International Journal of Computer Science
and Engineering (IJCSE)
ISSN 2278-9960
Vol. 2, Issue 3, July 2013, 35-46

International Academy of Science, Engineering and Technology
Connecting Researchers; Nurturing Innovations

VIRTUAL RESTORATION OF OLD DIGITAL PAINTINGS

SHRUTI GARG[1] & G. SAHOO[2]

[1]Assistant Professor, Department of Computer Science and Engineering, BIT, Mesra, Ranchi, Jharkhand, India

[2]Head, Department of Information Technology, BIT, Mesra, Ranchi, Jharkhand, India

ABSTRACT

A painting which was handled roughly or made from low quality paint or base are usually suffers from crack in a long run, which causes them to lose some of the information. So there is a requirement of restoration. In restoration, there are three steps involved crack detection-crack classification and filling or interpolation. In order to do the same top hat transform was applied to detect the cracks, and then supervised and unsupervised classification was done for crack classification. And lastly several statistical filters were applied to fill the cracks.

KEYWORDS: Crack Detection, Top-Hat Transform, Median Filter, Trimmed Filter, Back Propagation Neural Network, Fuzzy C Means Algorithm

INTRODUCTION

Old paintings which is of great historical and artistic importance, usually suffer from breaks in the substrate, the paint, or the varnish. These breaks can take a shape of rectangle, circle, spider-web, unidirectional, tree branches and random. These types of patterns are called cracks or craquelure which depends on the materials used for the painting, the painting technique of the artist, the atmospheric variations the painting has been exposed to, and manipulation and storage conditions. The legibility of image decreases due to the presence of cracks on the paintings. Therefore, painting restoration is a very demanding field that requires considerable expertise. Before each operation a great amount of planning is necessary because most of the restoration procedures are irreversible. However, digital image processing techniques can be used to detect and eliminate the cracks on digitized paintings. This type of restoration which is virtual in nature 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.

A system that is capable of tracking and interpolating cracks is presented in [1] but it requires the user to manually start with the initial point of the crack pattern to fill them. Another method for the detection of cracks using multi-oriented Gabor filters is presented in [2]. Crack detection and removal is however similar with the methods proposed for the detection and removal of scratches and other artifacts from motion picture films [3], [4] & [5] but these methods uses the information obtained over several adjacent frames for both detection and filling and thus are not applicable for the cracks in paintings. Other research areas that are closely related to crack removal include image inpainting which deals with the reconstruction of missing or damaged image areas by filling-in information from the neighboring areas, and disocclusion, i.e., recovery of object parts that are hidden behind other objects within an image. In this paper an integrated methodology for the detection and removal of cracks on digitized paintings is 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 (interpolation).

METHOD

The method of restoration of cracks on a painting consists of three stages. First, the local minima should be detected (they can be either cracks or painting brush strokes), by using a morphological high pass operator, called top-hat transform. A similar technique used for the detection of cracks is presented in [6]. The crack filling procedure must be applied only on the cracks and not on the dark brush strokes, which are also detected in the top hat transformation technique. In order to separate these brush strokes from cracks, the differences in the gray values of the cracks and brush strokes is used. The separation is obtained by classification through the implementation of the back propagation neural network and fuzzy c-mean classification can also be used for this separation. Finally, crack filling method is proposed which is based on order statistics filter.

Detection of Cracks

Cracks are the low luminance component of the image, that is, the dark details in the bright background. Therefore it can be considered as the 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 was presented in [7]. The detection of the cracks can be obtained with the implementation of a very useful morphological filter, called top-hat transformation. The top-hat transform which is described in [8] is a grayscale morphological filter defined as follows:

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

where $f_{nB}(x)$ is the opening of the function with the structuring set nB , defined as:

$$nB = B \oplus B \oplus B \oplus B \ldots\ldots B \quad (n\ times) \tag{2}$$

The opening $f_{nB}(x)$ 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 $f - f_{nB}$ contains only those peaks and no background at all. The cracks have usually very small luminance. Thus, for extracting the cracks, we must negate the luminance image and then apply the top-hat transformation. Alternatively, crack can also be detected by performing closing on the original image *f(x)* with the structuring set nB and then subtracting f*(x)* from the result of closing $f^{nB}(x)$.

$$y(x) = f^{nB}(x) - f(x) \tag{3}$$

However, we can control the result of crack detection procedure by choosing the appropriate values of the following parameters:

- The type and size of structuring element B;
- Number of times the dilation should be done.

