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A METHOD FOR VIRTUAL RESTORATION OF ARTWORKS

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ABSTRACT

Cracks are a strong indicator for the condition of an image. An affordable way to detect those cracks in old paintings and use image processing techniques to detect cracks in these images. In this paper methods used to accomplish this task based on mathematical morphology and curvature evaluation to segment images with respect to a precise geometric model to define crack-like patterns.

Keywords- *cracks, crack detection, crack filling, restoration, in painting, texture synthesis.*

I. INTRODUCTION

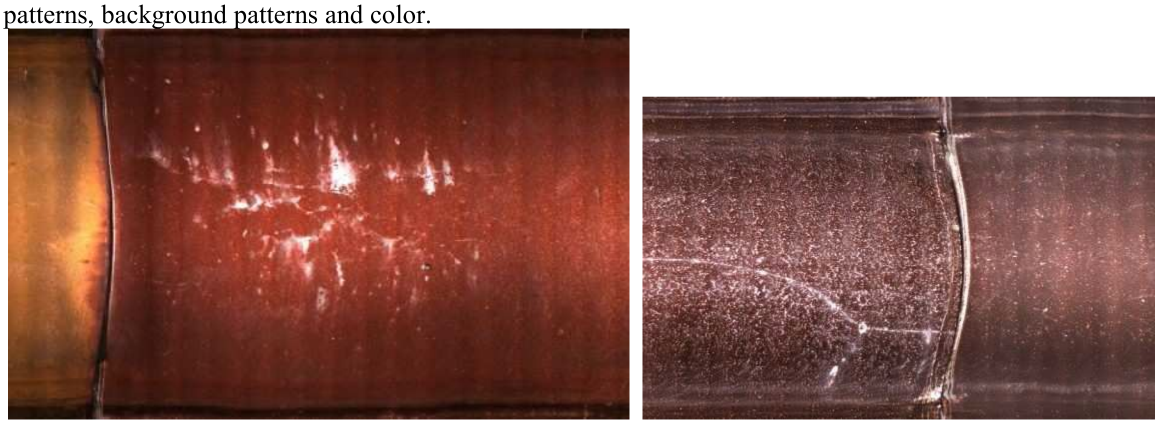
Many paintings, especially old ones, suffer from breaks in the substrate, the paint, or the varnish. These patterns are usually called cracks or craquelure and can be caused by aging, drying, and mechanical factors. Age cracks can result from non-uniform contraction in the canvas or wood-panel support 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. 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.

II. REVIEW WORKS

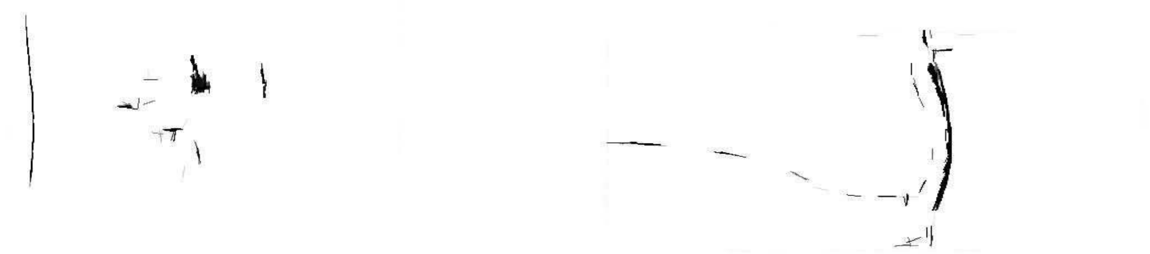
A system that is capable of tracking and interpolating cracks is presented in [1]. The user should manually select a point on each crack to be restored. A method for the detection of cracks using multi-oriented Gabor filters is presented in [2]. Crack detection and removal bears certain similarities with methods proposed for the detection and removal of scratches and other artifacts from motion picture films [3], [4], [5]. However, such methods rely on information obtained over several adjacent frames for both artifact detection and filling and thus are not directly applicable in the case of painting cracks. 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 [6], [7], [8], [9], [10] and textured image areas [11] have been developed. The former are usually based on partial differential equations (PDE) 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 [12]. The results obtained by these techniques are very good. A methodology 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 methodology is an extension of the crack removal framework presented in [13]. 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).

