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REVIEW ARTICLE

DETECTION AND REMOVAL OF CRACKS IN DIGITIZED PAINTINGS

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ABSTRACT

Several methods have been proposed for detection and removal of cracks in digitized paintings. Cracks deteriorate the quality of painting. A technique for the detection and removal of cracks in digitized image paintings that adapts and integrates a number of processing and analysis tools for digitized image painting is presented in this paper. The cracks are detected by thresholding the output of the morphological top-hat transform. After detecting cracks, a modified adaptive median filter (MAMF) is used to fill the cracks. The methodology performs very well on digitized paintings suffering from cracks.

INTRODUCTION

Old paintings suffer from breaks in their substrate, the coat, or the polish. This type of pattern is generally called crack. It may be caused by the effect of aging, of drying, and of some mechanical factors (Abas and Martinez, 2003). Aging cracks may be the outcome of non uniform reduction in the wood-panel support or canvas of the original painting that gives pressure on the painting layer. Cracks created due to drying are generally originated by the fading of volatile paint components and the resulting shrinkage of the paint. Lastly, cracks due to mechanical factors come from deformations of painting due to some exterior causes, e.g., impacts and vibrations. The cracks on the paintings decline the perceived image quality. A technique that is able to track and fill a crack is proposed in (Bami *et al*., 2000) but it requires the user to manually select a point on each crack to be restored. A method for the detection of cracks using multi-oriented Gabor filters is presented in (Abas and Martinez, 2002). Crack detection and removal bears certain similarities with methods proposed for the detection and removal of scratches and other artifacts from motion picture films (Joyeux *et al*., 1999 and Kokaram *et al*., 1995). However, such methods rely on information obtained over several adjacent frames for both artifact detection and filling and thus are not directly applicable in the case of painting cracks.

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A method for the elimination of the cracks using an infrared reflect gram of the painting is presented in (Hanbury *et al*., 2003). In this approach a viscous morphological reconstruction technique, based on a-priori information about the thickness of the cracks and its preferred orientation, is assumed for crack elimination. Abas and Martinez, 2003 have proposed a technique for the detection and classification of cracks using content based analysis. This method uses a morphological top-hat operator to detect the crack and fuzzy k-means clustering technique to classify the various crack patterns. . A similar problem of detection and filling of cracks has been treated by Giakoumis and Pitas (Giakoumis and Pitas, 1998). Their process first detects the crack using a morphological top-hat operator and then fills them using a trimmed median filter (Pitas and Venetsano Poulos, 1990) and an anisotropic diffusion filter. A methodology for the restoration of cracks on digitized paintings, which adapts and integrates a number of image processing and analysis tool is presented in this paper. It involves exact crack detection and filling method. Which adapts and integrates a number of image processing and analysis tool is presented in this paper. It involves exact crack detection and filling method.

A new crack detection model

Usually cracks have low luminance. Cracks having low luminance pixels with elongated structural characteristics are considered as local minima (Giakoumis and Pitas, 1998). A gray scale morphological filter called top-hat transform is used as crack detector to identify such minima. Top-hat transform is defined as

$$y(x)=f(x)-f_{nB}(x) \quad (1)$$

Where f(x) is the luminance component of the image under study and $f_{nB}$is the n times opening of the function f(x)

$$nB=B\oplus B\oplus\cdots\cdots\oplus B \quad (2)$$

where $\oplus$represents dilation operation.

And B is the structuring element which may be a square or a circle. The opening f_{nB} erases all peaks in which the structuring element nB cannot fit. The image f - f_{nB} contains only local minima and no background at all. So top-hat transform is applied on the negated luminance image. We have used square type structuring element of size 3×3. The number of dilations n=2.

A threshold operation on the grey scale output image generated by the top-hat transform is required to separate cracks from the rest of the image. A global threshold technique operating directly on the top-hat transform histogram is used to produce the binary image. Instead of using global threshold, the crack image can be locally processed using grid-based automatic threshold (Abas and Martinez, 2003).

Separation of the strokes from the cracks

Brush strokes have almost the same thickness and luminance features as cracks. The hair of a person in a portrait is an example. Therefore, the top-hat transform might misclassify these dark brush strokes as cracks. So it is very important to separate these brush strokes from the actual cracks, before the implementation of the crack filling procedure. Two methods to achieve this goal are described below.

Semi-automatic crack separation

The grassfire algorithm is applied that checks recursively for unclassified pixels with value 1 in the 8-neighborhood of each crack pixel. At the end of this procedure, the pixels in the binary image, which correspond to brush strokes that are not 8-connected to cracks will be removed.

