EUROGRAPHICS Workshop on Graphics and Cultural Heritage (2019)
S. Rizvic and K. Rodriguez Echavarria (Editors)

Crack Detection in Single- and Multi-Light Images of Painted Surfaces using Convolutional Neural Networks

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Abstract

Cracks represent an imminent danger for painted surfaces that needs to be alerted before degenerating into more severe aging effects, such as color loss. Automatic detection of cracks from painted surfaces' images would be therefore extremely useful for art conservators; however, classical image processing solutions are not effective to detect them, distinguish them from other lines or surface characteristics. A possible solution to improve the quality of crack detection exploits Multi-Light Image Collections (MLIC), that are often acquired in the Cultural Heritage domain thanks to the diffusion of the Reflectance Transformation Imaging (RTI) technique, allowing a low cost and rich digitization of artworks' surfaces. In this paper, we propose a pipeline for the detection of crack on egg-tempera paintings from multi-light image acquisitions and that can be used as well on single images. The method is based on single or multi-light edge detection and on a custom Convolutional Neural Network able to classify image patches around edge points as crack or non-crack, trained on RTI data. The pipeline is able to classify regions with cracks with good accuracy when applied on MLIC. Used on single images, it can give still reasonable results. The analysis of the performances for different lighting directions also reveals optimal lighting directions.

CCS Concepts

• ***Computing methodologies*** → ***Supervised learning by classification;*** *Cross-validation;* • ***Applied computing*** → *Fine arts;*

1. Introduction

Cracks are damage that can affect Cultural Heritage objects on many layers. For instance, as pointed out in [DRH15], cracks can affect not only the pictorial layer of a painting but the varnish and support layers as well. Cracks may occur due to several reasons: the drying of the paint layer (since the evaporation of organic components causes their shrinkage), external mechanical factors (vibrations, seism, impacts) and stress induced by aging or fluctuations of humidity with the passing of time [PPR*15], where the cracks burst as non-uniform contractions from the substrate layer through the superficial layer [DHN*13]. Hence, cracks represent a form of degradation both aging-dependent and aging-independent and the detection of such degradation at any stage in the lifecycle of artwork reveals meaningful clues for conservators. Moreover, in the case of paintings, the craquelure (which is the network of connected cracks) might also be associated with a certain school of painting and can be useful for recognizing the style of an artist [Buc97, Buc99]. Cracks are multi-surface phenomena, since, apart from paintings, they have been investigated in concrete surfaces as well [CD12, MP17]. In addition to this, cracks are often used for structural health monitoring of cultural heritage buildings, where commonly mechanical displacements lead to deep discontinuities in structural elements of the building such as ancient support walls [LCC*16].

In this paper we propose a novel approach for crack detection exploiting both MLIC typically acquired in the CH domain and Convolutional Neural Networks.

The idea is to exploit available multi-light image data of aged egg-tempera painting to develop a pipeline for crack detection in similarly painted surfaces based on (multi-image) edge detection and a custom CNN based classifier to select crack candidates and label them in a supervised manner.

The contribution of the work is both the demonstration of a practical pipeline that can be directly used on similar surfaces or retrained for other surface feature detection, an analysis of the improvements of the edge detection and classification approaches with MLIC data.

The paper is structured as follow. In Section 2, we review the related works. In section 3, we present the rationale of the method, the dataset used and describes all the processing steps. Finally, Section 4 presents the experimental results and section 5 concludes the paper.

2. Related Work

Automatic detection of cracks on digital images, especially in the case of painted surfaces, is particularly difficult, as the geometric and color features visually characterizing them are quite subtle and difficult to discriminate from those related to drawing lines, noise, and other aging effects.

The common pipeline for cracks classification in digital images is therefore complex, and usually involves a step of pre-processing consisting in morphological operators: white and black top-hat transformations [DRH15], opening, closing, spurring and cleaning [CD12].

After the pre-processing step, the classification of cracks proceeds either with an unsupervised, supervised or semi-supervised approach. In the unsupervised approach, usually, a combination of edge detection and further heuristics are used to label cracks [DHN*13].