These parameters affect the size of the final structuring element nB and must be chosen according to the thickness of the cracks to be detected. For our results the type of structuring element is square type whereas the size of structuring element that is used is 3× 3 and the number of times dilation operation is applied on the image is 2 as the thickness of cracks ranges from 2 to 6 pixels. The top-hat transform generates a grayscale 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 T can be chosen by inspecting the top-hat output histogram, so that only a small percentage of the pixels *t(k,l)* is above it. The thresholding is global, because T is chosen based on global information is given in [7]. In this case the threshold value T is taken as 23 which is providing good results[6]. The result of the thresholding is a binary image b *(k,l)* marking the possible crack locations which generates the crack map.

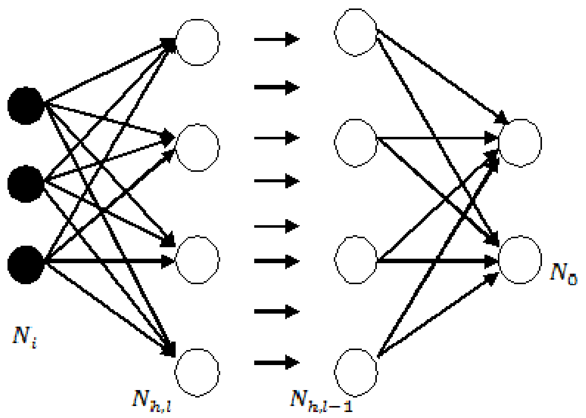
Crack Classification

In some paintings, there are certain areas where brush strokes have almost the same thickness and luminance features as that of crack. As brush strokes can be of any color and any thickness depending on the demand of the painting therefore it can be misclassified as cracks by the top-hat transform. 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. Two methods to achieve this goal are described as follows:

Classification Using Back Propagation Neural Network

It has been observed by analyzing some paintings that the gray values of cracks usually ranges from 0 to 122.4 while the gray values of the brush strokes may vary from 0 to 255 as brush strokes of any painting can be any value depending on the color of paint[6]. Thus, a great portion of the dark brush strokes, falsely detected by the top-hat transform can be separated from the cracks by using this information. This separation can be achieved by classification using a Back propagation neural network.

Back propagation [9] is a feed forward neural network which usually consists of three layers: input, output and hidden layer. The following figure shows the generalized back propagation neural network:



During the training phase, the training data is fed into to the input layer. The data is propagated to the hidden layer and then to the output layer. This is called the ***forward pass*** of the back propagation algorithm. One of the more popular activation functions for back propagation neural networks is the sigmoid [10], a real function $S_c : IR \rightarrow (0,1)$ defined by the expression:

$$s_c(x) = \frac{1}{1 + e^{-cx}}$$

In the forward pass, the nodes in hidden layer get input from all the nodes of the input layer, which are multiplied with appropriate weights and then summed. Similarly each node in output layer gets input from all the nodes from hidden layer, which are multiplied with appropriate weights and then summed. The output values of the output layer are then compared with the target output values**.** As it is the supervised learning the target output values are used to teach the network. The error of each neuron, which is essentially: target – actual output is calculated and propagated back toward hidden layer. This is called the ***backward pass*** of the back propagation algorithm. This error is then used to change the weights in such a way that the error will get smaller and thus the output values will get closer to the target values. During the testing phase, no learning takes place i.e., weight matrices are not changed. Each test vector is fed into the input layer.