Crack-like patterns or similar elongated structures appear in many applications of digital image processing and not only in those related to old paintings. Examples are medical images of blood vessels, images of fingerprints and satellite imagery of rivers and roads. Some common principles can be used in the extraction of all these different crack-like patterns in order to separate them from the rest of the image. This means that we can make use of the accumulated knowledge in digital image processing and a lot of existing algorithms for the detection of crack-like patterns.
The detection of cracks in underground pipelines is an important first step to keep sewer infrastructure intact. Up to now this is done by a visual inspection by a human operator. The images evaluated are usually taken with a closed circuit television (CCTV) system or with some kind of sewer scanner evaluation technology (SSET) which usually consists of a camera mounted on a robot manually controlled by the operator. The detection of weaknesses and cracks in the pipeline is done offline after taking the images. The success of this task is influenced by the experience, the skill level

and the concentration of the operator. Therefore, it is desirable to have an automated defect detection technology for reliable and reproducible results which are independent of the executing operator. The basic task for automated condition assessment of underground pipelines is to detect cracks, holes, joints and fissures in the images taken via CCTV or SSET. It has been observed that crack-like patterns in underground pipeline images seem to have a specific Gaussian profile. The paper that we are going to discuss ([IS05]) in more detail deals with the detection of these crack-like patterns in images. The techniques used in the paper for crack detection are mathematical morphology and linear filters. Figure 1 shows an example for cracks in underground pipeline images. Note that these cracks have different crack patterns, background patterns and color.



1. **(a)Two cracks with different crack patterns, background patterns and colors.**



(b) T**he two binary crack maps which are the result of the discussed approach when fed with the cracks from 1(a).**

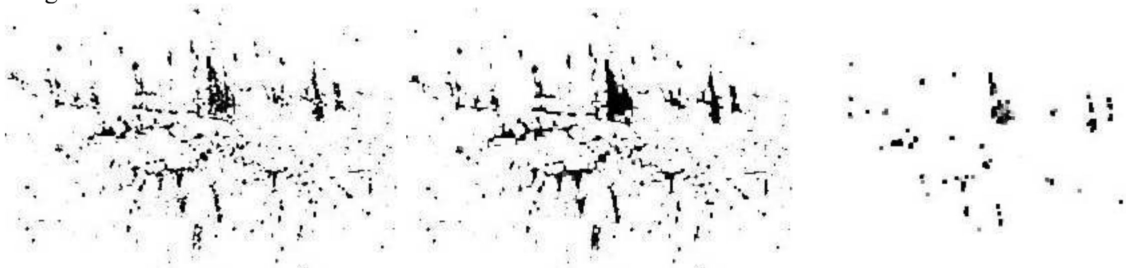
III. METHODS & RESULTS

Mathematical morphology is a tool for extracting image components with respect to geometric features of these components. Instead of just manipulating an image it allows for extracting features from the image that can be used for representation and description (with enough knowledge about the image domain this can be used to get semantic information about the image). For example in the given domain cracks can be segmented from the background and can be semantically described with a set of morphological filters. Mathematical morphology can be used to detect the boundaries of objects, their skeletons or their convex hulls. It is also often used as a pre- and post-processing technique, for example for thinning or pruning of edges. Morphological operations are based on simple expanding and shrinking operations with regard to a given structuring element. Originally mathematical morphology has been used for binary (black and white) images and has been extended later to be used with grayscale images as well. The most basic morphological operations are dilation and erosion. These operations are the basic expanding and shrinking operations mentioned before. Erosion is the dual of dilation and vice versa. An interesting thing to note is that dilation can be used to enhance the white portions of an image while the erosion will help to strengthen the black portions. While we assume that in general white is the background and black the foreground the erosion effectively expands the objects while dilation thinnens them. The dilation and erosion are shown below.

(a) Original image (b) Dilation (c) Erosion

Figure 2: Dilation and erosion

Opening and closing are combinations of two basic operations. The opening is the dual of the closing and vice versa. These operations can be used to remove small objects or to close small holes. The top-hat operation can be used to remove a certain feature from the image. We only give the definition for the case of grayscale images here since this is what we need for crack detection later.



(a) Original image (b) Opening (c) Closing

Figure 3: Opening and closing

(a) Original image (b) Erosion (c) Opening (d) Inverted result

Figure 4: Hull by top-hat: Image 4(a) contains the original image, 4(b) is the erosion of 4(a), 4(c) is the opening of 4(b) and 4(d) contains the inverted result.

