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Research Article

Identification and Inference of Cracks in Old Paintings Using Supervised Method

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Abstract: The older paintings are taken as input to find the crack and remove the crack using three steps: (a) identify crack (b) classify the crack (c) use trimmed median filter to get the quality of a rectified image. On many occasions the restoration of cracks in old paintings becomes a difficult task if it is done manually. So old paintings are digitized. It is evident that there is an increased need for carefully detailing the complexity of valuable sites with an improved accuracy. In the present paper a new effective methodology for digitizing the cracks that are caused by surrounding environment, particularly extreme changes in humidity and heat is presented. The digital paintings can be restored using different image processing techniques. When a painting is restored, the restorer must know which areas to be filled or recovered. MATLAB is used to build the code required to process and analyze the data. One of the most important findings of the paper is that the trimmed median filter technique is used to for the restoration of the digitized painting.

Keywords: Cracks classification, image, painting, trimmed median filter

INTRODUCTION

The older paintings suffer from breaks in the substrate, the paint, or the varnish. When we digitized these paintings, they can be modified using mathematical algorithms and cracks are eliminated so as to maintain the quality. The field of computer vision is concerned with extracting features and information from images in order to make analysis of images easier, so that more and more information can be extracted. In order to detect the cracks using Top-Hat Transforms with selective thresholding and separate the thin dark brush strokes and cracks by classification can be based on the following criterion based on the 'Hue' and 'Saturation' of the image, Finally cracks can be filled with Median Trimmed Filter. The technique consists of the following stages: The objective of the paper is to take older paintings are taken as input to find the crack and remove the crack using the three basic first identification of crack, classification of crack and by using trimmed median filter to get the quality image Detection of cracks, Separation of the thin dark brush strokes, which have been misidentified as cracks, Crack filling.

LITERATURE REVIEW

Solanki and Mahajan (2009) have performed an approach includes detection or identification and removal of cracks using digital image processing technique. The cracks are identified by thresholding the output of the top-hat transform. Then, wrongly identified as cracks are separated using a semi-automatic procedure based on region growing. Finally, order statistics filters are used to restore the image.

Abas and Martinez (2002) have proposed a method for the detection of cracks using multi oriented Gabor filters is presented:

- **Advantage of gabor filter:** It is used at different scales and spatial frequencies, edge tracking control of in detail.
- **Disadvantage of gabor filter:** Computational time is more.

An integrated methodology for the detection and removal of cracks on digitized paintings is presented by Giakoumis *et al*. (2006). The cracks are detected by thresholding the output of the morphological top-hat transform. Afterward, the thin dark brush strokes which have been misidentified as cracks are removed using either a median radial basis function neural network on hue and saturation data or a semi-automatic procedure based on region growing. Finally, crack filling using order statistics filters or controlled anisotropic diffusion is performed.

Yao *et al*. (2000) presented an entropy-based fuzzy clustering method is proposed. It automatically

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identifies the number and initial locations of cluster centers. It calculates the entropy at each data point and selects the data point with minimum entropy as the first cluster center. Next it removes all data points having similarity larger than a threshold with the chosen cluster center. This process is repeated till all data points are removed.

Barni *et al*. (2000) have presented a methodology for the restoration of cracks on digitized paintings, which adapts and integrates a number of image processing and analysis tools is proposed in this study. The methodology is an extension of the crack removal framework presented in Gauch and Pizer (1993). The technique consists of the following stages:

- Crack detection
- Separation of the thin dark brush strokes, which have been misidentified as cracks
- Crack filling

Ballester *et al*. (2001) presented a method of Filling-In by Joint Interpolation of Vector Fields and Gray Levels. A formal variational approach for filling-in regions of missing data in still images. However, all processing steps can be executed in real time and, thus, the user can instantly observe the effect of parameter tuning on the image under study and select in an intuitive way the values that achieve the optimal visual result.

Limitation:
User interaction is required to mark the regions to be filled-in: Different techniques and methodologies used for identification of crack in the domain of dynamic vibration of cracked structures have been comprehensively reviewed and their applications for damage detection have been described briefly by Karuppiah and Srivatsa (2012).