In this implementation, a back propagation network with two outputs is used. The first output represents the class of cracks while the second one the class of brush strokes. Input vectors that are fed to the network are two-dimensional and consisted of the gray values of pixels identified as cracks by the top-hat transform. The number of input units depends on the size of the image as the whole image is divided into smaller regions and any alteration done to these regions does not heavily affects the whole image. One hidden unit has been incorporated to the neural network. Training is carried out by presenting the network with the gray values for pixels corresponding to cracks and crack-like brush strokes. The whole system is trained and an updated weight is calculated for the inputs fed to the network. The weight updation is done based on backpropagation learning algorithm. This is the supervised training step as the target output is fed to the network which is calculated using the information of gray values of cracks and brush strokes. The calculated trained weight from the training phase can then be used to test the network to separate the brush strokes from cracks in the testing phase. Thus the back propagation neural network will able to classify pixels identified as cracks by the top-hat transform to cracks or brush strokes.

Unsupervised Crack Classification by Fuzzy C-Means Algorithm

In unsupervised classification we don't need to provide training data sets, the data is divided in clusters. After applying top hat transform output is crack map in which there will be some brush stokes classified as crack pixels. In order to classifying them into their appropriate category, fuzzy c-mean algorithm[22] is applied for unsupervised classification.

Crack Filling

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. Different approaches for interpolating information in structured which is discussed in [15]-[19] and textured image areas which is discussed in [20] have been developed. The technique that is used for the interpolation of cracks in this paper is based on the order statistics filter. Order statistics filter is a non linear spatial filter whose response is based on ordering or ranking the pixels contained in an image neighborhood and then replacing the value of the center pixel in the neighborhood with the value determined by the ranking result. This is implemented on each RGB channel independently and it affects only those pixels which belong to cracks. This procedure affects only those pixels which belong to cracks. Therefore, the filling procedure does not affect the useful content of the image.

All filters are selectively applied on the cracks, i.e., the center of the filter window traverses only the crack pixels. Thus, the crack pixels take values equal to the median of the local observations, i.e. equal to one of the neighboring pixels.

The non linear filters proposed for filling of the cracks are as follows:

Trimmed Mean Filter

A trimmed mean filter excludes the samples $x_{i+r,j+s}$ in the filter window, which is considerably smaller from the local median and averages the remaining pixels.

$$y_{ij} = \left(\sum\sum_A \propto_{rs} x_{i+r,j+s} \right) / \left(\sum\sum_A \propto_{rs} \right) \tag{4}$$

where,

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

where, q is a positive parameter.

Modified Trimmed Mean Filter

Modified trimmed mean filter performs mean filtering 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 as follows:

$$\propto_{rs} = \begin{cases} 0, & if\ b(k,l) = 1 \\ 1, & otherwise \end{cases} \quad (5)$$

Alternative Mean Median Filter

In this method alternatively mean filter and median filter was applied on the crack pixels. To avoid smoothing effect median filter on the overall image pixels can be used. Firstly 13 × 13 mean filter is applied on the crack pixels followed by 3 × 3 median filter. Recursively size of mean filter will decrease, e.g. 9 × 9 mean filter and size of median filter will increase, e.g. 5 × 5 median filter.

Variable Median Filter

The problem with the standard median filter 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 non crack pixel count. This may however, result in replacing a crack pixel by another crack pixel, thus, failing in our aim. Therefore median filter with varying window size surrounding the crack pixel were used. The variations depend on the nature of pixels surrounding the crack pixels in the local region of window. If window is have more than 50% of crack pixels then window size will be increased to 5x5 and soon.

Controlled Anisotropic Diffusion

Anisotropic diffusion [23] is an image enhancement method that successfully combines smoothing of slowly varying intensity regions and edge enhancement. Anisotropic diffusion is described by the following Partial Differential Equation:

$$\frac{\partial I(x,y,t)}{\partial t} = div\big(\ c(x,y,t)\nabla I(x,y,t)\big)$$

$$= c(x,y,t)\Delta I(x,y,t) + \nabla c(x,y,t) \cdot \nabla I(x,y,t) \quad (6)$$

where div denotes the divergence operator and ∇, Δ the gradient and Laplacian operators with respect to the space variables x, y . At each position and iteration, diffusion is controlled by the conduction (or diffusion) coefficients $c(x,y,t)$.

