Virtual restoration of cracks in digitized image of paintings

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Abstract. An integrated methodology for the detection and removal of cracks on digitized image is presented in this paper. Crack-like pattern detection have been a matter of high concern among researchers mostly for its useful contribution to a variety of applications. The results presented here regard the craquelure of old paintings, however, the same methodology can be used for a much wider set of application. Many images contain similar patterns: crack in protective coating for polymers and other surfaces; fatigue crack in MEMS/NEMS; crack in epoxies used for underfill and encapsulation microelectronics components; etc. In this paper the cracks are detected by thresholding the output of the morphological top-hat transform. Afterwards, the thin dark brush strokes which have been misidentified as cracks are removed using automatic procedure. Finally, crack filling using texture synthesis algorithms. The methodology has been shown to perform very well on digitized images suffering from cracks.

1. Introduction
Every day, digital image processing techniques are used in all science fields. In digital image analysis, crack-like pattern detection, better known as ridge-valley structure extraction in some literature [1-4], has been a matter of high concern among researchers, mostly for its potentially useful contribution to a variety of applications. Many old painting suffer from breaks in substrate, the paint, or varnish. These patterns are usually called craquelure and can be caused by aging, drying, and mechanical factors. Many other images contain similar patterns, such as fatigue crack in MEMS/NEMS, crack in epoxies used for underfill and encapsulation microelectronics components, etc. All these examples are current areas of research in the modeling and classification fields for which the results in this dissertation can find an application.

Image processing techniques used to detect and remove crack can be employed to inspection and/or diagnosis. Besides it can be useful for, improve her perceptiveness (legibility) of the digital images. In particularly this is true for the digital images used for didactic or multimedia applications.

An integrated methodology for the detection and removal of cracks on digitized paintings is presented in this paper. Here we focus the attention on the possibility of classification and virtual cancellation of cracks on digitized old paintings. In this way, a “virtual” restoration is performed. It 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 nondestructive tool for the planning of the actual restoration [5].

A methodology to identify and to restore the present cracks on digital images is introduced in this paper. The technique consists of the following stages:
• Detection of the cracks.
• Separation of the brush strokes, which have been misidentified as cracks.
• Implementation of the crack filling procedure.

The outline of the paper is as follows. Section 2 describes the craquelure formation. The crack-detection procedure is presented in Section 3. The method for filling the cracks is proposed in Section 4. Section 5 concludes the dissertation by outlining the contributions of this work and discussing potentials for the future.

2. Craquelure Formation
Craquelure is the pattern of cracks that develop across a painting with age [6]. It is apparent in all older pictures and influences their appearance to greater or lesser extent. Figure 1 shows an example of craquelure in a painting.

![Figure 1. Example of a painting with cracks.](image)

This network of fine cracks depends on the materials used for the painting, the painting technique of the artist, the atmospheric variations the painting has been exposed to, and, of course, manipulation and/or storage conditions [7]. Generally, the paint layer is protected by the varnish and problems occur when the originally transparent varnish becomes yellowish or greenish or simply loses its transparency during ageing. As the paint layer ages, the solvent is no longer capable of keeping the paint layer intact, thus cracks begin to form. This is the most common reason behind the forming of cracks. Other known reasons include physical tensions within the structure of the painting and external impacts such as in human handling.

The pattern of cracks is a visible record of the physical tensions within the structure of the painting. The ways in which tensions are generated and dissipated are dependent upon the choice of materials and methods of construction employed by the artist [8]. Craquelure can be a very important element in judging authenticity, use of material or environmental and physical impact because these can lead to different craquelure patterns. Although most conservation of fine artwork relies on manual inspection of deterioration signs, the ability to screen the whole collection semi-automatically is believed to be a useful contribution to preservation. It is hoped that the mass screening of craquelure patterns will help to establish a better platform for conservators to identify the cause of damage [9].

3. Detection of the Crack
Crack-like pattern detection, also known in some literature as ridge-valley structure extraction, has been a matter of high concern among researchers mostly for its useful contribution to a variety of...
applications [10-12]. In this paper, we present a method to identify and extract the craquelure pattern based on the algorithms developed by Giakoumis et al. [5], Abas [8, 13], Iyer et al. [14].

Crack usually have low luminance (bright cracks) or high luminance (light cracks) and, thus can be considered as local intensity minima (or maxima) with rather elongated structural characteristics. Therefore, a crack detection can be applied on the luminance component of an image should be able to identify such minima (or maxima).

For our reference, we will define a two-dimensional (2D) grayscale image (luminance component) having a range of $[I_{\min}, I_{\max}]$ as a functional $F: \mathbb{R}^2 \rightarrow [I_{\min}, I_{\max}]$ and a 2D structural element as a functional $B: \mathbb{R}^2 \rightarrow \mathbb{B}$ where $\mathbb{B}$ is the set of the neighborhoods of the origin.

