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A PRAGMATIC TECHNIQUE FOR DETECTION AND REMOVAL OF CRACKS IN DIGITIZED PAINTINGS

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ABSTRACT
A Pragmatic technique for the detection and removal of cracks on digitized paintings is presented in this paper. The cracks are detected by thresholding the output of the morphological top-hat and bottom-hat transforms. And the outputs of the crack detection stage are compared to know which transform gives better results. Finally, crack filling using order statistics filters is done. These techniques have shown to perform very well on digitized paintings suffering from cracks.

KEY WORDS- *Detection of cracks, order statistics filters, top-hat transform, bottom-hat transform, virtual restoration of paintings.*

I. INTRODUCTION
We generally see paintings, especially old ones; suffer from breaks in the substrate, the paint, or the varnish. These patterns are usually called cracks or craquelure and can be caused by aging, drying, and mechanical factors. Age cracks can result from non uniform contraction in the canvas or wood-panel support of the painting, which stresses the layers of the painting. Drying cracks are usually caused by the evaporation of volatile paint components and the consequent shrinkage of the paint. Finally mechanical cracks result from painting deformations due to external causes, e.g., vibrations and impacts. The appearance of cracks on paintings deteriorates the image quality. However, one can use digital image processing techniques to detect and eliminate the cracks on digitized paintings. Such a "virtual" restoration can provide clues to art historians, museum curators and the general public on how the painting would look like in its initial state, i.e., without the cracks. Furthermore, it can be used as a non destructive tool for the planning of the actual restoration. The user should manually select a point on each crack to be restored. A method for the detection of cracks using transformation techniques is discussed in crack detection phase. Other research areas that are closely related to crack removal include image in painting which deals with the reconstruction of missing or damaged image areas by filling in information from the neighbouring areas, and disocclusion, i.e., recovery of object parts that are hidden behind other objects within an image. Methods developed in these areas assume that the regions where information has to be filled in are known. Different approaches for interpolating information in structured and textured image areas have been developed. The former are usually based on partial differential equations (PDEs) and on the calculus of variations whereas the latter rely on texture synthesis principles. A technique that decomposes the image to textured and structured areas and uses appropriate interpolation techniques depending on the area where the missing information lies has also been proposed. The results obtained by these techniques are very good. Different techniques for the restoration of cracks on digitized paintings, which adapts and integrates a number of image processing and analysis tools is proposed in this paper. The technique consists of the following stages:

- ***crack detection;***
- ***crack filling (interpolation).***

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. The results obtained after restoration of deteriorated images was very positive. This paper is organized as follows. Section II describes the crack-detection procedure. Methods for filling the cracks with image content from neighbouring pixels are proposed in Section III. Conclusions and discussion follow.

II. 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 the top-hat and bottom-hat transform is proposed in this paper. The major part is the structuring element and it is a shape, used to probe or interact with a given image, with the purpose of drawing conclusions on how this shape fits or misses the shapes in the image. It is typically used in morphological operations, such as dilation, erosion, opening, and closing, as well as the hit-or-miss transform. According to Georges Matheron, knowledge about an object (e.g., an image) depends on the manner in which we probe (observe) it. In particular, the choice of a certain s.e. for a particular morphological operation influences the information one can obtain. There are two main characteristics that are directly related to s.e.s:

- **Shape**. For example, the s.e. can be a ``ball" or a line; convex or a ring, etc. By choosing a particular s.e., one sets a way of differentiating some objects (or parts of objects) from others, according to their shape or spatial orientation.

- **Size**. For example, one s.e. can be a 3×3square or a 21×21square. Setting the size of the structuring element is similar to setting the observation scale, and setting the criterion to differentiate image objects or features according to size.