With the purpose of restoring the Ghent Altarpiece, [RCP*11] propose a crack detection workflow followed by crack inpainting. For reducing the noise in the image, they initially apply anisotropic diffusion filtering and proceed with crack detection based on a multiscale morphological approach by switching the structuring element within the top-hat transform to different sizes. In addition, they explore the distinct contrast provided by the color channels of RGB and HSV color spaces either for identifying cracks with extreme brightness values or for isolating the misidentified cracks. Thus, they found that the green channel is enhancing the dark cracks, while the blue channel enhances the bright cracks. Similarly, they were able to distinguish between deceivingly crack-resembling elements (brows) and dark cracks, by applying heuristic on the saturation channel of the HSV image. As an extension of the work in [RCP*11], in [CRG*13] two other methods are proposed except the multiscale top-hat transform: the oriented elongated filters originally applied for blood vessels segmentation and the k-SVD dictionary learning with hysteresis thresholding. In order to validate these methods, a semi-automatic clustering is performed with a k-means algorithm that receives as input a feature vector composed of several joint color and shape properties of the crack pixels and their neighborhood. The latter is particularly descriptive of the bright borders that usually surrounds cracks. In [PPR*15], built on top of [RCP*11] and [CRG*13], a semi-supervised approach is adopted for crack detection in multimodal images (visible, infrared and x-ray radiography). The rationale of their improved method lies in using a Bayesian conditional tensor factorization (BCTF), by estimating for each multimodal pixel the posterior probability of pertaining to the "cracks" class.

Nonetheless, in the case of crack detection in paintings, [DHN*13] suggest that a supervised approach is highly recommended because there are elements within a painting (especially thin and dark brushstrokes on a bright background or bright brushstrokes on a dark background) that visually resemble the structure of a crack, so the unsupervised algorithm outputs increased false positives.

Among the supervised learning approaches applied in the image processing domain, the most popular now is clearly the use of Convolutional Neural Networks (CNN). CNN's have been used

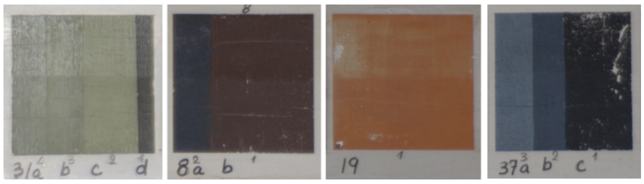

Figure 1: *Artificially aged egg-tempera samples. Images are taken from the original MLIC captures featuring 50 different light directions.*

to solve the problem of automatic crack detection in concrete surfaces [CCB17]. In [PMK*16], CNNs are combined with 3D modeling for spotting defects in tunnel infrastructures. In [OBH04], authors improve a standard genetic algorithm by training a CNN, with only a minor increase in cracks' classification accuracy for general-purpose tasks.

Another interesting option for better crack detection is the use of Multi-Light imaging, aka Photometric Stereo or Reflectance Transformation Imaging. This kind of image acquisition, consisting in taking multiple photos from a single viewpoint with changing light direction is quite popular in the Cultural Heritage domain as it can be obtained with low-cost setups and provides an effective visualization of surfaces [PDC*19]. Multi-Light image collections (MLIC) have been used for crack detection [MBW*14, K*15, SHM14, LTJ13, SCM*18], typically using few lights and specific setups.

3. The proposed approach

To develop and validate crack detection algorithms based on Multi-Light Image Collections (MLIC), we rely on a set of acquisitions obtained from a European project on the analysis of artworks' aging, Scan4Reco [DDT16]. In this project, mockups of wood pantings have been realized using different pigments and coatings and then artificially aged to characterize degradation effects. All the items have been acquired at different aging steps with a free-form RTI setup, with the acquisition and processing pipelines presented in [CPM*16]. The calibration procedures applied results in a set of 50 intensity-compensated images, with estimated light direction [GCD*18].