Gray-scale morphological dilation and erosion can be visualized as working with two images namely the image being processed $F$ and the structuring element $B$. Each structuring element has a specific shape that act as a probe. Basic morphological operators with respect with respect to the structuring element $B$, a scaling factor $q$, image $F$ and a processing point $P\in \mathbb{R}^2$ can be defined as:

Gray-scale erosion and dilation are defined as [10]:

\[
\begin{align*}
\text{erosion:} & \quad \epsilon^q_B(F)(P) = \text{MIN}_{P_{i}\in P, B(P_i)}(F_i) \\
\text{dilation:} & \quad \delta^q_B(F)(P) = \text{MAX}_{P_{i}\in P, B(P_i)}(F_i) \\
\text{opening:} & \quad \gamma^q_B(F) = \epsilon^q_B(\delta^q_B(F)) \\
\text{closing:} & \quad \phi^q_B(F) = \delta^q_B(\epsilon^q_B(F))
\end{align*}
\]

Dilatation, in general, causes objects to dilate or grow in size; erosion cause objects to shrink. The amount and the way that they grow or shrink depend upon the choice of the structuring element $B$. The opening operation is somewhat like erosion in that it tends to remove some of the foreground (bright) pixels from the edges of regions of foreground pixels. However, it is less destructive than erosion in general. As with other morphological operators, the exact operation is determined by a structuring element. The effect of this operator is to preserve foreground regions that have a similar shape to the structuring element, or that can completely contain the structuring element, while eliminating all other regions of foreground pixels. However, “closing” is similar in some ways to dilation in that it tends to enlarge boundaries of foreground (bright) regions in an image (and shrink background color holes in such regions), but it is less destructive of the original boundary shape. The effect of this operator is to preserve background regions that have a similar shape to this structuring element, or that can completely contain the structuring element, while eliminating all other regions of background pixels. Cracks can be detected with the implementation of a very useful morphological filter known as the top-hat transformation developed by Meyer [15]. These details can be lines or areas with particular sizes. Top-hat operators can function as a closing or opening operator based on the features to extract from an image. Opening top-hat operators (OTH) will detect bright details in an image while closing top-hat operators (CTH) (or also sometimes known as the bottom-hat operator) are designed to detect dark details. Formulation for OTH and CTH are shown denoted by Equations (3.5) and (3.6) respectively.

\[
\begin{align*}
\text{Opening Top-Hat:} & \quad OTH^q_B(F) = F - \gamma^q_B(F) \\
\text{Closing Top-Hat:} & \quad CTH^q_B(F) = \phi^q_B(F) - F
\end{align*}
\]

The top-hat operator can be tuned for detection of specific features by modifying two important parameters [16]:

- The shape and the size of the structuring element $S$. A square-shaped or disk-shaped structuring element may be used. The size must be carefully selected according to the thickness of the crack to be detected.
- The number of times in which erosion or dilation is performed.

The transformation produces a grey-scale image with the desired features enhanced to a certain level.
Opening top-hat operators will detect bright details in an image while closing top-hat operators (or also sometimes known as the bottom-hat operator) are designed to detect dark details [8, 14]. Figure 2 shows an example of craquelure identification obtained with opening top-hat operator.

![Figure 2. Example of craquelure identification by OTH.](image)

Figure 3 shows an example of craquelure identification obtained with closing top-hat operator.

![Figure 3. Example of craquelure identification by CTH.](image)

The top-hat transformation produces a grayscale output image \( t(k; l) \). If its value is large, the corresponding pixel belongs to a crack (or crack-like element). Otherwise, this pixel location corresponds to background. Therefore, a thresholding operation is required to separate cracks from the background.

3.1. Separation of the brush strokes from the cracks

In some paintings, thin dark brush strokes exist (e.g. in hair), which have almost the same features (thickness, luminance) as cracks. Therefore, it is possible that the top-hat transform misclassifies these brush strokes as cracks. Thus, in order to avoid any undesirable alterations to original image, it is very important to separate these brush strokes from actual cracks, before the implementation of the crack filling procedure is necessary to prevent undesirable alterations to the image. Such a separation can be done on the basis of the hue and saturation values of the corresponding pixels. In the HSV color model (also called HSB - Hue, Saturation, Brightness), hue (H) is associated with the dominant wavelength in a mixture of light wavelengths and represents the color type (such as red, green). It ranges from 0 to 360 degree, with red at 0 degree, green at 120 degree, blue at 240 degree and so on. Saturation (S) refers to amount of white light mixed with a certain hue. The lower the saturation of a color, the more "grayness" is present and the more faded the color will appear. Saturation ranges are
from 0 to 100%. In this work saturation is presenting in range 0-255. Value (V) refers to the brightness of the color. Value ranges are from 0-100% [5].