Technique for inspection and interpolation of cracks in digitized paintings presented by Giakoumis *et al*. (2006). Here, Cracks are identified by using top-hat Transform, whereas the breaks, which are misclassified as cracks, are separated by a semiautomatic approach. Crack interpolation is performed by suitable modified order statistics filters.

A method for the detection of cracks using multi oriented Gabor filters is presented by Lopez *et al*. (1999):

- **Advantage of gabor filter:** It is used at different scales and spatial frequencies, edge tracking control of in detail.
- **Disadvantage of gabor filter:** Computational time is more.

Gauch and Pizer (1993) method for artwork restoration applications. On one hand, powerful tools can be offered to artwork restorers to help them analyze the status of the paintings and foresee the final result of the actual restoration before performing it. However, this requires further research to develop effective algorithms for producing and processing high-resolution multispectral (for example, visible, infrared, ultraviolet, X ray) images of artworks.

On the other hand, a virtually restored copy of a painting can be obtained with the aim of showing which areas could be the original aspect of the artwork. This second type of application seems particularly interesting for increasing the quality of the content of famous museum Web sites, as well as for effectively achieving educational purposes.

A methodology for the restoration of cracks on digitized paintings, which adapts and integrates a number of image processing and analysis tools is proposed in by Barni *et al*. (2000) and the methodology is an extension of the crack removal framework presented. The technique consists of the following stages:

- Crack detection
- Separation of the thin dark brush strokes, which have been misidentified as cracks
- Crack filling

A certain degree of user interaction, most notably in the crack-detection stage, is required for optimal results. User interaction is rather unavoidable since the large variations observed in the typology of cracks would lead any fully automatic algorithm to failure. However, all processing steps can be executed in real time and, thus, the user can instantly observe the effect of parameter tuning on the image under study and select in an intuitive way the values that achieve the optimal visual result. Needless to say, only subjective optimality criteria can be used in this case since no ground truth data are available. The opinion of restoration experts that inspected the virtually restored images was very positive.

Bors and Pitas (1996) proposed an integrated strategy for crack detection and filling in digitized paintings. Cracks are detected by using top-hat transform, whereas the thin dark brush strokes, which are misidentified as cracks, are separated either by an automatic technique (MRBF networks) or by a semi-automatic approach. Appropriately modified order statistics filters or controlled anisotropic diffusion performs crack interpolation. The goal of the paper is to restore the old cracked paintings image by finding the cracks in the gray scale image and filling cracks with neighbor pixel values using a median filter.

MATERIALS AND METHODS

Detection of cracks: Cracks usually have low luminance and, thus, can be considered as local intensity minima with rather elongated structural characteristics. Therefore, a crack detector can be applied on the luminance component of an image and should be able to identify such minima. A crack-detection procedure based on top-hat bottom-hat morphological transforms is described in this study. The parameters are the following:

- Structuring element type: square
- Structuring element size: 3×3
- Number of dilations in (2): 2

The Morphological transform generates a grayscale output image where pixels with a large gray value are potential crack or crack-like elements. Therefore, a thresholding operation is required to separate cracks from the rest of the image. The threshold can be chosen by a trial and error procedure. As explained by the concept discussed above, we use only the 'luminance' component of the image. Hence we use the MATLAB function:

rgb2ntsc (im) ------> RGB to YIQ model

where,
Y = Luminance. Hence we use the ' Y' component.

Top hat transform can be implemented by the following equation:

$$y\ (x) = f(x)\text{-}fnb\ (x)$$

where,
f(x) = Original negated image
fnb(x) = Opening of the image f(x)

The structuring element is 'B' and 'n' represents the number of times we do dilation i.e., $n\ B = B\ dilate\ B\ dilate\ B\ dilate\ \ldots\ldots\ (n\ times)$.

The parameters are chosen as used by the authors of the research paper i.e.:

Structuring element: square, Size: 3×3, No. of dilations ('n'): 2.

Selective thresholding: Since the pixels representing cracks have high gray values, we set a suitable threshold to distinguish the cracks from the rest of the image.
i.e.:

$$imcracks = imtophat > t$$

where, t taken was 0.13.