In order to obtain a numerical solution to the diffusion equation, discretization of the spatial and time coordinates and approximation of the differential operators by finite difference operators should be performed. A 4-nearest neighbor discretization of the Laplacian operator can be used:

$$I_{i,j}^{t+1} = I_{i,j}^{t} + \lambda \left[c_N \cdot D_N I + c_S . D_s I + c_E \cdot D_E I + c_W \cdot D_W I \right]_{i,j}^{t} \quad (7)$$

where $0 \leq \lambda \leq \frac{1}{4}$ for the scheme to be stable, N, S, E, W are the mnemonics for North, South, East, West and the symbol D indicates the nearest neighbor differences:

$$D_N I_{i,j} = I_{i-1,j} - I_{i,j}$$

$$D_S I_{i,j} = I_{i+1,j} - I_{i,j}$$

$$D_E I_{i,j} = I_{i,j+1} - I_{i,j}$$

$$D_W I_{i,j} = I_{i,j-1} - I_{i,j} \quad (8)$$

The conduction coefficients are updated at every iteration as a function of the brightness gradient:

$$c_{N_{i,j}}^{t} = g\left(\| D_N I_{i,j}^{t} \| \right)$$

$$c_{S_{i,j}}^{t} = g\left(\| D_S I_{i,j}^{t} \| \right)$$

$$c_{E_{i,j}}^{t} = g\left(\| D_E I_{i,j}^{t} \| \right)$$

$$c_{W_{i,j}}^{t} = g\left(\| D_W I_{i,j}^{t} \| \right) \quad (9)$$

The following function $g(\cdot)$, proposed in [23], has been used in this case:

$$g(\nabla I) = \frac{1}{1 + \frac{\| \nabla I \|^2}{K}} \quad (10)$$

The constant *K is* manually fixed which is taken 30 in this case. In order to fill the cracks, the anisotropic diffusion algorithm was applied selectively, in neighborhoods centered on crack pixels. All pixels within these neighborhoods participate in the diffusion process.

However, only the values of the crack pixels are updated in the output image. The experimental results of this filter are very promising. However, we can have even better results, if we modify the classical anisotropic diffusion filter, by taking into account crack orientation. For example, if the crack is horizontal we can use only the North and the South neighbors, because the West and the East neighbors belong also to the crack. In order to find the directions of the cracks, we apply the Hough Transform [24].

RESULTS

An integrated strategy for crack classification and filling had been presented for digitized paintings. Cracks are detected by using top hat transform and thresholding operation on cracked painting.

The parameters chosen for this technique are: Structuring element as square, size as 3×3 and number of dilations (n) as 2. After top hat transform the result is threshold using the threshold value 23[6]. This will generate the following results:

Crack Detection

Figure 1: Original Image

Figure 2: Result after Applying Top Hat Transform

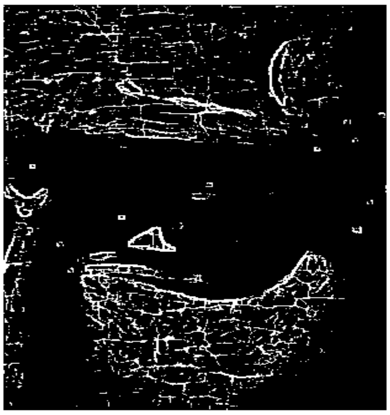


Figure 3: Crack Map after Applying Thresholding

The thin dark brush strokes, which are misidentified as cracks, are separated by back propagation neural network and fuzzy c mean clustering approach. The methods and their results that are used for the separation of misidentified cracks are as follows:

Crack Classification

Supervised Crack Classification Using Back Propagation Algorithm

The back propagation neural network is implemented on the gray values of the cracked digitized painting using the information from the binary output image b(k,l) of the top-hat transform.