Our idea is to exploit the multi-light images, captured at the second aging step representing 36 painted squares with different pigments and coatings, and presenting visible cracks that can have been annotated by experts to develop and test a novel approach to automatically identify regions with cracks on egg-tempera paintings.

The proposed method is based on a processing pipeline able to automatically identify crack regions in single and multi-light images. The pipeline is based on a (multi-light) edge detection and on a Convolutional Neural Network-based labeling of image patches around edges. The processing pipeline is summarized in Figure 2.

In the following subsections, we present the rationale of the different steps.

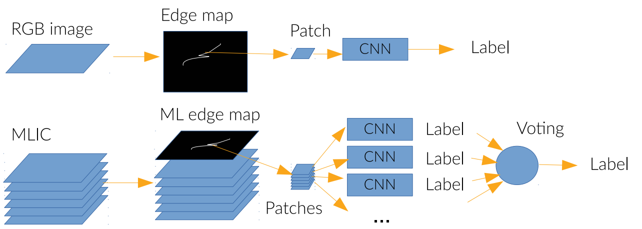

Figure 2: *The proposed crack detection pipeline: edges are extracted on single images or MLICs and single or multiple patches around each edge location are classified with the same CNN-based classifier. In the case of MLIC based crack detection, edge labels corresponding to the different patches are combined by majority voting.*

3.1. Edge detection and cracks

Figure 3 shows that the detection of the cracks identified in these images by CH experts is quite hard. The top row show two images of a MLIC of cracked egg tempera and the second edge maps extracting thresholding Sobel gradient magnitude estimation. Part of the cracks are not visible in both images and consequently in the edge maps. The complete detection of the cracks is possible looking at the whole dataset and it is reasonably captured by multi-light edge detection.

A few methods have been proposed to extract edges from MLIC/RTI data. For example Brognara et al. [BCDG13] localize edges as maximal variations of 3D normals computed from Polynomial Texture Map fitting. Pan et al [Pan16] also use PTM coefficients, but estimate edges using the idea of Di Zenzo [DZ86] for multidimensional image edge detection, e.g. estimating the Jacobian matrix and evaluating eigenvalues to determine gradient magnitude and direction.

In our work we just applied the Jacobian approach on the set of the intensity images of the MLIC collection to recover a gradient intensity, that is thresholded in a conservative way to recover a superset of the edge points that are considered as candidate crack locations. An example result of the procedure is represented in the left image of the bottom row of Figure 3.

3.1.1. Ground truth crack annotation

The annotation of the ground truth crack position has been performed as follows: experts were provided with selected images of the MLIC where cracks were maximally visible and the edge map provided by the multi-light edge detector. They had to draw a polygonal area including the edges that should be classified as a crack. The annotation resulted in binary maps corresponding to each of the 36 MLIC used.

3.2. CNN-based edge classification

To automatically label detected edges as crack or non-crack, we consider $31x31$ patch around them and train a classifier based on a Convolutional Neural Network (CNN). CNNs [GB10] are powerful learning tools demonstrating superior performance on both visual object recognition and image classification tasks [KSH12]. As the number and the direction of the input lights are not necessarily the same in different acquisitions, we designed a classifier predicting the feature class (crack/non-crack) based on a single image patch. After the training process, the classifier can then be used both to classify features extracted on a single image, or to classify features extracted on a multi-light acquisition using a voting approach: given an edge point extracted on a multi-light image collection, we apply the classifier to all the patches of the images centered in the point and assign the most frequent label.