The opening 'fnb' of a function is a low-pass nonlinear filter that erases all peaks (local maxima) in which the structuring element 'nB' cannot fit. Thus, the image 'f-fnb' contains only those peaks and no background at all. Hence, the cracks which are the local minima are segmented by taking the top hat transform of the negated image.

Crack classification: In some paintings, certain areas exist where brush strokes have almost the same thickness and luminance future as cracks. The hair of a person in a portrait could be such an area. Therefore, the Morphological transform might misclassify these dark brush strokes as original image, in order to avoid any undesirable alterations to the original image, it is important to separate these brush strokes from the actual cracks, before the implementation of cracks filling procedure. Hence it is required to classify the undecided white pixels of transformed image. This can be obtained by the various supervised and unsupervised classification methods.

Given: From the statistical analysis of digitized paintings by Karuppiah and Srivatsa (2014) concluded that the classification can be based on the following criterion based on the 'Hue' and 'Saturation' of the image:

H value:
0-60° --------> Crack
0-360° -------> Brush Strokes

S value:
0.3-0.7 --------> Crack
0.0-0.4 --------> Brush Stroke

Hence pixels can be surely classified based on:

if(H(i, j)>0 && H(i, j)<60 && S(i, j) > 0.4 && S(i, j) < = 0.7 && im2(i, j) = = 1)----->Crack
if(H(i, j)>0 && H(i, j)<360 && S(i,j)>0 && S(i, j)< = 0.3 &&
im2(i, j) = = 1) -------> Brush stroke
else if (im2(i, j) = = 1) -----> Undecided !
where im2(i, j) = = 1 represent the white pixels in the Top Hat transformed image.

CRACK FILLING METHODS

After identifying cracks and separating misclassified brush strokes, the final task is to restore the image using local image information (i.e., information from neighboring pixels) to fill (interpolate) the cracks. Two classes of techniques, utilizing order statistics filtering and anisotropic diffusion are proposed for this purpose. Both are implemented on each Red, Green, Black (RGB) channel independently and affect only those pixels which belong to cracks. Therefore, provided that the identified crack pixels are indeed crack pixels, the filling procedure does not affect the "useful" content of the image.

Using MTM (Modified Trimmed Mean) filter: A variation of the Modified Trimmed Mean (MTM) filter which excludes the samples xi+r, j+s in the filter window, which are considerably smaller than local median and averages the remaining pixels as follows:

$$y_{ij} = \frac{\sum\sum_A \alpha_{rs} x_{i+r,j+s}}{\sum\sum_A \alpha_{rs}}$$

The summations cover the entire filter window A. The filter coefficients are chosen as follows:

$$\alpha_{rs} = \begin{cases} 0 & \text{if } med\{x_{ij}\} - x_{i+r,j+s} \geq q \\ 1 & \text{otherwise} \end{cases}$$

The amount of trimming depends on the positive parameter q.
We tried another variation of MTM filter:

It performs averaging only on those pixels that are not part of the crack, i.e., it utilizes information from the binary output image b(k, l) of the top hat transform. In this case, the filter coefficients are chosen as follows:

$$\alpha_{rs} = \begin{cases} 1 & \text{if } b(k,l) = 1 \\ 0 & \text{otherwise} \end{cases}$$

Mask size: For the above variant of the MTM filter, even smaller filter windows can be use d, since crack pixels do not contribute to the filter output. Thus, it suffices that the window is 1 pixel wider than the widest crack.

RESULTS AND DISCUSSION

Cracks usually have low luminance and thus can be considered as local intensity minima with rather elongated structural characteristics. Therefore, a crack detector can be applied on the luminance component of an image and should be able to identify such minima.

