An Image Inpainting Method Considering Edge Connectivity of Defects

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***Abstract*—In this paper, we propose a new image inpainting method that improves the line distortion and unnatural coloration in the restoration area observed in the conventional methods. Many deep learning inpainting methods have been proposed in recent years. However, these conventional methods have problems with distorted lines and unnatural colors in the restoration area. We solve the problems of the reconstruction of distorted lines and unnatural color simultaneously by applying edge generator from EdgeConnect to DeepFill v2. Through evaluation experiments, we show that the proposed model is better than the conventional methods in PSNR and SSIM of images with clear color boundaries and complex edges.**

Keywords—image inpainting, image restoration

I. Introduction

In recent years, there is a growing need for image inpainting since social media such as Instagram and Facebook have grown exponentially. Image inpainting is a task of filling in missing regions of an image. It allows to restore a photograph that is partially missing due to damage or staining, or to remove unnecessary objects and people that have appeared in the photograph.

In general, there are two traditional techniques for image inpainting: diffusion-based and patch-based. Diffusion-based methods propagate higher-order derivatives of image information from the boundary into the missing regions. Patch-based methods fill in the missing regions by searching for the similar patches and copying the image data from these patches. These two methods, however, cannot reconstruct a large missing region.

To address this limitation, several deep learning methods for image inpainting were introduced over the last few years. Yu *et al.* [1] proposed DeepFill v2 that allows to filling in free-form missing regions. This method often reconstructs distorted lines without guide lines sketched manually by users. To generate guide lines automatically, Nazeri *et al.* [2] proposed EdgeConnect, which is a network using edge maps. This method, however, has problems with unnatural colors in the restoration area since the reconstruction of edge map is not always accurate.

In this paper, we propose a new image inpainting method that improves the line distortion and unnatural coloration in the restoration area observed in the conventional methods. Our method consists of edge generator based on EdgeConnect and image inpainting network based on DeepFill v2.

II. Related Work

DeepFill v2 is a deep learning method based on Generative Adversarial Network (GAN) [1]. It achieves inpainting in free-form missing regions by adopting the architecture of Gated Convolution and SN-PatchGAN. It uses Gated Convolution-based CNN as GAN generator and SN-PatchGAN as discriminator. In addition to inpainting only using RGB images and mask images, it can fill in missing regions along the guide lines sketched by the user into the sketch channel along with RGB images and mask images.

EdgeConnect is an image inpainting method that uses edge maps [2]. Edge map indicates whether each pixel is an edge or not. It consists of two GANs: 1) edge generator that repairs the edge map, and 2) image completion network that repairs the entire image. First, edge map of RGB image with mask is generated, and edges in missing regions are repaired with edge generator. Next, image inpainting is performed along the repaired edges with image completion network. To stabilize training, spectral normalization (SN) is applied to both generator and discriminator of edge generator.

Deep Fill v2 often unable to reproduce complex details with accurate lines. To solve this problem, it requires the complicated effort of drawing a manual line. EdgeConnect can generate guide lines automatically. However, it has problems with unnatural colors in the restoration area where the reconstructed edges are wrong or interrupted. In this paper, we solve the problems of the reconstruction of distorted lines and unnatural color at the same time by applying edge generator from EdgeConnect to DeepFill v2.

III. Proposed Method

In order to improve the line distortion of DeepFill v2 and unnatural coloring of EdgeConnect, we propose an image inpainting method that consists of two stages: 1) edge generator from EdgeConnect that extracts and corrects edges, and 2) image inpainting network from DeepFill v2 that repairs along the corrected edges. The outline of the proposed method is shown in Fig. 1.

First, the edge generator fills in missing regions of RGB image by EdgeConnect, then it generates an edge map of the output images by DexiNed[3]. The edge map is finally inverted the colors shown in Fig. 2. Then, image inpainting network fills in missing regions of RGB image along the generated edge map by DeepFill v2.