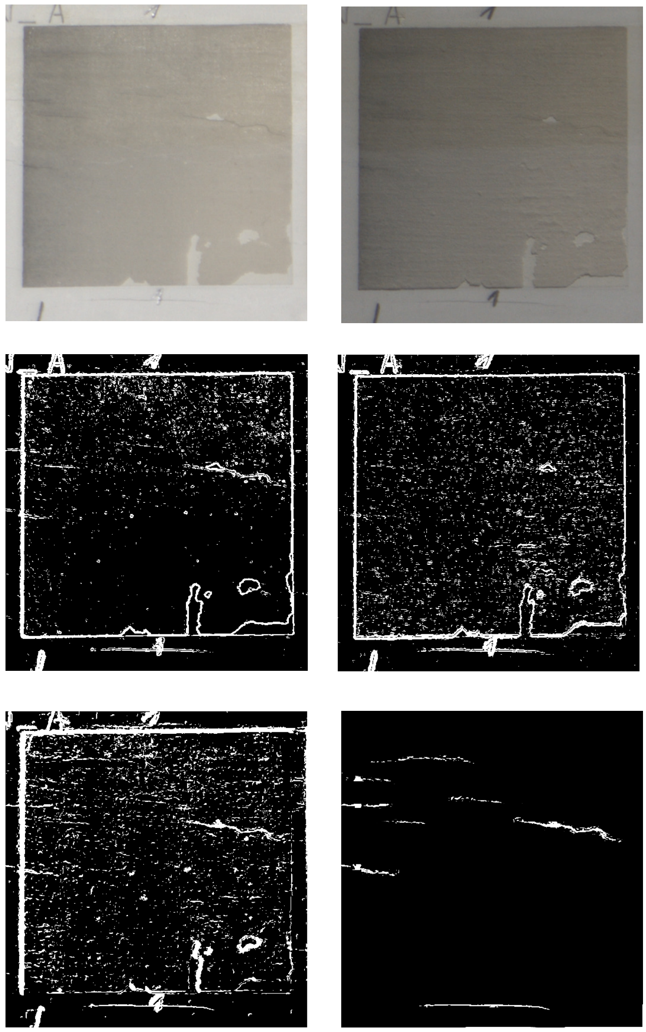

Figure 3: *Top row: two images of an egg tempera sample MLIC. The visibility of the surface features changes with respect to the light direction i.e. more visible on the high elevation and less visible on the low elevation. Middle row: the corresponding edge maps estimated on the single images. Bottom row: MLIC based edge detection (first column) and edge points annotated as cracks (second column).*

3.2.1. Patch dataset creation and labelling

To train the classifier, we considered a subset of the ground truth crack pixels (avoiding to take close pixels that would result in heavily correlated patches) and, for each MLIC, an equal number of positive(crack) and negative(noncrack) samples, Figure 4.

To evaluate the patch classification method and the full pipeline, we divided the dataset, using 30 MLICs of painted squares and the corresponding annotated patches as a training set, and the remaining 6 painted squares and the corresponding patches as a test set, both for the classifier evaluation and the full crack detection pipeline testing.

3.2.2. Network architecture

Figure 5 shows our CNN model. It contains six convolutional layers and three fully connected layers. The first two fully-connected layers have 100 neurons each and the last one contains 2 neurons. The input is a 31x31 grayscale patch, like those obtained with the procedure described in Section 3.2.1). In the first layer, the input patch is convolved with 32 filters of size 3x3, outputting 32 feature maps of size 31x31 each. In the second layer, the same operation is performed followed by 2x2 max-pooling and subsampling by a factor 2. In the third and fourth layers, the feature maps are convolved with 64 3x3 filters and followed by 2x2 max-pooling and subsampling, resulting in 64 7x7 feature maps. In the fifth and sixth layers, input features are convolved with 128 3x3 filters and followed by max-pooling. The output of the last fully connected layer is fed to a 2-way softmax which produces a distribution over the 2 class labels. All hidden layers are equipped with the Rectified Linear Unit (ReLU) activation function.

The model is trained on 54,810 training samples which contain an equal number of positive and negative samples and validated on 6,087 samples. It is trained using Adam optimization algorithm [KB14] with a batch size of 64 examples, a learning rate of 0.0003, a Gradient decay factor of 0.9 and squared gradient decay factor of 0.99. We found that this combination of parameters was important for the model to learn. Batch normalization and dropout layers [SHK*14], which can prevent overfitting, with a rate of 0.2 (20% dropout) are also used. It is trained on a GeForce RTX 2080 Ti machine with a single GPU.