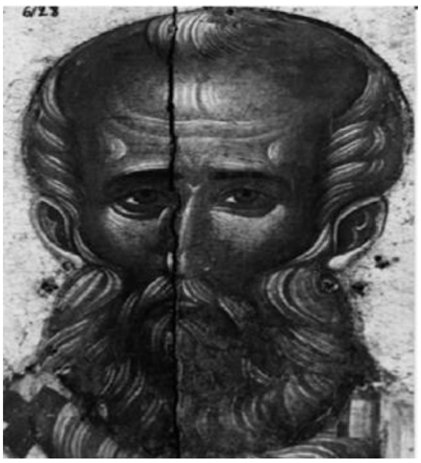

Fig.1. Original old painting with cracks (test image 1)

Fig. 2. Threshold output of the top-hat transform. A number of brush strokes have been misidentified as cracks

Fig. 3. The separated brush strokes after the application of the MRBF technique

Fig.4. Original old image with cracks (test image 2)

Fig.5. Image after Top Hat Transform and Selective Threshold of test image 2

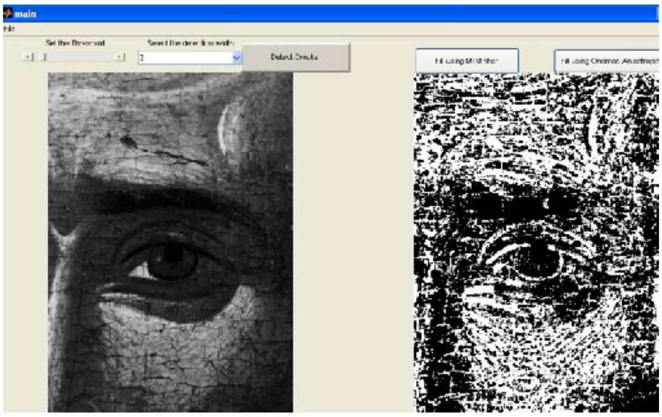

Fig.6. Representing the Mat lab screen with original image and the top-hat transform output for test image 2.

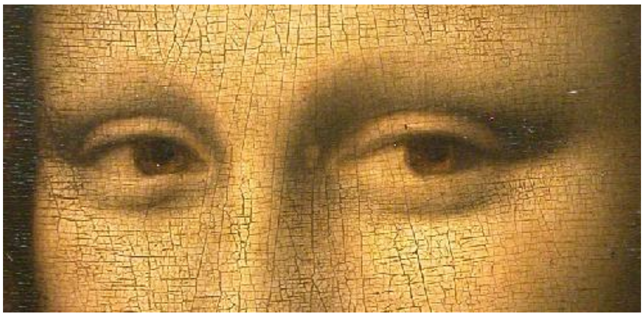

Fig.7. Original old image with cracks (test image 3)

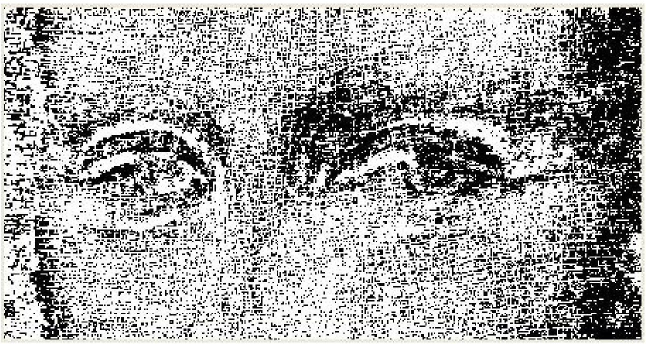

Fig.8. Image after Top Hat Transform and Selective Threshold of test image 3

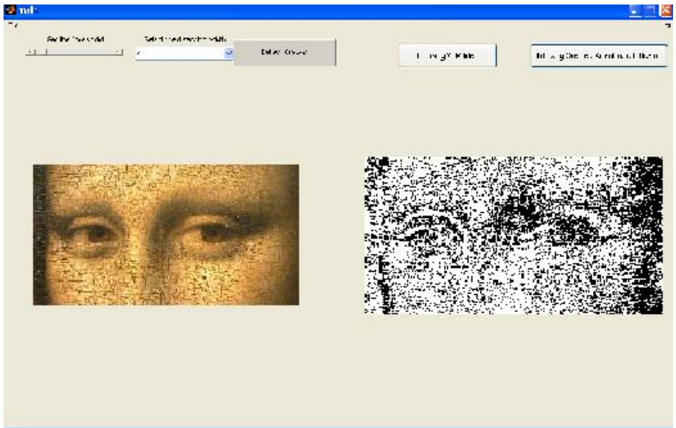

Fig.9. Representing the Mat lab screen with original image and the top-hat transform output for test image 3.

Fig.10. Original old image with cracks (test image 4).

Fig.11. Image after Top Hat Transform and Selective Threshold of test image 4.

Discrimination on the basis of hue and saturation

Hue of cracks ranges from 0^0 to 60^0 whereas hue of the dark brush strokes varies from 0^0 to 360^0.Crack saturation ranges from 0.3 to 0.7 whereas brush stroke saturation ranges from 0 to 0.4. Great portion of the dark brush strokes can be separated from the cracks by classification using Median Radial Basis Function (MRBF) neural networks.

