DIGITAL RESTORATION OF TORN FILMS USING FILTERING TECHNIQUES

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ABSTRACT- The acceptance of digital imaging is motivating many photography enthusiasts to transfer their photographic archive to digital form. Scans of negatives and positives are preferred to be scanned at high resolution which makes small cracks and scratches very apparent. These unsightly defects have become an important issue for consumers. Filtering techniques are used for the restoration process which is fully automatic whereas the existing systems were semi-automatic or completely manual. The method used for the detection of tear is dilation process and top-hat transform. Top-hat transform might misinterpret dark brush strokes as cracks. In order to avoid these unwanted alterations to the original image, brush strokes are separated from the actual cracks using clustering technique. Tear removal includes order statistics filtering which deals with the reconstruction of missing or damaged image areas.

Keywords- Image Restoration, Top-hat transform, Dilation, Clustering, Order statistics filtering

I. INTRODUCTION

Image restoration is one of the major topics in image processing which is a well studied problem and there are many algorithms for deblurring and denoising. Many paintings particularly old paintings suffer from breaks in the background, the paint or the varnish. These patterns are usually called cracks or tear and can be caused due to aging, drying and mechanical factors which divides the image into two parts(Fig.1). The problems occur due to the existence of tear are image quality deterioration and damaged image data along the tear boundary. Digital image processing techniques are used to detect and eliminate the cracks on digitized paintings.

In previous systems, torn frames are detected by using an algorithm called graph cut segmentation *[1][2]*. Once it detects the crack it segments it into two regions along the tear boundary. After delineating the tear boundary, relative displacement between the segmented regions is estimated using a global-motion estimation technique *[3]*. To estimate global motion separate histograms for each region are used. Finally, the reconstruction of damaged image data*[10]* was performed by the existing dirt and sparkle removal algorithms and it requires the user to manually start with the initial point of the crack pattern to fill them. The algorithms used for the detection and removal of crack was semi-automatic and tedious to detect crack in very dark image areas.

Fig1 Image damaged by tear

In this paper, we have proposed filtering techniques for the detection and removal of crack. The results obtained by these techniques are fully automatic. The technique consists of the following stages:

- Dilation process
- Top Hat Transformation
- SOM clustering technique
- Crack filling method

The image is pre-processed by morphological operation called dilation and processed by top hat transform to detect the crack. Top hat might misclassify dark brush strokes as cracks. In order to avoid any undesirable changes to the original image, brush strokes must be separated from cracks. For this purpose, we are applying clustering technique called Self Organizing Feature Map (SOFM). After the detection of cracks, order statistics filtering and anisotropic diffusion are applied. It fills the information by comparing the current pixel with the neighbor pixel.

II. DILATION PROCESS

Morphology is a broad set of image processing operation that processes images based on shapes. Morphological operations apply a structuring element to an input image, creating an output image of the same size. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. By choosing the size and shape of the neighborhood, a morphological operation that is sensitive to specific shapes in the input image is constructed.

	NW	N	NE	
	W		E	
	SW	S	ES	

The dilation is the basic morphological expansion operation. The dilation operator takes two pieces of data as inputs. The first is the image which is to be dilated. The second is a set of coordinate points known as a structuring element. Dilation adds pixels to the boundaries of objects in an image, the number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element which is used to process the image.

This pre-processing technique is implemented to identify the cracks in image based on the top-hat transform process. Before the top- hat transform process, the image is converted to a dilated one by dilation process. Dilation process converts the image into high luminance (intensity) image by comparing the current pixel value with the neighbor pixel value.

If the intensity value is greater than a particular value then set the current pixel to white (i.e.255) otherwise set current pixel itself. This process is followed to the whole image to detect crack in an image.

Fig2 Dilated image

III. TOP HAT TRANSFORMATION

This can be used to eliminate particular features of an image. The top-hat transform is a grayscale morphological filter defined as follows

$$y(x) = f(x) - fnB(x)$$

where $fnB(x)$ is the opening of the function $f(x)$ with the structuring set nB, defined as:

$nB = B \oplus B \oplus \ldots\ldots \oplus B$ (n times) denotes the dilation operation

