INTERNATIONAL JOURNAL OF PURE AND APPLIED RESEARCH IN ENGINEERING AND TECHNOLOGY

A PATH FOR HORIZING YOUR INNOVATIVE WORK

SPECIAL ISSUE FOR INTERNATIONAL LEVEL CONFERENCE "ADVANCES IN SCIENCE, TECHNOLOGY & MANAGEMENT" (IC-ASTM)

RESTORATION OF OLD PAINTINGS CRACK DETECTION AND REMOVAL

MRS R. A. TALEY

Asst Prof Dept of CSE, College of Engg & Tech, Akola.

Abstract: Everyday digital image processing is used in all areas of science. With the help of image processing tools, various digital image processing can be applied for restoration of old painting. Ancient paintings are cultural heritage for ones country and must be preserved or restored. With the passage of time, painting gets Detroit. Cracking is one of the most common deteriorations found in old paintings. The paper presents the approach for restoration of old painting which are suffering from cracks. The approach includes crack detection and removal of the crack. This paper aims at the removal of the cracks from old paintings and to give its original view. Keywords: cracks, crack detection, crack filling, restoration.

Keywords: Cracks, Crack Detection, Crack Filling, Restoration

Corresponding Author: MRS R. A. TALEY

Co Author: -

Access Online On:

www.ijpret.com

How to Cite This Article:

R. A. Taley, IJPRET, 2017; Volume 6 (2): 444-452

PAPER-QR CODE

INTRODUCTION

Many 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 perceived image quality. However, one can use digital image processing techniques to detect and eliminate the cracks on digitized paintings

Related Work
Steps/Methods
There are three basic steps in above problem namely:
1)Crack Detection.
2)Crack classification (as a brush storke or crack segment).
3)Crack filling.

Step 1: Crack Detection:

Concept:
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.

Technique: Top Hat transform & Selective thresholding.
- As explained by the concept used above ,we use only the 'luminance' component of the image .Hence we use the matlab function :

rgb2ntsc (im) $\rightarrow$ RGB to YIQ model.
Where Y=luminance
Hence we use the ' Y' component.

- Top hat transform can be implemented by the following equation :

$y\,x = f\,x - fnb\,(x)$
Where f(x)=original negated image

fnb(x)=opening of the image f(x)
Here 'B' is the structuring element & 'n' represents the number of times we do dilation i.e.

$nB = B\ dilate\ B\ dilate\ B\ dilate\ \ldots\ldots\ldots(n\ times)$

Aliter:
The above method can be replicated by performing closing on the original image f(x) with the structuring set nB and then subtracting f(x) from the result of closing fnB(x):
$$y\,(x) = f^{nb}\,(x) - f(x)$$

445

- **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.

$imcrac = imtop\ hat > t$ where t taken was 0.13.

Explanation (how do we get cracks with brushstrokes using a top-hat transform)

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.

Step 2: Crack Classification:

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 could be such an area. 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.

Given: From the statistical analysis of 47 digitized paintings (done by the author) he concluded that the classification can be based on the following criterion based on the 'Hue' & 'Saturation' of the image:

H value : 0-60 degrees ☐☐Crack
0-360 degrees ☐☐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**

elseif (im2(i, j)==1) ☐☐**Undecided !**   **Correctly classified detected**

Where im2(i, j)==1 represent the white pixels in the Top Hat transformed image.

Hence we need to classify the undecided white pixels of the Top-hat transformed image. This can be done by :
Technique: Classification using MRBF based neural network.
- **Currently we tried the 'Gaussian Classifier' to classify between brush strokes and cracks.**

Taking the correctly classified samples as the training samples and by using the Gaussian classification equation
$gi(x) = -1/2 * (x-\mu i)^T \Sigma i^{-1} (x-\mu i) - d/2 * ln(2\pi) - \frac{1}{2} ln|\Sigma i| + ln(P(\omega i))$

Step 3: Crack Filling Methods:

a)Using MTM (Modified Trimmed Mean) filter:

446

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 from the local median and averages the remaining pixels.

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

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 varation 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 in 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 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.

b) Using Weighted median filter:

We apply the following equation for crack filling:

$$y_i = med(w_{-\nu} \Diamond x_{i-\nu}, \dots, w_\nu \Diamond x_{i+\nu})$$

Where $w \Diamond x$ denotes duplication of x;w times.

Mask Size:
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 (e.g. 1) for the pixels centrally located within the window (which are usually part of the crack) and bigger ones(e.g. 2 or 3) for the other pixels.
Here we have used 1 for the crack pixels and 2 for other pixels.
c)Doing iteration:

447

As after doing iterations the image gets smoothed ,so we apply a high boost filter to sharpen the image.
Results:

Crack Detection / The Top Hat transform results :

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

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

1) **Test Image 1**

Original Image with crack   After Top Hat transform & Selective Thresholding.

Results for Test image 1)

Total white pixels in the Top Hat transformed image : 8085

After Classification with given H & S parameters:

Total sure Crack pixels : 3662

Total sure Brush Stroke : 816

Unclassified : 3607

After Gaussian classification

Total Crack pixels : 6739 (3662+3077 (from Gaussian))

Total Brush pixels : 1346 (816+530 (from Gaussian)).