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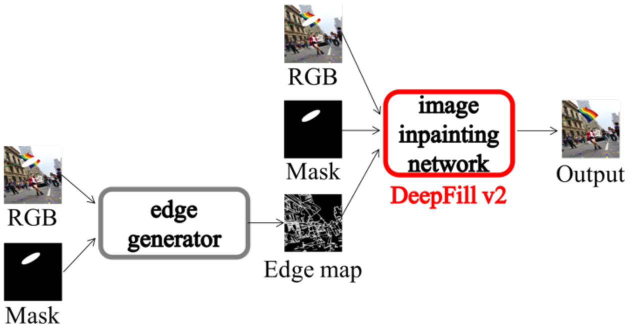

Fig. 1. Outline of our proposed method

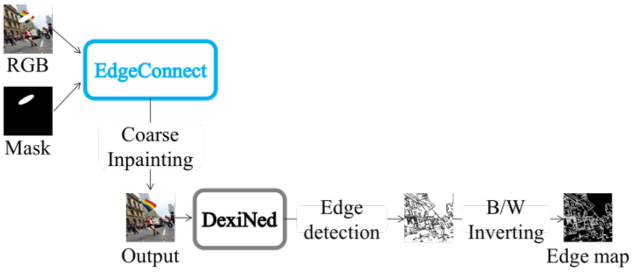

Fig. 2. Structure of edge generator

IV. Experiments

We used 1,434,892 images from the dataset, Places365 [4] to train DeepFill v2. In order to enable a sketch channel of DeepFill v2, we use Canny filter [5] to generate edge maps of the training data for DeepFill v2.

For our experiments, we randomly selected 15 images from Places365. Then, we tested these images by our model, DeepFill v2, and EdgeConnect. The test results of our model are shown in Fig. 3.

The upper and middle rows of Fig. 3 show the successful examples of the proposed method. Compared with the conventional methods such as Gated Convolution and EdgeConnect, the images generated by our proposed model are visually natural. On the other hand, the lower row of Fig. 3 shows the example of failure of the proposed method. We measure the quality of our 15 result images using PSNR and SSIM[6]. The results of the conventional methods show better values in both of PSNR and SSIM than those of our proposed model.

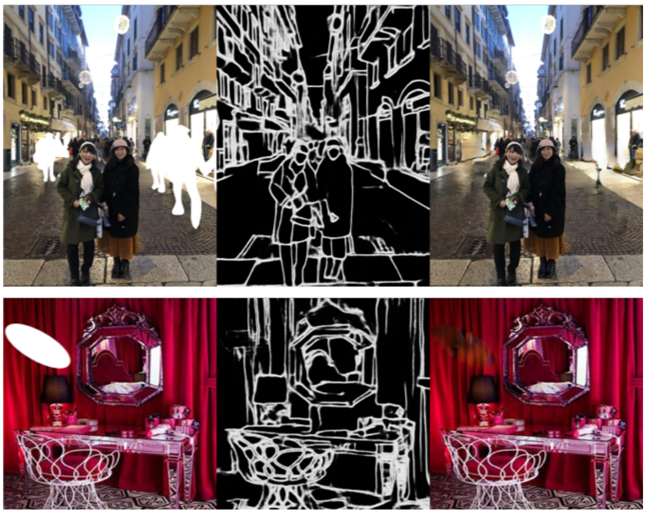

Fig. 3. Input image, generated edges, inpainted results *(left to right)*

TABLE I. Quantitive results over Places2 with models: DeepFill v2 (DF), EdgeConnect (EC), our proposed model (OURS)

	DF	***EC***	***OURS***
PSNR	37.1764	37.8552	**38.2318**
SSIM	0.9924	0.9943	**0.9945**

Fig. 4. Quality Comparison for Places2 with models: Input image, DeepFill v2, EdgeConnect, our proposed model *(left to right)*

It is easy to repair the images with vague color boundaries, gradations, and simple edges in a natural way without an edge map as a guide. Therefore, the conventional methods give better results than the proposed method for such images. On the other hand, for images with clear color boundaries or complex edges, the proposed method, which uses an edge map as a guide, is expected to give better results. Thus, we selected 4 images with clear color boundaries and complex edges, and measure the quality of those images using PSNR and SSIM as shown in Table I. We also compare images generated by our method with those generated by other state-of-the-art techniques as shown in Fig. 4.

From Table I, PSNR and SSIM of our proposed model are higher than those of the conventional methods. Our proposed method provides better results than the conventional method in repairing images with clear color boundaries and complex edges in missing regions.

V. Conclusion

In this paper, we proposed a new image inpainting method based on Gated Convolution and EdgeConnect. We trained Gated Convolution in the experiments and performed image inpainting using our proposed method. As a result, our model is better than the conventional methods in PSNR and SSIM of images with clear color boundaries and complex edges.

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