of damaged images 03 and 04, (b) and (e) represent respectively images with the best qualitive quality after being restored by single algorithm, (c) and (f) represent respectively images with the best quantitative indicator after being inpainting by single algorithm. In the damaged image 03, there are missing semantics of the eye part, broken small plaques and broken creases. PIC was used to inpainting missing eye, Gated inpainting small plaque damage, GSR inpainting crease damage. The small plaque damage in damage Figure 04 will be inpainting by Gated, the crease damage will be inpainting by GSR, and the long and thin line damage will be inpainting by CDD.

(a)zone inpainting (b)PIC (c) GSR (d) zone inpainting (e)CDD (f)GSR

Fig. 7 Zone-based inpainting effect

The image after zone-based inpainting is compared with the best image inpainting by single algorithm, In the damaged image 03, there is no inpainting trace in the missing part of the plague. Due to the training data set, the color of the eye is different from that of the original eye. Subjectively, compared with the CDD single algorithm, the effect of inpainting damaged long and thin hair and clothing lines is better, but because the damage of the hair is too messy, the inpainting marks look heavier. The subject visual effect of the picture after zone-based inpainting is better. However, the quantitative indicator in results obtained by using zone-based inpainting are not satisfactory.

4. Conclusion

A specific image inpainting algorithm is fit to only zone of damaged type. After zone division of input face image had been classified to such as big/small plaque, big/small slender line breakage. Correct inpainting algorithm were identified according to the zone type, through a series of experiments. PIC and gated CNN were adopted to fill bigger or smaller plaque zone respectively. CDD could be employed to complete the thinner and longer slender line breakage. And GSR could be employed to complete the wider slender line breakage. Combined with these best choices, a zone-based inpainting algorithm, we called, could fill the whole image effectively. More human-oriented visual emerged after the image inpainting.

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