The opening can be used to remove small objects from the image and the closing removes small holes. As mentioned earlier our background definition for crack images is the opposite of the usual definition in mathematical morphology so here opening and closing operations have a different effect: here the closing removes small objects while the opening removes small holes! In figure 3 you see an example for a closing and an opening. Sub figure 3(b) shows the opening of 3(a). As you can see small holes have been closed while the smaller objects around remained unchanged. Figure 3(c) shows the closing of 3(a) where small objects have been removed and holes were retained.

Top-hat can be used to eliminate particular features from an image. The general method is to apply an opening or closing to an image followed by a subtraction with the original image with the order depending on the type of the feature. This is especially useful to subtract the background from the real object. While in many situations it is problematic to get a representation of the background it is in most cases easier to get a rough estimate of the features in the image. So to get the background you remove the feature from the image. If you now subtract this background image with the feature removed from the original image you will only get the desired feature. The order of the subtraction operation depends once more on what you consider to be the background and what the foreground.

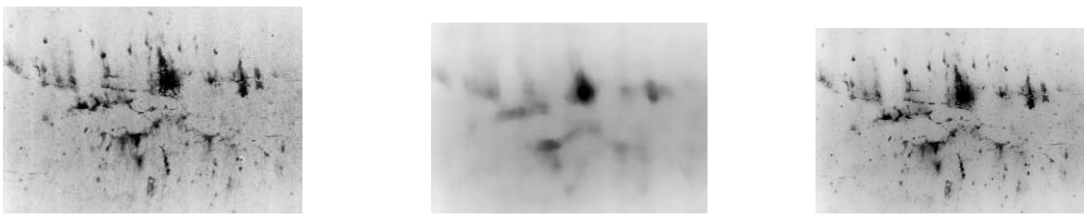
We apply the dilation or erosion with the isotropic structuring element to the first image and then use the second image to confine the result. Usually this is repeated until stability of the result has been reached and further application does not change the result anymore. This way the number of iterations does not have to be defined before running the operation. These transformations are called geodesic reconstruction. By applying the basic morphological operations with an isotropic structuring element the original image (marker) is expanded or shrunken by one pixel in each iteration. This marker image is then confined by a so-called mask image. The number of iterations then gives a measure for the distance of the pixels.

Pictures of zebras and of dalmatians have black and white pixels, and in about the same number, too. The differences between the two are based on the ordering and characteristic appearance of groups of pixels in the image, rather than the individual pixel values. We have seen before that mathematical morphology can be used to determine this information if a geometric model of the object that should be recognized is known before. Morphology segments the image by given geometrical patterns. Here we are going to introduce methods for obtaining descriptions of the appearance of a small group of pixels. We use weighted sums of pixel values and its neighbours. Depending on the weight matrix we can use it to find different image patterns.

An effective way to interpolate the cracks is to apply median or other order statistics filters in their neighbourhood. 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 neighbouring non-crack pixels. Further improvements were obtained by taking into account crack orientation, i.e., by applying the operation only in a direction perpendicular to the crack direction. For example, if the crack is horizontal, one can use only the North and the South neighbors, since the West and the East neighbors belong also to the crack. In order to find the directions of the cracks, the Hough Transform was applied.
The crack image consists of three steps:

1. Improve the contrast of the RGB pipe image by enhancing the dark (crack) pixels from the "background" image.
2. Perform crack enhancement by applying two morphological filters and a linear filter combination for edge detection.
3. Detect the cracks by applying a set of morphological filters with a rotating linear structuring element.

We now describe pre-processing of crack image. First a median filter is applied to each of the R, G and B planes of the RGB image. The window size used for the media filter is 15×15 which makes it a strong smoothing filter after which the images are quite blurry. Small features are removed by this filter from the image and this can help to reduce the noise in the image. This median image is now the background image. The next step is a comparison of the original (foreground) and the background image. This basically is a minimum filter which takes the minimum of the background and the foreground image. In general this procedure slightly extends the scratches with a blurry surrounding. This enhances the contrast only very little. The median will in general narrow the distance between the highest and the lowest intensity. The following minimum comparison will restore the darkest features from the original image while preserving the higher lower intensity bound and thus lowering the contrast. After the pre-processing small holes have been closed. Objects tend to have a softer border. It is interesting to note that during the experiments good results could be produced by using a morphological smoothing (closing followed by an opening for cracks).