Using the top hat transform:
Crack detection/the top hat transform results: In some paintings, certain areas exist where brush strokes have almost the same thickness and luminance features as cracks. The hair of a person in a portrait. Therefore, the top-hat transform might misclassify these dark brush strokes as cracks. Thus, in order to avoid any undesirable alterations 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 (Fig. 1 and 2):

Fig. 1: Original image with cracks

Fig. 2: After the crack detection using top-hat morphological transform

Fig. 3: Brush stroke image after classification based on HSV value

MTM filter

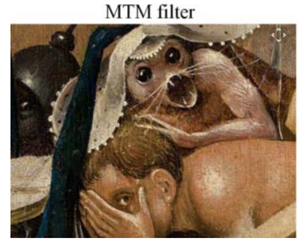

Fig. 4: Cracks filled image using

Finally Using MTM (Modified Trimmed Mean) filter to fill the cracked images and to get the final image finally we calculate the PSNR value of the processed image with the original image with structuring element is as follows (Fig. 3 and 4) (Table 1).

Peak signal to noise ratio
$= 10\log \frac{(2^n - 1)^2}{MSR} = 10\log \frac{256^2}{MSR}$

Table 2 Structuring Element Diamond 8 is minimum error value so i conclude that diamond is best for using this image classification and filling. The following histogram will show the result in Fig. 5 and 6.