In structuring element there are two major concepts they are ***HIT*** and ***FIT:***

FIT: All on pixels in the structuring element cover on pixels in the image

HIT: Any on pixel in the structuring element covers an on pixel in the image

The top hat transform performs opening operation i.e erosion followed by dilation:

$$A \circ B = (A \ominus B) \oplus B \qquad (1)$$

Here A is the image and B is the structuring element.
It is nothing but union operation performed on the structuring element and the image

$$A \circ B = \bigcup_{B_x \subseteq A} B_x \qquad (2)$$

The two major concepts are erosion and dilation - Erosion of image *f* by structuring element *s* is given by

$$f \ominus s$$

The structuring element s is positioned with its origin at *(x, y)* and the new pixel value is determined using the rule:

$$g(x,y) = \begin{cases} 1 \text{ if } s \text{ fits } f \\ 0 \text{ otherwise} \end{cases}$$

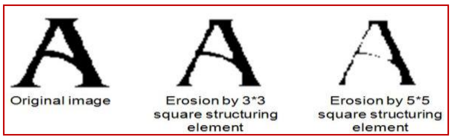

Fig 1: Example of erosion.

Dilation of image *f* by structuring element *s* is given by

$$f \oplus s$$

The structuring element s is positioned with its origin at *(x, y)* and the new pixel value is determined using the rule:

$$g(x,y) = \begin{cases} 1 \text{ if } s \text{ hits } f \\ 0 \text{ otherwise} \end{cases}$$

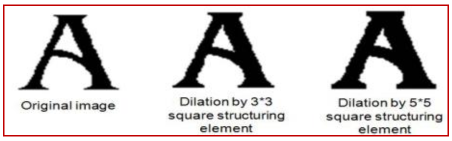

Fig 2: Example of dilation.

And bottom-hat transform is an operation that extracts small elements and details from given images. Then in this closing of images takes place. Closing operation is nothing but dilation and then erosion.

$$A \bullet B = (A \oplus B) \ominus B \qquad (3)$$

Here A is the image and B is the structuring element.
It is nothing but intersection operation performed on the structuring element and the image

$$A \bullet B = (A^c \circ B^s)^c \qquad (4)$$

Where X^c denotes the complement of X relative to E.

$$X^c = \{x \in E | x \notin X\} \qquad (5)$$

The top-hat transform generates a greyscale output image t(k,l) where pixels with a large grey value are potential crack or crack-like elements. Therefore, a thresholding operation on t(k,l) 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. The low computational complexity of the thresholding operation enables the user to view the crack-detection results in real time while changing the threshold value, e.g., by moving a slider. This fact makes interactive threshold selection very effective and intuitive. Alternatively, threshold selection can be done by inspecting the histogram t(k,l) of for a lobe close to the maximum intensity value (which will most probably correspond to crack or crack-like pixels), and assigning it a value that separates this lobe from the rest of the intensities. The result of the thresholding is a binary image b(k,l) marking the possible crack locations. Instead of this global thersholding technique, more complex thresholding schemes, which use a spatially varying threshold, can be used. Obviously, as the threshold value increases the number of image pixels that are identified as cracks decreases. Thus, certain cracks, especially in dark image areas where the local minimum condition may not be satisfied, can remain undetected. In principle, it is more preferable to select the threshold so that some cracks remain undetected than to choose a threshold that would result in the detection of all cracks but will also falsely identify as cracks, and subsequently modify, other image structures. The thresholded (binary) output of the top-hat transform on the luminance component of an image containing cracks.And thus we can complete the crack detection stage.

III. CRACK-FILLING METHODS

After identifying cracks 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 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. Image in painting techniques like the ones cited in Section I can also be used for crack filling. The performance of the crack filling methods presented below was judged by visual inspection of the results. The results have been verified and the images are being restored.

3.1 Crack Filling Based on Order Statistics Filters

An effective way to interpolate the cracks is to apply median or other order statistics filters in their neighborhood. All filters are selectively applied on the cracks, i.e., the center of the filter window traverses only the crack pixels. If the filter window is sufficiently large, the crack pixels within the window will be outliers and will be rejected. Thus, the crack pixel will be assigned the value of one of the neighboring non crack pixels.

The following filters can be used for this purpose.