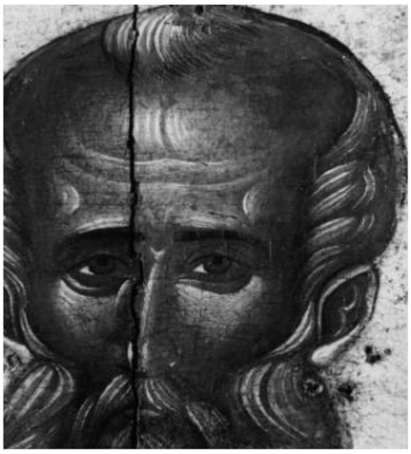


Figure 4: Original Image

Figure 5: Crack Map before Classification

Unsupervised Crack Classification by Fuzzy C-Means Algorithm

The fuzzy partition is also implemented on the gray values of the cracked digitized painting using the information from the binary output image b(k,l) of the top-hat transform. This will generate the following results:

Figure 6: Crack Map after Supervised Classification

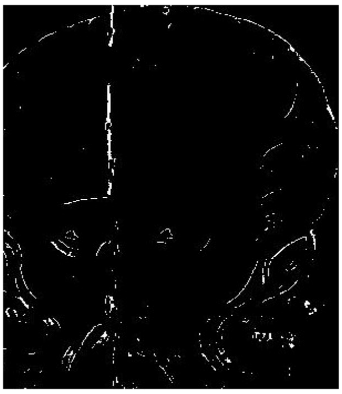


Figure 7: Cracks Map after Unsupervised Classification

Crack Filling

Crack filling is performed appropriately by modified order statistics filters. The methodology has been applied for the virtual restoration of images and was found very effective. The methods and their results that are used for interpolation are as follows:

Modified Trimmed Mean Filter

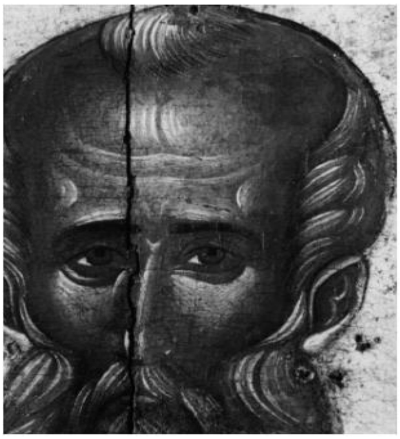


Figure 8: Original Image

Figure: 9: Result after Applying Modified Trimmed Mean Filter

Figure 10: Crack Map before Filling

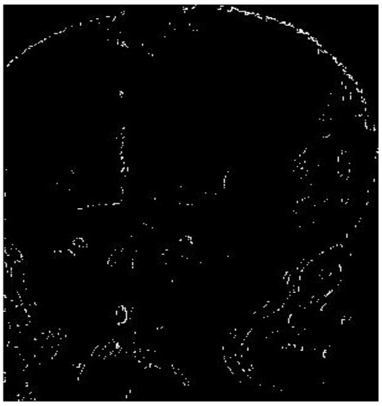


Figure 11: Crack Map after Filling

Trimmed Mean Filter

Figure 12: Result after Applying Trimmed Mean Filter

Figure 13: Result after Applying Trimmed Mean Filter

Alternative Mean Median Filter

Figure 14: Result after Applying Alternative Mean Median Filter

Figure 15: Result after Applying Alternative Mean Median Filter

Alternative mean median filter or trimmed mean filter or trimmed median filter does not depend upon the number of crack pixels in the filter window. And thus it may replace the crack pixel with another crack pixel. Therefore, a variable size median filter can be used taking account the number crack pixels in the window.

Variable Size Median Filter

Figure 16: Result after Applying Variable Size Median Filter

Figure 17: Result after Applying Variable Size Median Filter

Controlled Anisotropic Diffusion

Figure 18: Result after Applying Controlled Anisotropic Diffussion

Figure 19: Result after Applying Controlled Anisotropic Diffusion

CONCLUSIONS

The results presented in this work regard the craquelure of old paintings, however, we find fuzzy classification is better than back propagation algorithm by visually matching the result with the original image. All algorithms presented here are tested only on gray paintings. Image processing techniques used to detect and remove crack can be employed to inspection and/or diagnosis in many scientific field. There are certain aspects of the proposed methodology that can be further improved. For example; the crack detection algorithm can be applied locally which will select a low threshold value. Edge detection and segmentation can also be performed which will confine the filling of cracks that cross edges or region borders to pixels from the corresponding region. Use of image inpainting techniques given in [15] could also improve results in that aspect.