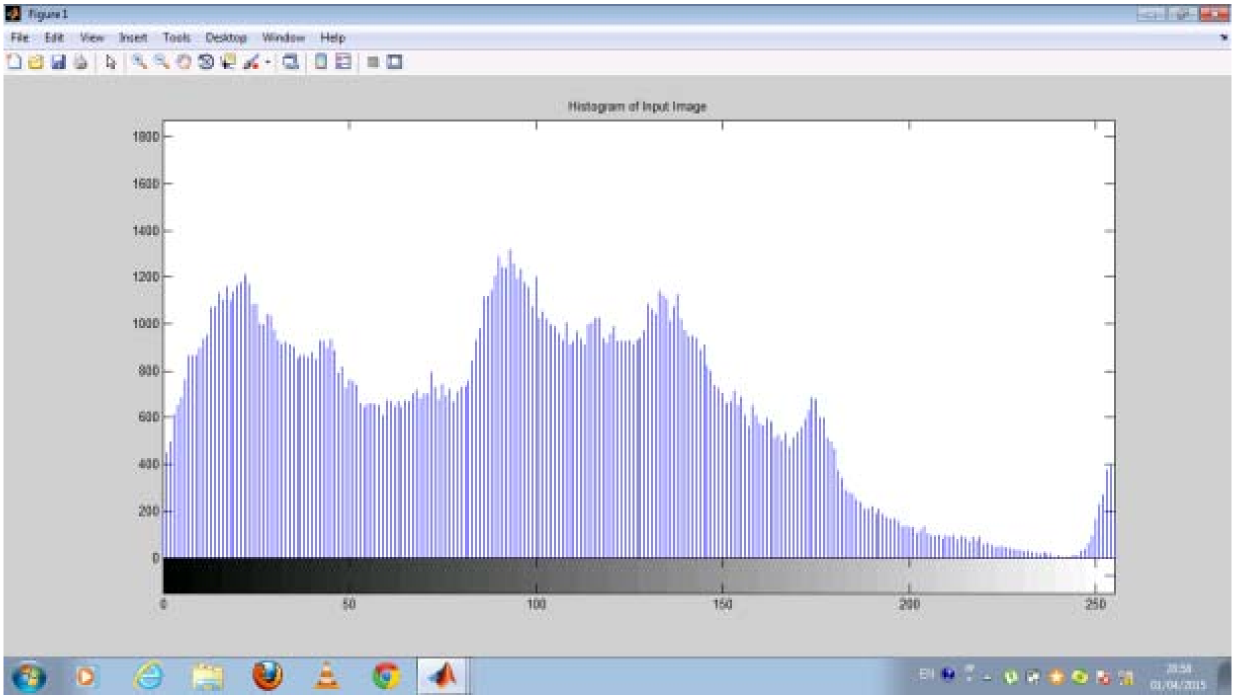

Fig. 5: Histogram of original image

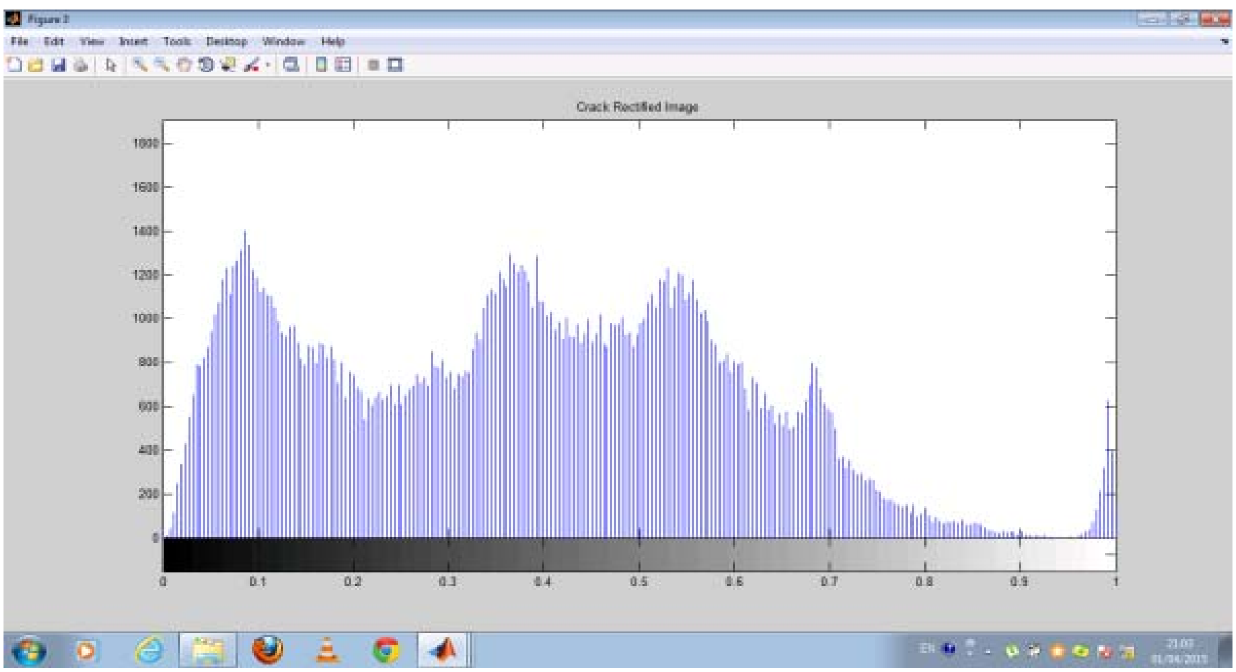

Fig. 6: Histogram of final image

Table 1: Describes the structuring element type Square with error value

Square	PSNR for RGB to gray scale	PSNR for grayscale and crack filled
Struct Ele = 2	7.59436	30.3333
Struct Ele = 3	7.83452	25.8377
Struct Ele = 4	8.01367	23.5238
Struct Ele = 5	8.15028	22.0694
Struct Ele = 6	8.25656	20.9745
Struct Ele = 8	8.43618	19.26

Table 2: Structuring element square 8 is to minimum error value

Diamond	PSNR for RGB to gray scale	PSNR for grayscale and crack filled
Struct Ele = 4	8.28617	20.3363
Struct Ele = 3	8.131508	21.8136
Struct Ele = 5	8.40676	19.1906
Struct Ele = 6	8.51034	18.2189
Struct Ele = 7	8.59591	17.3456
Struct Ele = 9	8.7404	15.9331
Struct Ele = 8	8.67534	16.6116

CONCLUSION

This study proposed a strategy for crack detection and filling in digitized printing. Cracks are detected using Top-hat transform, while the dark brush strokes misidentified as cracks are separated by LVQ methods. Modified trimmed filter is used to fill cracks. This methodology is acknowledged as one of the effective methods by restoration experts. The limitation of this methodology is that certain aspects can be further improved, i.e., for example, the detection of cracks located on dark images where the intensity of crack pixels is close to the intensity of the crack region. This shortcoming can be overcome by applying the crack detection algorithm locally on this area and select a low threshold value. The other limitation i.e., filling the cracks that cross the border between different regions of different colors can be overcome by filling in cracks in different regions with different colors. Another improvement would be aiming at the use of non linear multi channel filter (e.g., variants of vector median filter) instead of processing each color independently. The improvement mentioned above pave way for future study in this area.

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