Automatic Damage Recovery of Old Photos Based on Convolutional Neural Network

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***Abstract*— Most of the methods for repairing old photos today are to manually process them using image editing software, such as Photoshop. The time of manual repairing is directly proportional to the damage degree of the photo, which is time consuming and laborious. Therefore, this paper proposes a two-stage convolution network to automatically repair damaged old photos. The first stage will detect the damaged areas of the photos, and the second stage will repair these areas. The experiment results demonstrates our method can successfully detect and repair the damage of the photos.**

Keywords—Damaged old photos, Image repariment, Image restoration, Image inpainting, Convolutional Neural Network.

I. INTRODUCTION

Old images are often subject to human damage or environmental influences during the preservation process. In order to recover the damaged areas, the most common method at present is to repair them artificially one by one through the photo editing software.

With the advent of image inpainting algorithms [1-3], the damaged areas can be automatically repaired based on the predefined damage marker of the image, whereas the integrity and consistency of the original image are still maintain, which can save a lot of repairing time. The damage marks required by these algorithms can be divided into semi-automatic [1, 2] and fully automatic methods [3] depending on whether or not to manually mark the damaged area. Semi-automatic method [1, 2] is the most common way at present. The area to be damaged is manually marked and then repaired by algorithm. Although it can save the repair time, the process of marking the area is still laborious. The fully automatic method is less common. The literature work [3] can automatically detect and then repair the damaged area, but it can only detect the simple and obvious damage, and the repairing ability still has room for improvement.

In order to solve the above problems, this paper proposes a fully automatic algorithm using Convolutional Neural Network (CNN) architecture. The algorithm proposed in this paper will automatically mark the damaged area in the image to save the time of manual marking, and then repair the damaged area without changing the consistency to the original photos, such as the overall tone of the photo.

II. PROPOSED METHODS

This section will introduce the two-stage model structure and design concept presented in this paper. Fig. 1 shows the schematic diagram of the architecture proposed in this paper. The first stage is used to detect and mark the location of the damage in the image. The second stage is to repair these areas and produce a recovered image.

A. Network Architecture

The two-stage model in this paper uses the same model architecture (except the output layer) but different parameter sets. The model structure is shown in Fig. 2. It can be divided into three parts, namely the feature extraction layer, the intermediate network layer and the feature reconstruction layer. The extraction layer and the reconstruction layer are all 3x3 convolutional layers with 64 channels, and the middle layer is three convolutional blocks designed by us to analyze the features acquired by the extraction layers.

B. Convolutional blocks

The purpose of the convolution block is to take the features of the extraction layer for analysis. The convolutional block of this paper combines two concepts of parallel structure and channel attention to improve the performance of the model

We design two branches in our convolutional blocks based on the parallel structure of GoogleNet [4]. The first branch is a two-layer 3x3 convolutional layer with 64 channels and ReLU activation functions, followed by channel attention. The other branch is channel attention mechanism, through which we can find out more important features from both shallow and deep layers respectively.

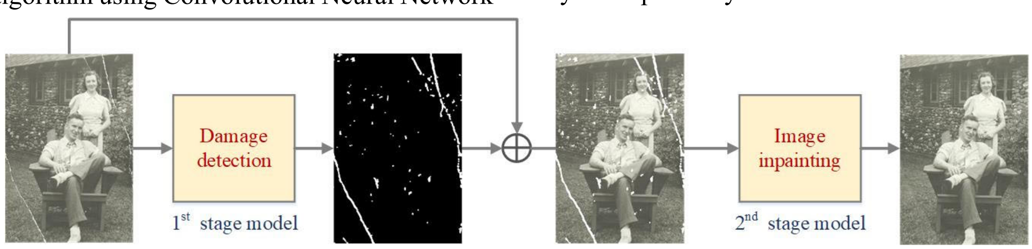

Fig. 1 Schematic architecture for proposed method

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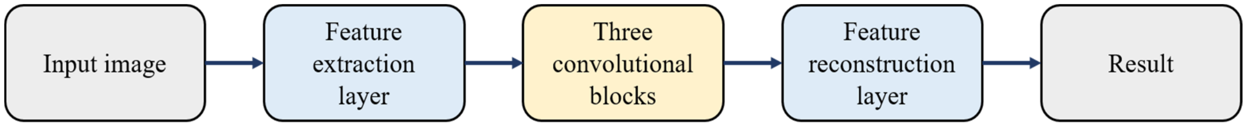