Step 2: Crack Classification :

Results :

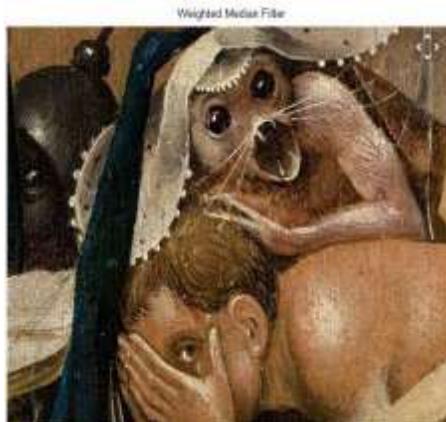**Step 3: Crack Filling Methods:**

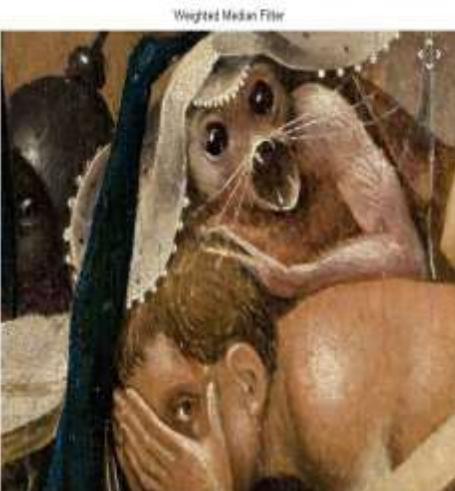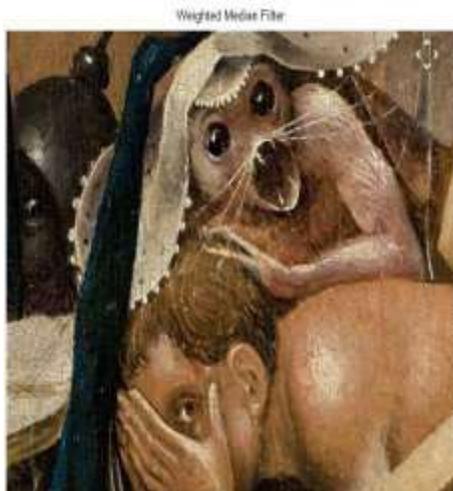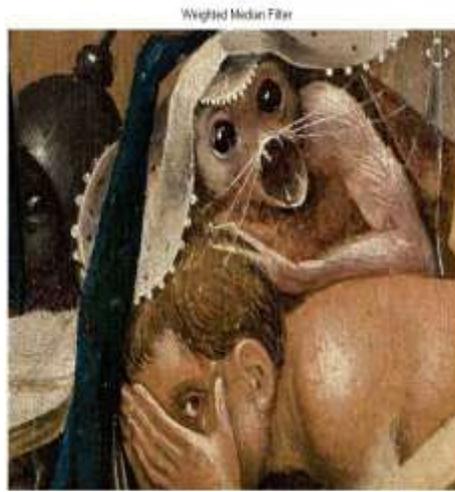**a)Using MTM (Modified Trimmed Mean) filter:**

Original Image   Cracks Interpolated

b)Using Weighted median filter:

c)Doing iteration:

Iteration 1

Iteration 2

Iteration 3

Iteration 4
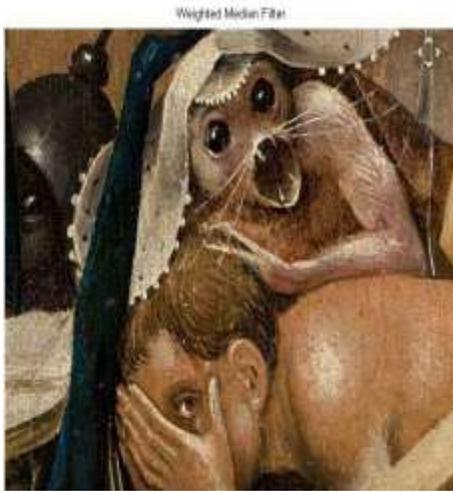
Sharpened Image

Conclusion

In this paper, we did 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 using a gaussian classifier.
- Crack interpolation is performed by appropriately modified filters.

Improvement yet to be done:

1) 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.
2) 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 color. In such situations, it might be the case that part of the crack in one area is filled with color from the other area, resulting in small spurs of color in the border between the two regions
3) Use of image inpainting techniques could also improve results

REFERENCES:

1. Research Paper: Digital image processing techniques for the detection and removal of cracks in digitized paintings .
2. Research paper:-Digital Automated restoration of manuscripts and antique printed books.
3. "Digital Image Processing Techniques for the Detection and Removal of Cracks in Digitized Paintings" Ioannis Giakoumis, Nikos Nikolaidis, (2006) IEEE. [2] "Image Processing Methods for the Restoration of Digitized Paintings" Abhilekh Gupta, Vineet Khandelwal, Abhinav Gupta and M. C.Srivastava July-September 2008 Thammasat International journal of science and technology.
4. "A Pragmatic technique for detection and removal of cracks in digitized paintings" Pranob Charles , Balaji, V.V.S. Murthy,Rajendra Prasad, Sripath Roy , Purnachand , Suresh International Journal of Modern Engineering Research (IJMER).

451

5. "Digital image restoration techniques and automation", Ninad Pradhan,Clemson University (2004). [5] "Inpainting approach to repair cracked images" Shilpa,Nisha Sharma, International Journal of Application or Innovation in Engineering & Management (IJAIEM), October (2012).

6. "Image Processing for Virtual Restoration of Artwork",Mauro barni ,Franco Bartolini (2000),IEEE [7] www.wikipedia.org/texturesynthesis