• Median filter

$$y_i = \mathrm{med}(x_{i-\nu}, \ldots, x_i, \ldots, x_{i+\nu}) \tag{6}$$

• Recursive median filter

$$y_i = \mathrm{med}(y_{i-\nu}, \ldots, y_{i-1}, x_i, \ldots, x_{i+\nu}) \tag{7}$$

Where the $y_{i-\nu}, \ldots\ldots, y_{i-1}$ are the already computed median output samples. For both the recursive median and the median filter, the filter window (considering only rectangular windows) should be approximately 50% wider than the widest (thickest) crack appearing on the image.This is necessary to guarantee that the filter output is selected to be the value of a noncrack pixel. Smaller windows will result in cracks that will not be sufficiently filled whereas windows that are much wider than the cracks will create large homogeneous areas, thus distorting fine image details.

• Weighted median filter

$$y_i = \mathrm{med}(w_{-\nu} \Diamond x_{i-\nu}, \ldots, w_\nu \Diamond x_{i+\nu}) \tag{8}$$

Where $w \Diamond x$ denotes duplication of times. For this filter, smaller filter windows (e.g., windows that are approximately
30% wider than the widest crack appearing on the image) can be used since the probability that a color value corresponding to a crack is selected as the filter output (a fact that would result in the crack pixel under investigation not being filled effectively by the filter) can be limited by using small weights for the pixels centrally located within the window (which are usually part of the crack) and bigger ones for the other pixels.

The filter coefficients are chosen as follows:

$$\alpha_{rs} = \begin{cases} 0, & \text{if } \mathrm{med}\{x_{ij}\} - x_{i+r,j+s} \geq q \\ 1, & \text{otherwise} \end{cases} . \tag{10}$$

The amount of trimming depends on the positive parameter. Data of small value deviating strongly from the local median (which correspond usually to cracks) are trimmed out. Windows used along with this variant of the MTM filter can also be smaller than those used for the median and recursive median filters since a portion of the crack pixels is expected to be rejected by the trimming procedure.

•And after finding the threshold output which contain only binary values for the pixels i.e either 1 or 0.All the pixels with value 1 indicate non cracked part of the image and all the pixel with values 0 indicate cracked pixels where the data is missing. Now we collect the matrix columns and rows of the pixel with value 0 by using the condition:

$$\text{if } b(i,j)=0 \tag{11}$$

Now after obtaining the row and column values of the pixels where the data is missing we now use the mean value of the neighborhood pixels as shown below:

Table 1 : Neighbouring Pixels of cracked pixel

B1	B2	B3
B4	B5	B6
B7	B8	B9

Here in the above table let B5 is the cracked pixel or the pixel with value 0 and now we calculate the mean of the neighbor pixels using:

$$\text{Mean}=(B1+ B2+ B3+ B4+ B5+ B6+ B7+ B8+ B9)/N \tag{12}$$

N=no of pixels .

Now after we get the mean value and we substitute the mean value in place of the missing data likewise we perform the same operation on all the missing pixel values and we get the missing data and we can reconstruct the image.

The median operator can be used instead of the arithmetic mean in (9). And after finding the assigning the pixel For this variant of the MTM filter, even smaller filter windows can be used, since crack pixels do not contribute to the filter output. Thus, it suffices that the window is 1 pixel wider than the widest crack. The result of the application of the second variation of the modified trimmed mean filter on the painting depicted in Fig. 3 (filter size 5x5). Another image restored by the same crack-filling approach can be seen in Fig. 4 (filter size 3x3). Extensive experimentation proved that this filter gives the best results among all filters presented above according to the evaluations. The superiority of this filter can be attributed to the fact that only non crack pixels contribute to its output. Thus the cracks can be interpolated.

