# Identification, Analysis, and Elimination of Craquelures in Old Oil Painting Images

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## Abstract

*In this study, an integrated approach to identifying, analyzing and eliminating craquelures in high resolution oil paintings in images is proposed. It starts by identifying the craquelure networks in the oil painting via utilizing morphological top-hat operator, and follows by running a newly-devised crack line tracing algorithm to obtain properties of all the individual crack line segment such as the length and orientation. Closed regions in the craquelure netowrks is subsequently searched to extract further information about the craquelure patterns. Then, an improved recursive median filters is proposed to carry out the virtual restoration of the oil painting. The study concludes by presenting the experimental results which demonstrate good performance on oil painting craquelure analysis and virtual restoration.*

## 1. Introduction

A great portion of old oil painting are subject to the problem of craquelures in the substrate, the paint or the varnish. When exposed to a dry environment, loss of water occurs steadily, resulting in a non-uniform contraction of the varnish and eventually in cracking. The existence of craquelures greatly deteriorates the quality of the paintings.

On the other hand, it is very important to examine the craquelures in oil paintings since it not only assists in assessing the degree of damage of the oil painting, but also provides clues in judging the authenticity, use of material or environment and physical impact[1]. In recent years digitization technology has been increasingly attracting the eyes of people in the community of cultural heritage preservation, archiving, restoration and research whereas digital image processing techniques are playing important role in enhancing the capability of this community.

Previous studies[2][3] on craquelures in digital images of oil paintings mostly focused on the detection of the craquelure network and the removal of them. Unfortunately, less attention was paid to the detailed and quantitative geometric properties of the craquelure networks which are of great significance in understanding the patterns of these networks. In this study, besides a deep discussion of identification of craquelures in old oil painting images, great effort is made to the analysis of the craquelure networks in a quantitative fashion. To this end, craquelures detected from the original image is thinned firstly to reduce the complexity while preserving the essential information. Then, individual craquelure lines are traced to determine the detailed quantitative information as the length, orientation and distribution. Finally, the method for extracting shapes are also given as one step of craquelure analysis since closed regions occur under some occasions. An improved crackquelure filling technique based on recursive median filter is also proposed in order to perform an effective virtual restoration to the oil paintings.

This study is organized as follows: Section 2 gives a description of the craquelure detection method followed by a craquelue analysis procedure in Section 3 where craquelure thinning, craquelure tracing and closed region extraction are discussed respectively in three sub-sections. Improved method for virtual restoration of old oil painting with craquelures are examined in Section 4. Section 5 shows the experimental results and the conclusion is drawn in Section 6.

## 2. Craquelure detection

Identification of craquelure-like pattern, also known as ridge-valley structure extraction in some literature, has been a research topic of high concern due to its immerse existence in digital images from a variety of applications[4]. Craquelures are usually taken as having low luminance(black craquelures) or high luminance(bright craquelures), and thus can be considered as local intensity minima or maxima with rather elongated structural characteristics. The implementation of craquelure detection could be achieved by employing a very useful gray-scale morphological operator, namely top-hat transformation[5]. Top-hat filters are defined as:

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

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

$$nB = B \circ B \circ \cdots \circ B \ \ (n\,times) \tag{2}$$

The opening operator plays the role of a low-pass filter and thus the top-hat filter behaves to enhance bright(high luminance) points. This is the case where craquelures have much higher luminance than their neighborhood pixels. On the contrary, if luminance of the craquelure pixels are lower than that of its neighboring pixels, then, a bottom-hat operator defined as first performing closing operations to the original image with the structuring element for a certain number of times and then subtracting the original, should be used to identify the craquelures.

Structuring element used in top-hat or bottom-hat operators has great influence on the result of the craquelure detection. There are several factors to be considered:

(1)The type and size of the structure elements. The most commonly used structuring elements have a shape of square or disk. Determination of element size depends on the thickness of width of the craquelure present in images.

(2)The number of times for which the opening operation is performed in the top-hat operator. It is impossible to obtain all the craquelures in an image by applying top-hat or bottom-hat operator only once with a fixed structuring element to the image due to the complexity of a real painting. Careful selections and combinations of these operation and parameter should be conducted in terms of the specific oil painting with the purpose of detecting all the craquelures in the painting and avoid misidentification.

After the top-hat filtering operation, a threshold is used to separate the craquelure networks from the image and subsequently a binary image is created where the craquelure network appears as white pixels and the black pixels as the background.