In our tests, this architecture seemed better suited for the task with respect to several other CNNs tested, like other deep networks originally developed for crack detection in concrete [LLW18] or LeNet5 [LBB*98] which has an architecture with a lower number of convolutional layers and a lower number of filters. The network we adopted is a reasonable tradeoff between complexity and trainability.

3.3. Full detection pipeline

Using the trained classifier, the idea of the method is to use the proposed pipeline to automatically extract crack points as follows: if the input is a single image, a Sobel edge detection is performed using a conservative threshold, and then candidate points are classified. Finally, the map of positive points is post-processed by removing isolated points. In the case of MLIC data, the edge map is extracted with the Di Zenzo like multi-light edge detection, for all the pixels we classify all the corresponding patch and obtain the final label with majority voting. Finally, we post-process the map removing isolated points.

4. Results

In our experiments, we both evaluated the performances of the patch classification on the dataset created from the Scan4Reco painted samples and evaluated the use of the detection pipeline to automatically detect cracks.

4.1. Patch classification

To evaluate the quality of the edge classification, we evaluated the classification accuracy on the annotated dataset patches extracted from the six test squares. Table 1 shows the classification errors for the patches of the different MLIC test data obtained with single image classification and MLIC classification based on the same CNN-based classifier and majority voting. The accuracy is not very high, but the task is quite hard due to the differences in pigments and coatings used in the different squares. The use of MLIC data makes the classification more accurate as expected. If we look at the results obtained with single images, however, we see that the accuracy is not that bad, and depends on the light direction. If we consider the variation in classification accuracy versus the elevation of the light used, it is possible to see (Table 2) that using perpendicular lights the automatic classification works better (this may be counter-intuitive, as a typical way of inspecting surfaces changing light direction is the use of raking lights.

Test square	Single Image	Voting
1	65.64	72.26
2	81.33	90.08
3	85.24	90.49
4	87.11	87.85
5	75.01	75.14
6	66.65	76.87
Avg.	**76.83**	**82.12**

Table 1: *Classification accuracy for the dataset patches extracted on the 6 test painted squares. We report average accuracy obtained on single patch classification and the average accuracy on voting based MLIC-based classification*

4.2. Automatic crack detection

To automatically detect cracks from single light images it is, however, necessary also to rely on single image edge detection, that is less able to recover all the correct candidate crack points to be classified.

Figure 6 shows the cracks detected on six test squares. Results seem good despite the quite hard visibility of the cracks and the huge amount of clutter, removed during post-processing using simple morphological operator, area opening.

The results obtained on the multi-light data (middle row) appear

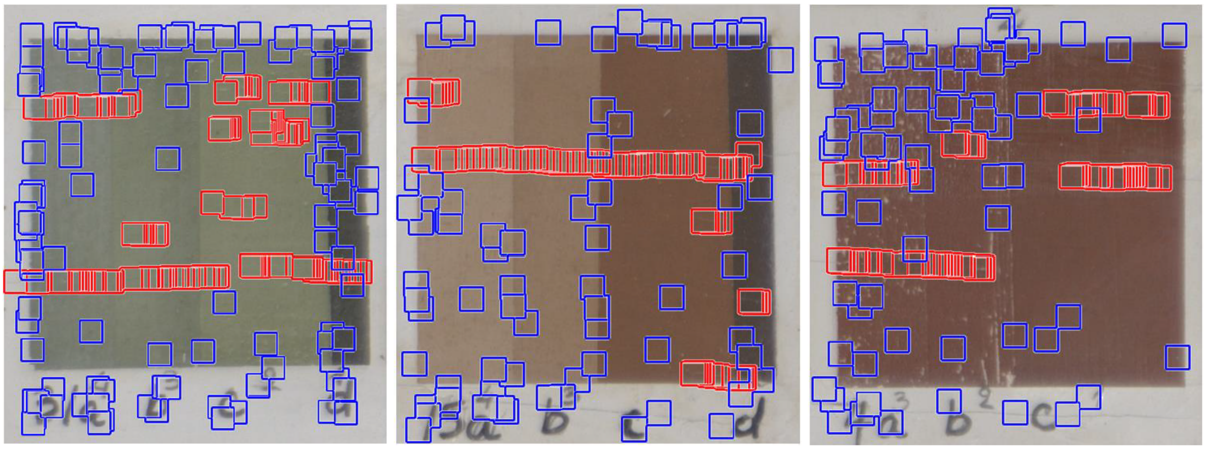

Figure 4: *Examples of positive (red) and negative (blue) patches centered in edge points and used to train (and test) the classification of candidate crack points.*