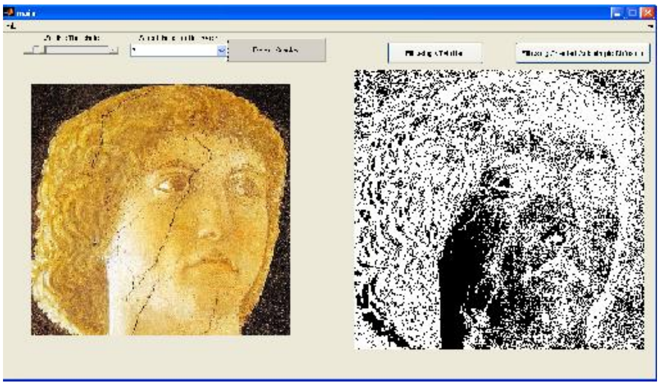

Fig.12. Representing the Mat lab screen with original image and the top-hat transform output for test image 4.

A MRBF network with two outputs is used. The first output represents the class of cracks while the second output represents the class of brush strokes. Input vectors are two-dimensional and consist of the hue and saturation values of pixels identified as cracks by the top-hat transform. In our implementation three hidden units have been taken. Training was carried out by presenting the network with hue and saturation values for pixels corresponding to cracks and crack-like brush strokes. However, appropriately selected training sets can be used to train the system to separate cracks from brush strokes on paintings of different artistic styles or content. The aim of this post-processing step was twofold: to remove pixels that are neither cracks nor crack-like brush strokes and to separate cracks and crack-like brush strokes for the supervised step of the training procedure. In this supervised training step, the network was presented with these labeled inputs, i.e., pairs of hue-saturation values that corresponded to image pixels that have been identified as belonging to cracks and crack-like brush strokes. After the training session, the MRBF neural network was able to classify pixels identified as cracks by the top hat transform to cracks or brush strokes. The trained network has been tested on 12 images from the training set and 15 images that did not belong to the training set. A threshold top-hat transforms output containing many brush strokes e.g. hair is illustrated in Figure 2. A great part of these brush strokes is separated by the MRBF, as can be seen in Figure 3. The original image can be seen in Figure 1.

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 or interpolate the cracks. Technique of order statistics filtering is used for this purpose. The performance of the crack filling method presented below is judged by visual inspection of the results. Crack filling based on order statistics filters is an efficient means to interpolate the cracks and is to apply median or other order statistics filters in their neighborhood. All filters are applied upon the cracks selectively, i.e., the core of the filter window passes through only the pixels of crack. If the filter window is sufficiently huge, the pixels of crack within the window will lie outside and shall be rejected. Thus, the pixels of crack will be assigned with the cost of one of the adjacent non crack pixels. We use a new filter known as a Modified Adaptive Median Filter (MAMF) which works on each RGB channel independently only on the crack pixel locations, so that quality of the content in other pixels is not affected. This nonlinear filter, in addition to crack filling, preserves the edges of the paintings. Since we intend to use ancient paintings whose original version is not known for detection and elimination of cracks, our method of filling can be judged qualitatively just by visual inspection only. The standard median filter could be used for filling the crack, but the problem with this method lies on its fixed window size and that there could always be a possibility that crack pixel count in the local region may exceed the noncrack pixel count.

This may however, result in replacing a crack pixel by another crack pixel, thus, failing in our aim. We therefore propose a modified version of an adaptive median filter in which the window size surrounding the crack pixel can be varied. This variation depends on the nature of pixels surrounding the crack pixels in the local region of window. MAMF runs only over the crack pixels so that information in other pixel is kept intact. The size of the filter window surrounding each crack pixel is evaluated based on the number of crack pixels in the local region of the window. If the number of crack pixels in the local region exceeds some threshold value, the size of the window is expanded till it falls below the threshold. In our case, a threshold value is set to be equal to 25% of the number of pixels in the window. When the number crack pixels in the local region falls below this threshold level, the size of the window satisfying the condition is treated as the order *N* of the filter for processing the crack pixel under observation. *N* will be different for all crack pixels in the painting and is evaluated adaptively. Processing here refers to replacement of crack pixel under observation by the median of the local observations i. e., equal to one, among the neighboring pixels. The filled crack pixels are defined by:

$$y_i = med\,(x_{i-j} \ldots x_i \ldots x_{i+j}) \quad \ldots\ldots\ldots\ldots (3)$$

Where *x* are the pixels in the local region of the window and $j = (N-1)/2$. For color paintings the same process is used on three independent channels individually and then combined to obtain crack filled color paintings. The results of the application are illustrated by the Figures 4 -12.

Conclusion

Cracks are detected by implementing the process of the top-hat transform, while the dark thin image brush strokes, those are misidentified as if cracks are parted either by an approach called semi-automatic approach or by an automatic method (MRBF networks).Process of crack interpolation is done by order statistics filters. The process has been implemented for the effective restoration of images in digital form and was found efficient by restoration experts."

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