## 3.Craquelure analysis

Craquelure analysis comes into play after the detection of craquelures. There are three steps involved in this study: craquelure thinning, craquelure line tracing and closed-region extraction.

### 3.1 Craquelure thinning

Characteristics of craquelures such as the length, orientation, density could be determined without knowing the widths of the craquelures, therefore, it is reasonable to perform thinning operation to the detected cracks in order to reduce the complexity of craquelure analysis. Thinning is the process of reducing an object in a digital image to the minimum size while preserving the topological and geometric properties. The output of the thinning process is a one-pixel-wide line presentation of patterns in images. With the line patterns, the amount of data needed to be processed is reduced, the analysis of shape can be more easily made, extraction of critical features such as end points, junction points and connections among components would be more amenable[6].

In this study, a thinning technique proposed by Zhang and Suen[7] is employed. The method is composed of two sub-iterations where the first iteration deletes the south-east boundary points and the north-west corner while the other iteration removes the north-west boundary points and the south-east corner points. End points and pixel connectivity are preserved and each pattern is thinned down to a 'skeleton' of unitary thickness in the output image.

### 3.2 Craquelure tracing

Top-hat or bottom-hat operator and the subsequent thinning operation creates a binary image of craquelures. To understand the properties of specific craquelure lines, it is essential to separate the cracks out of the binary image and represent them individually. In this study, a craquelure tracing algorithm is developed with the purpose of extracting individual craquelure lines from the binary image and creating a quantitative description of the cracks.

To trace the individual crack lines, the first step is to group all the craquelure pixels into six classes according to the number of neighboring pixel a pixel has within its 3*3 image window:

(1)An Endpoint has only one neighbor;

(2)A Linepoint pixel has two neighbors where the two neighbors are connected merely via the Linepoint pixel;

(3)A Node is a pixel having more than two surrounding pixels in the 3*3 image window;

(4)A Gate is the pixel which is one of the neighbors of a Node pixel;

(5)An Island is a pixel without any surrounding pixels;

(6)A Noise pixel is defined as the pixel which does not belong to any of the group above.

From the classification of craquelure pixels above, craquelure line segments can be classified into three categories accordingly in terms of the types of its two end pixels:

Type I: Endpoint to Endpoint;

Type II: Endpoint to Node;

Type III: Node to Node.

The proposed method first traces craquelure line segments of Type I and Type II. It starts with an Endpoint pixel and checks if it has a neighbor of Linepoint, Endpoint or Gate. If the neighbor is a Linepoint, then it iteratively traces the next pixel on the current craquelure line; if the neighbor is an Endpoint, then the tracing procedure terminates with the current craquelure line; and if the neighbor is a Gate, the tracing ends with its corresponding Node pixel. After this process, all the craquelure lines left fall into the group of Type III. The tracing of these line segments starts with a Node, and it proceeds in a similar way as the tracing of Type I and Type II line segment does. Lengths of the craquelure line segments are measured as the tracing process goes, and orientations of the lines are determined by the two ends.

### 3.3 Extraction of closed region

An obvious phenomenon about the craquelure lines in some image or image are is that some Type III craquelure line segments could form closed region with varying shapes and areas. From a mathematical point of view, the craquelure network in an image can be understood as a plane graph where the information is conveyed by the vertices and edges. In this paper, all the Node pixels can be viewed as the vertices and Type II and Type III craquelure lines can be reckoned as edges of the graph. Therefore, extraction of closed regions is a problem of looking for all regions of a plane graph. The problem was well-addressed by X. Y. Jiang and H. Bunke[8]. The input to the algorithm is a plane graph with straight line segments which is represented by a list of undirected edges in arbitrary order. In this study, although craquelure lines can be viewed as undirected edges of a graph with its edges expressed by two vertices. A closed region in this algorithm is represented by a sequence of wedges which are defined by two edges having a vertex in common. The algorithm can be divided into two phases where all the wedges in the graph are found in the first phase and then wedges are grouped into regions during the second phase. The algorithm is cost-effective both in time and space.

## 4. Craquelure filling

With all the cracks identified, the next step is to estimate the initial state of the painting by filling the cracks with the information of the local image regions around the cracks. A lot of methods have been studied to solve this problem, such as texture synthesis, median filters and anisotropic diffusion filters[3]. Texture synthesis algorithms construct a large texture image from a small sample image by using the characteristics of its content. Median filters assume that the filter window is large enough to take pixel values of the cracks as outliers and reject them, thus replacing the pixel values of the cracks by the median of the local observations. Anisotropic diffusion is a non-linear partial differential equation-based diffusion process and has the ability of smoothing noise successfully while respecting the region boundaries and small structures within image. In this paper, crack filling is achieved by using a directionally-trimmed median filter.