(a) Original image (b) Median (c) Compared

Figure 5: Pre-processing of the image: The original image 5(a) is first treated with a median filter 15 × 15 which results in 5(b). This is then compared to the original image and the minimum is calculated in 5(c)
Before finally detecting the cracks some steps of enhancement are applied to the pre-processed image material.

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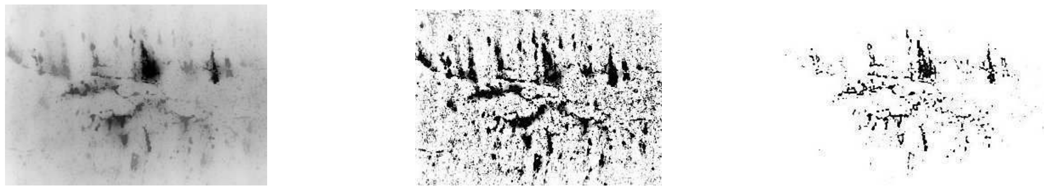
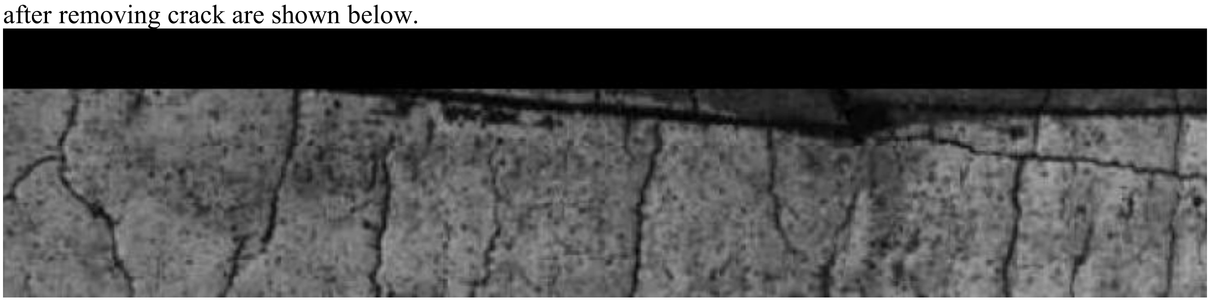
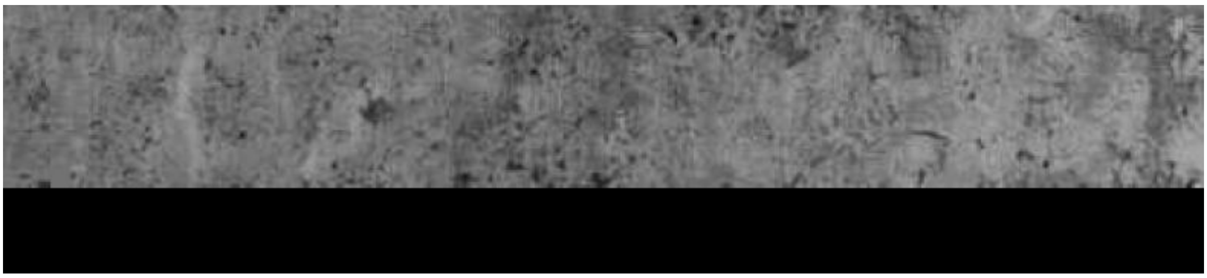


(a) Closing (b) Sum of top-hats (c) Laplacian of Gaussian
Figure 6: Enhancement of the image: 6(a) the compared image 5(c) is closed with the linear SEs, 6(b) is the result of the proposed sum of top-hats, 6(c) is the Laplacian of Gaussian of the closed image 6(a).

Training was carried out by presenting the network with hue and saturation values for pixels corresponding to cracks and crack-like brush strokes. Data from 24 digitized portable religious icons from the Byzantine era were used for this purpose. The system trained using this specific training set can be considered to be optimized for paintings of this style and its use on paintings of other style might result in somewhat suboptimal results. Results of crack image and image after removing crack are shown below.





IV. CONCLUSIONS

The trained network has been tested on 12 images from the training set and 15 images (of the same artistic style and era) that did not belong to the training set. Naturally, the performance of the cracks / brush strokes separation procedure was judged only in a subjective manner (i.e. by visual inspection of the results), as ground truth data (i.e. brush strokes-free crack images) are not available. In this paper, we have presented an integrated strategy for 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. Crack interpolation is performed by appropriately modified order statistics filters or controlled anisotropic diffusion. The methodology has been applied for the virtual restoration of images and was found very effective by restoration experts.

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