IV RESULTS

Fig3: Original image

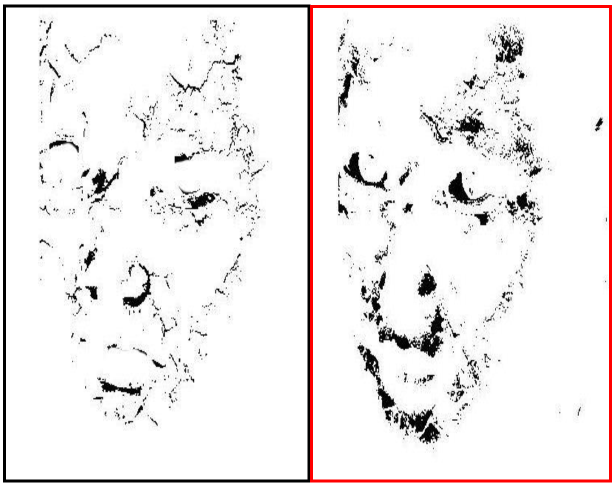

Fig 4 a) Threshold output of bottom hat transform
b) Threshold output of top hat transform

Fig5: Cracks Interpolated and reconstructed image.

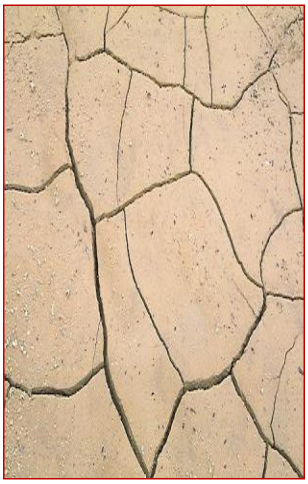

Fig6:original painting

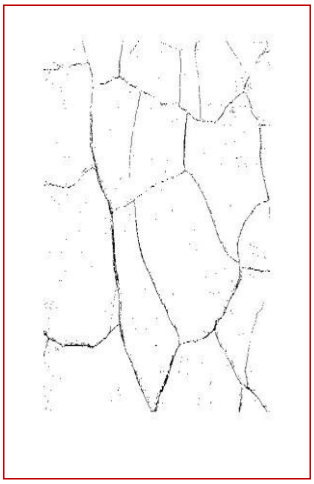

Fig7: output after applying transform and thresholding.

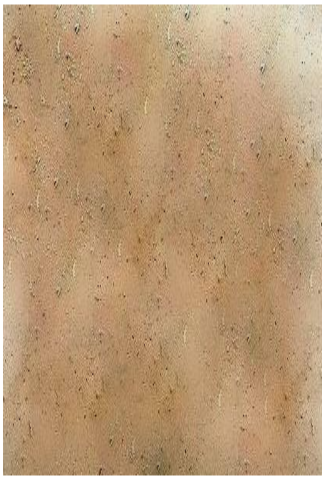

Fig8: Reconstructed Image.

V. CONCLUSIONS AND DISCUSSION

In this paper, we have presented advanced techniques for detection and filling in digitized paintings. Cracks are detected by using top-hat & bottom hat transforms and compared the results and observed that bottom hat transform yields better results. Crack interpolation is performed by appropriately modified order statistics filters. The methodology has been applied for the virtual restoration of images and was found very effective. However, there are certain aspects of the proposed methodology that can be further improved. For example, the crack-detection stage is not very efficient in detecting cracks located on very dark image areas, since in these areas the intensity of crack pixels is very close to the intensity of the surrounding region. A possible solution to this shortcoming would be to apply the crack-detection algorithm locally on this area and select a low threshold value. Another situation where the system (more particularly, the crack filling stage) does not perform as efficiently as expected is in the case of cracks that cross the border between regions of different colour. In such situations, it might be the case that part of the crack in one area is filled with colour from the other area, resulting in small spurs of colour in the border between the two regions. However, this phenomenon is rather seldom and, furthermore, the extent of these erroneously filled areas is very small (2–3 pixels maximum). A possible solution would be to perform edge detection or segmentation on the image and confine the filling of cracks that cross edges or region borders to pixels from the corresponding region. Use of image in painting techniques could also improve results in that aspect. Another improvement of the crack filling stage could aim at using properly adapted versions of nonlinear multichannel filters (e.g., variants of the vector median filter) instead of processing each colour channel independently. These improvements will be the topic of future work on this subject. This can be implemented for the pavement crack detection which has very importance now a days.

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