A median filter output the median of the image window as:

$$y_i = med(y_{i-v},\cdots,y_{i-1},x_i,\cdots,x_{i+v}) \tag{3}$$

For high resolution images, the thickness of the craquelure lines are usually large, even the thinnest ones are wider than one pixel. Moreover, craquelures mostly creeps along a curve of some forms, in other words, they are highly directional. Therefore, the neighboring pixels of a craquelure location are defective and it is better not to use them for the restoration. In this study, median filters are modified from three aspects to improve the filling performance:

(1) The advantage of a recursive median filter, defined as Eq.(4) is employed:

$$y_i = med(y_{i-v},\cdots,y_{i-1},x_i,\cdots,x_{i+v}) \tag{4}$$

where the 1D filter window is centered at $x_i$ with a size of $2v$+1, $y_{i-v}$,...,$y_{i-1}$ are the already computed output samples on the left side of the window center and $x_i$,...$x_{i+v}$ are the original pixel values on the right side of the window center.

(2)craquelure pixels are excluded from the filter window.

(3)Since the craquelure locations are directional, the filter window is chosen to be linear in the direction perpendicular to that of the craquelure pixel. To determine the direction of a craquelure pixel $I_{(i,j)}$, 4 angles are defined with respect to the pixel coordinates within the squared neighborhood window of size ($2N$+1)*($2N$+1):

(a) 0° : $I_{(i,j-N)}$,...,$I_{(i,j-1)}$,$I_{(i,j+1)}$,...,$I_{(i,j+N)}$

(b) 45° : $I_{(i+N,j-N)}$,...,$I_{(i+1,j-1)}$,$I_{(i-1,j+1)}$,...,$I_{(i-N,j+N)}$

(c) 90° : *(α+90)mod 180*,...,$I_{(i-1,j)}$,$I_{(i+1,j)}$,...,$I_{(i+N,j)}$

(d)135° : $I_{(i-N,j-N)}$,...,$I_{(i-1,j-1)}$,$I_{(i+1,j+1)}$,...,$I_{(i+N,j+N)}$

If the direction of the craquelure pixel is $\alpha$ degrees, then the direction of the filter window would be ($\alpha$+90) *mod 180* degrees.

Window size is a parameter of great importance since too small a size is not able to fill the cracking areas and a too large one would cause image quality deterioration to regions outside the cracks.

## 5. Experiments and results

In this study, an old oil painting collected by the Art Gallery of New South Wales in Australia is used to evaluate the performance of the proposed technique. It is one of the series of precious portraits of King *Henry VIII* of England in history. The painting was created by an unknown Anglo-Netherlandish artist in between 1535-1540 and was produced on an oak panel which has a slight convex warp. A network of craquelure covers over the whole surface and some prominent cracks creep along the wool grain. The painting was digitized at a resolution of 1200dpi and so high a resolution enables us to observe and analyze the microscopic level details of the painting content at the scale of 20 micrometers per pixel in a non-contact and non-invasive way.

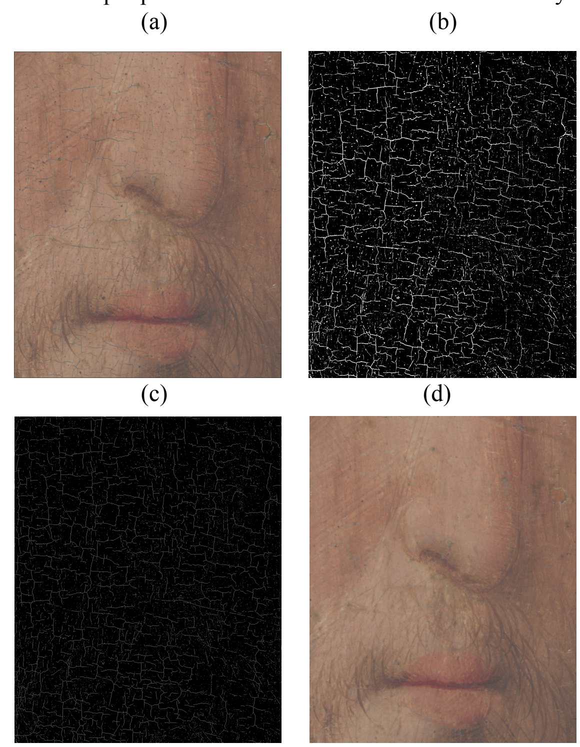



***Figure.1*** *Detection, analysis and virtual restoration of craquelure in oil paintings:(a)the original image with craquelures; (b)craquelure network detected from (a); (c)craquelure network after thinning; (d)restored image by crack filling*