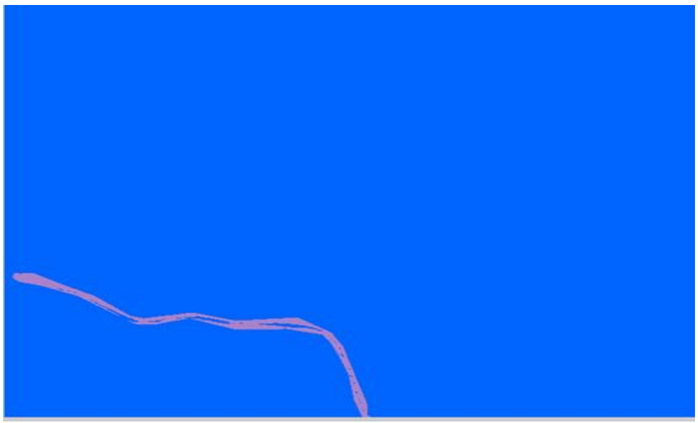
Fig3 Image with dark gray scale

The output of the dilation image has taken as input to the Top-hat transform. Top-hat transform convert the image into the dark gray scale image. In this method set the current pixel which is difference of original image pixel and the dilation image pixel. Usually in gray scale the cracks are large gray value. So here it can easily detect the cracks which are large gray value. Otherwise the pixel location corresponds to the background. The top-hat transform generates a grayscale output image where pixels with a large gray value are potential crack or crack-like elements. Therefore, a threshold operation is required to separate cracks from the rest of the image. The threshold can be chosen by a trial and error procedure, i.e., by inspecting its effect on the resulting crack map.

IV. SOM CLUSTERING TECHNIQUE

In some paintings, there exist some areas where the brush strokes have almost the same thickness and luminance features as cracks. For example, the hair of a person in a portrait could be such an area. In those cases the top-hat transform might misinterpret these brush strokes as cracks. Thus, in order to avoid these unwanted changes to the original image, it is very important to separate these brush strokes from the actual cracks, before the implementation of the crack filling procedure. Those brush strokes can be removed by using Self-Organizing Map*[8][9]* in which the brush stroke detection and removal is fully automatic. A self-organizing map (SOM) or self- organizing feature map (SOFM) is a type of Artificial Neural Network (ANN) that is trained using unsupervised learning.

The SOM initially calculates features for each pixel such as mean, variance, number of occurrences in histogram, intensity values for each pixel. The SOM consists of a regular, usually two-dimensional (2-D), grid of map units. Each unit is represented by a prototype vector. The units are connected to adjacent ones by a neighborhood relation. The number of map units, that varies from a few dozen to several thousand, determines the accuracy and the generalization capability of the SOM. During training, the SOM forms elastic net that folds onto “cloud” which is formed by the input data. Data points which lies near each other in the input space are mapped to nearby map units. Thus, the SOM could be interpreted as a topology which preserves mapping from input space onto the 2-D grid of map units. The SOM is trained iteratively and at each step of training, a sample vector is randomly chosen from the input data set. Then, distance between the sample vectors and all the prototype vectors are computed. The best matching unit (BMU) is then calculated which is the mapping unit with prototype closest to the sample vector. Next, the prototype vector is updated. The BMU which is calculated and its topological neighbors are moved closer to the input vector in the input space. The prototype vector is updated. Finally, the crack fall under one category and the brush stroke in another category. Then a separate color is given to each cluster to highlight the crack alone, thus removing the brush strokes.



a) Color Image

b) Binary Image

Fig5. Brush strokes separated from cracks

V. CRACK FILLING METHOD

After detecting the cracks and separating misclassified brush strokes, the final task is to restore the missing image data using local image information (i.e., information from neighboring pixels). Two classes of techniques, utilizing order statistics filtering and anisotropic diffusion are proposed for this purpose. Order statistics filtering is implemented on each RGB channel independently and affect only those pixels which belong to cracks. The filling procedure does not affect the actual information of the image.

A. Order Statistics Filtering

An effective way for removing the cracks is by applying median filter*[5]* or order statistics*[6][7]* filtering technique in their neighborhood. All filters are selectively applied on the cracks. If the filter window is adequately large, the crack pixels inside the window will be outliers and will be rejected. Thus, the crack pixel will be assigned with the value of one of the neighboring non-crack pixels. The following filters can be used for this purpose:

Median filter:

$$y_i = med(x_{i-\nu}, \ldots, x_i, \ldots, x_{i+\nu})$$

Recursive median filter:

$$y_i = med(y_{i-\nu}, \ldots, y_{i-1}, x_i, \ldots, x_{i+\nu})$$

where the $y_{i-\nu}, \ldots, y_{i-1}$ are the already computed median output samples

B. Anisotropic diffusion

Anisotropic diffusion is an image enhancement technique which combines smoothing of slowly varying intensity regions with edge enhancement. Smoothing is modeled as a diffusion process which allows along homogeneous regions and reserves region boundaries.

Fig6. Restored image

VI. CONCLUSION

In this paper, we proposed filtering techniques for the detection and restoration of line cracks in digital image. The dark brush strokes which are misidentified as cracks are separated by an automatic technique (SOFM). Crack interpolation is performed by appropriately modified order statistics filtering and controlled anisotropic diffusion is used to reduce the image noise. By selectively applying filtering techniques the quality of the image can be further improved.

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