REFERENCES

1. M. Barni, F. Bartolini, V. Cappellini(April-June 2000) Image processing for virtual restoration of artworks IEEE Multimedia vol. 7 no. 2 pp. 34-37.

2. F. Abas, K. Martinez (2002) Craquelure Analysis for Content-based Retrieval, in Proc. 14th International Conference on Digital Signal Processing vol 1 pp. 111-114.

3. L. Joyeux, O. Buisson, B. Besserer, S. Boukir(1999) Detection and removal of line scratches in motion picture films in Proc. IEEE International Conference on Computer Vision and Pattern Recognitionpp 548-553.

4. A.Kokaram, R. Morris, W. Fitzgerald, P. Rayner(November 1995) Detection of missing data in image sequences IEEE Transactions on Image Processing vol. 4 no. 11 pp. 1496-1508

5. A. Kokaram, R. Morris, W. Fitzgerald, P. Rayner(November 1995) Interpolation of missing data in image sequences IEEE Transactions on Image Processing vol. 4 no. 11 pp. 1509-1519.

6. I. Giakoumis, N. Nikolaidis, and L Pitas(Jan. 2006) Digital Image Processing Techniques for the Detection and Removal of Cracks in Digitized Paintings IEEE Transactions on Image Processing vol. 15 No.1 pp. 178- 188

7. I. Giakoumis, I. Pitas (June 1998) Digital Restoration of Painting Cracks IEEE Int. Symposium on Circuits and Systems (ISCAS' 98) California USA.

8. F. Meyer, (1979) Iterative image transforms for an automatic screening of cervical smears, Journal Histoch.Cytochem vol.27 pp. 128–135.

9. S. Rajashekharan et al(2005) Neural Network ,Fuzzy Logic and Genetic Algorithms-Synthesis and Application Prentice Hall Wiley ch.- 3 pp 34-86

10. F.Karray et al (2005) Soft Computing and Intelligent System Design-Theory, Tools and Applications Addison Wesley pp 249-293.

11. I. Nedeljkovic(2004), Image classification based on fuzzy logic- The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol 34, part XXX,

    http://www.isprs.org/proceedings/XXXV/congress/comm6/papers/685.pdf

12. D. Dubois, H. Prade (2000) Fundamentals of fuzzy sets Kluwer Academic Publishers

13. R. Fuller(1991), On product-sum of triangular fuzzy numbers Fuzzy Sets and Systems vol. 41(1) pp. 83–87.

14. L.A. Zadeh(2000) Fuzzy sets Information Control vol. 8 pp. 338–353, 1965.

15. M. Bertalmio,G. Sapiro, V. Caselles, C. Ballester(2000) Image inpainting in Proc. SIGGRAPH pp. 417–424.

16. M. Ballester, V. Bertalmio, G.Caselles, G. Sapiro, J Verdera(Aug 2001) Filling-in by joint interpolation of vector fields and gray levels IEEE Trans. Image Process vol. 10 no. 8 pp. 1200–1211.

17. S. Masnou , J. M. Morel(1998) Level lines based disocclusion in Proc. IEEE Int. Conf. Image Process vol. III pp. 259–263.

18. T. Chan, J. Shen(2001) Non-texture inpaintings by curvature-driven diffusions J. Vis. Commun. Image Represen vol. 12 no. 4 pp. 436–449.

19. S. Esedoglu, J. Shen(2002) Digital inpainting based on the Mumford- Shah-Euler image model Eur. J. Appl. Math vol. 13 pp. 353–370.

20. A. Efros, T. Leung(1999) Texture synthesis by nonparametric sampling in Proc. IEEE Int. Conf. Computer Vision pp. 1033–1038.

21. Jha, R., Garg, S., Sahoo, G.(2011) Crack Filling in Old Digital Paintings. International Journal of Graphics and Image Processing, vol. 1 issue 2 pp. 210-214.

22. Fuzzy c-mean clustering algorithm, http://home.dei.polimi.it/matteucc/Clustering/tutorial_html/cmeans.html

23. Hough P. (1962) A Method and Means for Recognizing Complex Patterns, *U.S. Patent*, No. 3, pp. 69-65.