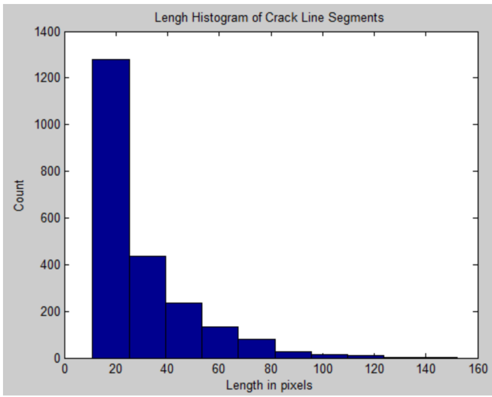
Fig.1 demonstrates the result of the experiment. Fig.1(a) shows the original image region of interest with obvious craquelures. The size of the image region is 1867pixel by 2287pixel. Fig.1(b) gives the craquelure network detected by top-hat transformation from Fig.1(a); Fig.1(c) is the one-pixel width craquelure network after performing thinning on Fig.1(b); and Fig1.(d) shows the result of virtual restoration as a result of craquelure filling.

Table.2 summarizes various types of pixels defined in this study for tracing the crack lines.

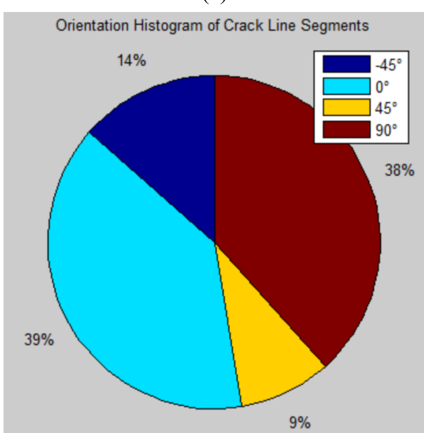
**Table.1: Pixel Classification in Craquelure Tracing**

| Type of pixel | Number |
|---|---|
| Endpoint | 22432 |
| Linepoint | 76229 |
| Node | 874 |
| Gate | 2627 |
| Island | 5454 |
| Noise | 136 |

In this study, crack line segments with length less than 10 pixels are considered as noise and thus ignored in the statistic. As a consequence, there are 2217 crack line segments in the image shown as Fig.1(a) and the maximum length among all the crack line segments is 152 pixels. Fig.2 shows the histogram of the length and orientation of all these crack line segments. The orientations are determined by the two ends of a line segment and for the purpose of clarity, only four major orientations are defined in this study as -45°, 0°, 45° and 90°.




(a)




(b)

***Figure.2*** *Length and Orientation Histogram of Crack Line Segments.*

From Fig.2(a) it is easy to know that the length of a large portion of crack line segments is between 11pixels and 20pixels and most of the crack lines have a length less than 80 pixels. From Fig.2(b) it is obvious that the percent of crack lines at horizontal direction is almost the same as the percent at vertical direction and the direction of these two occupy over 80 percent of all the crack line segments.

## 6. Conclusion

The experimental result shows that morphological top-hat and bottom-hat operators are quite powerful in enhancing the constrast between the bright foreground and the dark craquelures or the vise. A thresholding operation is sufficiently effective to separate the cracks and thus produces a binary image with 1's representing the craquelures. The binary craquelure lines are thinned and each specific line is traced and analyzed subsequently. Statistical information about the craquelures are conducted as well to give a better understanding of craquelure distributions. The restoration of the digitized painting is considered as an image reconstruction process. The proposed variant of median filter is used to fill the craquelures of various thickness and patterns and the effectiveness is verified by the experiment.

The experiment conducted in this paper merely puts the emphasis on craquelures existing in images of oil paintings. However, similar image features can be also found in images of other applications such as cracks in protective coating for polymers, fatigue cracks in MEMS, etc. Therefore, the method proposed in this paper should be able to contribute to a much wider range of applications.

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