By statistical analysis of typical digitized old painting images, it has been concluded that the hue of the cracks usually ranges from to 0° to 60°. On the contrary, we observed that the hue of dark brush strokes varies, as expected, in the entire gamut [0°, 360°]. Furthermore, crack saturation ranges usually from 0.3 to 0.7, while brush stroke saturation ranges from 0 to 0.4. Thus, on the basis of these differences, a great portion of the dark brush strokes, falsely detected by the top-hat transform, can be separated from the cracks. This separation can be achieved by classification using a median radial basis functions (MRBF) neural network, which is a robust version of radial basis functions (RBF) network [17]. The input vectors of the network consist of the hue and saturation values of pixels identified as cracks by the top hat transform. During the recall phase each input is assigned to one of the two available output classes (cracks and thin dark brush strokes).

4. Reconstruction of defective pixels (crack-filling methods)

After identifying cracks, the next task is to restore the image using local image information to fill (interpolate) the cracks.

The correction of defective pixels can be viewed as an image reconstruction task. Within it, the pixel being repaired, as well as much of its neighboring pixels, may be defective, i.e., their values are only loosely related to the respective original values. The values at these pixels should thus be ignored by the reconstruction algorithm.

At this stage of the solution, we assume that the defects are already detected. Two approaches to image restoration of missing regions, in literature, are image inpainting and texture synthesis.

Image inpainting attempts to fill in, a defective image region, in a natural way. The pixels in the defective image are treated as missing. The algorithm iteratively solves some partial differential equations that smoothly propagate the information to the surrounding missing region preserving the gradients apparent in the boundary.

Texture synthesis algorithms are concerned with producing a large texture image from a small sample of a texture. The resulting texture image should appear to arise from the same texture to a human observer. The texture should not appear to be duplicated or artificial. In our work we have used this approach to reconstruct defective pixels. Particularly, we have used the algorithms developed by Bergman et al. [18]

The used reconstruction algorithm uses a defect map, and is intended to overcome the shortcomings of local reconstruction, in particular in textured areas. Rather than averaging, it copies like textures from elsewhere in the image.

The reconstruction algorithms, developed in this paper, works according to the following procedure.

Let $D$ and $R$ be positive integers such that $D < R$. Typical values for $D$ and $R$, for example, are $D = 5$ and $R = 100$. At each defective pixel $i$,

1. Let $C_i$ be the context of the defective pixel $i$. The context includes all color channels of the pixels in a $D \times D$ neighborhood around pixel $i$.
2. Look at all the $D \times D$ neighborhoods, $N_j$, in an $R \times R$ region around pixel $i$. Neighborhoods with defective pixels are excluded from the search.
3. Find the neighborhood $N_j$ which is most similar to $C_i$. Specifically, for every neighborhood $N_j$, compute the sum of squared differences between the non-defective pixels of $C_i$ and the corresponding pixels of $N_j$. Let $N_j$ be the neighborhood with the lowest sum of squared differences.
4. If the sum of squared differences is below a pre-defined threshold, replace the defective pixels in $C_i$ with the corresponding pixel values from $N_j$.
5. Otherwise replace pixel $i$ with the median value of its $D \times D$ neighborhood.
Note that in step 4 several pixels are typically replaced. Replacing several pixels together has two advantages. The first advantage is speed, because the number of searches for matching neighborhoods is reduced. The second is, perhaps surprisingly, in image quality. Work in texture synthesis [11] has shown that texture is duplicated better when groups of pixels are copied rather than single pixels. In step 5, when no “good enough” context is found, the algorithm defaults to the median solution. Figure 4 shows the results obtained with the used algorithm of reconstruction.

![Figure 4](image)

**Figure 4.** Example of reconstruction results. The resulting repair is shown in (b).

To evaluate the performance of the proposed methodology, we have tested the algorithms with varying crack pattern, color, and background. In our tests the size of the images is 1024 × 1024 [pixels]. The first test is performed (see Figure 5(a)) on a particular of the fresco “The expulsion from the Eden” (Sistine Chapel – The Vatican City). Figure 5(b) shows cracks enhanced by a closing top-hat operator (CTH) operator, while figure 5(c) shows the thresholding operation. Finally, figure 5(d) shows the reconstruction of defective pixels.

![Figure 5](image)

**Figure 5.** Virtual restoration of the fresco: particular of “The expulsion from the Eden”.

A second test has been realized on the image of an old painting with bright cracks (Figure 6(a)). Figure 6(b) shows the crack enhancement obtained with opening top-hat operator (OTH), while the figure 6(c) displays the results thresholding. The result of the crack filling is shows in figure 6(d).
5. Conclusion
This paper presented a new full automatic methodology for detection and removal cracks on digital image. The results presented in this paper regard the craquelure of old paintings, however, the same algorithms can be used for a much wider set of application. Many images contain similar patterns: crack in protective coating for polymers and other surfaces; fatigue crack in MEMS/NEMS; crack in epoxies used for underfill and encapsulation microelectronics components; etc.

Image processing techniques used to detect and remove crack can be employed to inspection and/or diagnosis in many scientific field. Besides it can be useful for, improve her perceptiveness (legibility) of the digital images. In particularly this is true for the digital images used for didactic or multimedia applications.

The software works well in the individualization and reconstruction of cracks. However, future works have to study other types of defects that are present in the digital images, such as dust, scratch, spot light, etc.

6. References
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