Fig. 2 Structure of proposed model

Channel attention originates from the inability of the human eye to receive all information while viewing an image, and can only process information on certain regions. SENet [5] applied this concept to image classification model respectively, to find out the most representative parts of the extracted features. This paper also adopts the concept similar to SENet [5] because the damage part usually catches human vision. This concept gives higher weights to more important features while reducing the influence of less important features.

Next, we concatenate the features of two branches, and then analyze these features through subsequent networks.

C. Short connection

Our model combines the shortcut connection concept of ResNet [6] to pass the feature information of the shallow network to the deep network for reconstruction, avoiding the phenomenon of gradient disappearance and maintaining the stability of the model training process.

III. Experiments

A. Settings for Training

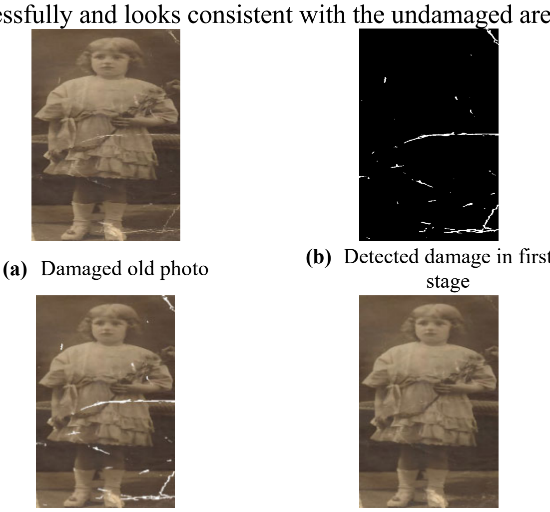
A total of 190 old images with different contents were collected from the Internet, of which 100 were undamaged and 90 were damaged. Since the first stage was to detect the damaged area, we randomly picked out 50 damaged images as the training set and manually labeled the damaged areas of them, thereby generating the training data for the first stage model. The rest of damaged images are used to validate and test the experimental results. To create the second stage of the data set, we used 100 pieces of undamaged old photos and 50 damage masks to generate and generate 5000 pieces of training materials. Note that the technique of data augmentation is used in all of our dataset creation.

Because the tasks of the two-stage model are different, we choose different loss functions to evaluate the performance of the model. The first-stage model is to distinguish the damaged or undamaged areas of the old photos, binary cross entropy is used as the loss function. In the second stage of the model, MAE is used to train and judge the error between the model prediction and ground truth.

B. Evaluation

After the damaged area is completely repaired, the repair result may be slightly different from the original image, and it is not justifiable to use PSNR or SSIM to calculate the image difference. Therefore, the repaired results of this paper is evaluated subjectively.

Figure 3 shows the results of each stage. It can be seen from Fig. 3 (c) that most of the obvious damaged areas in the old photos have been detected. Fig. 3 (d) shows the image by applying our detection and repairing method. It can be observed that the area detected in Fig. 3 (c) has been repaired successfully and looks consistent with the undamaged areas.



(a) Damaged old photo **(b)** Detected damage in first stage

(c) Overlaid image of (a) and (b) **(d)** Repaired old photo

Fig. 3 Results of our proposed method

IV. Conclusions

We propose a two-stage network architecture to detect and repair damaged old photos automatically. Our network uses the same model architecture in each stage (except the output layer) but different parameter sets for damage detection and repairment. The concepts of parallel structure and channel attention is integrated in our network to enhance the performance. Experiments show that our method can accurately identify the distorted areas and successfully repair them.

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