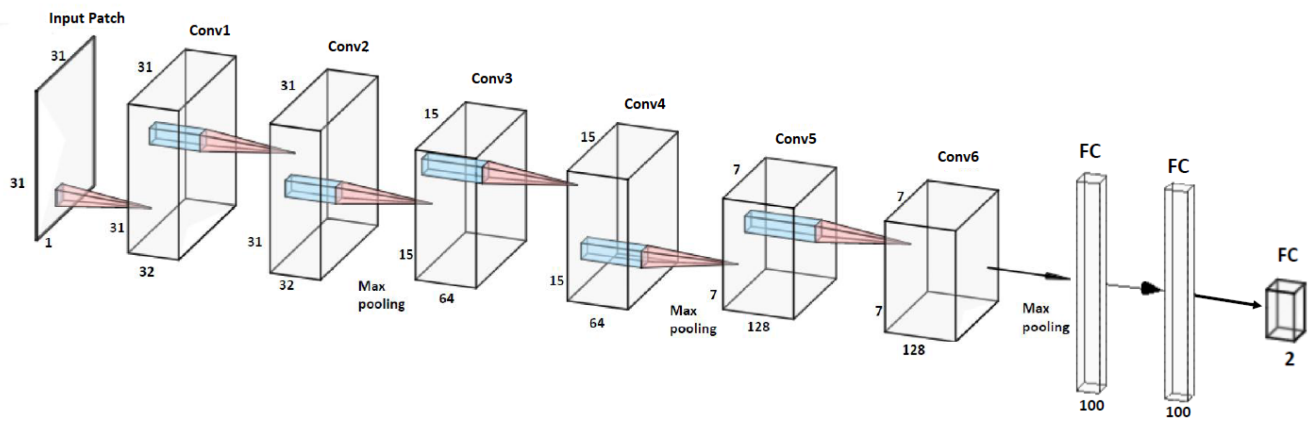

Figure 5: *An illustration of the architecture of our CNN. Conv#: layers corresponding to convolution operations and max-pooling: max pooling applied on the previous layer.*

	Accuracy (%) in elevation range		
	0-30 deg.	30-60 deg.	60-90 deg.
1	60.75	64.63	68.92
2	77.01	82.39	84.60
3	81.31	87.56	86.84
4	85.63	87.88	87.83
5	67.87	77.96	81.77
6	58.96	66.11	74.88
Avg.	**71.92**	**77.75**	**80.81**

Table 2: *Average accuracy in single patch edge classification for selected elevation ranges. Cracks are better recognized when the illumination is from higher elevation angles.*

better than those obtained on the single image example, that is, however, rather good. This is due to the better quality of both the edge detection performed with the multi-light Di Zenzo approach and the better classification accuracy obtained using CNN.

As can be seen in figure 7, in the case of prediction on single images, the quality appears better on high elevations despite the middle and low elevations are also providing satisfactory results. If we see the crack map lines superimposed over the image(cyan points), on the high elevations(right image), the cracks maps lines are continuous. This continuity shows in most of the cases that the classifier is able to classify the crack points correctly. Probably the increased illumination intensity and the subsequent inter-reflections are more effective than raking light for the enhancement of the crack details.

To demonstrate the crack detection on real paintings, we used our method on a MLIC scan of a MLIC capture of real artwork, e.g. the Icon St. Michele (17^{th} - 18^{th} century). It is an egg tempera painting on wood support and includes some regions with cracks. As can be shown in Figure 8, it is possible to see that the proposed

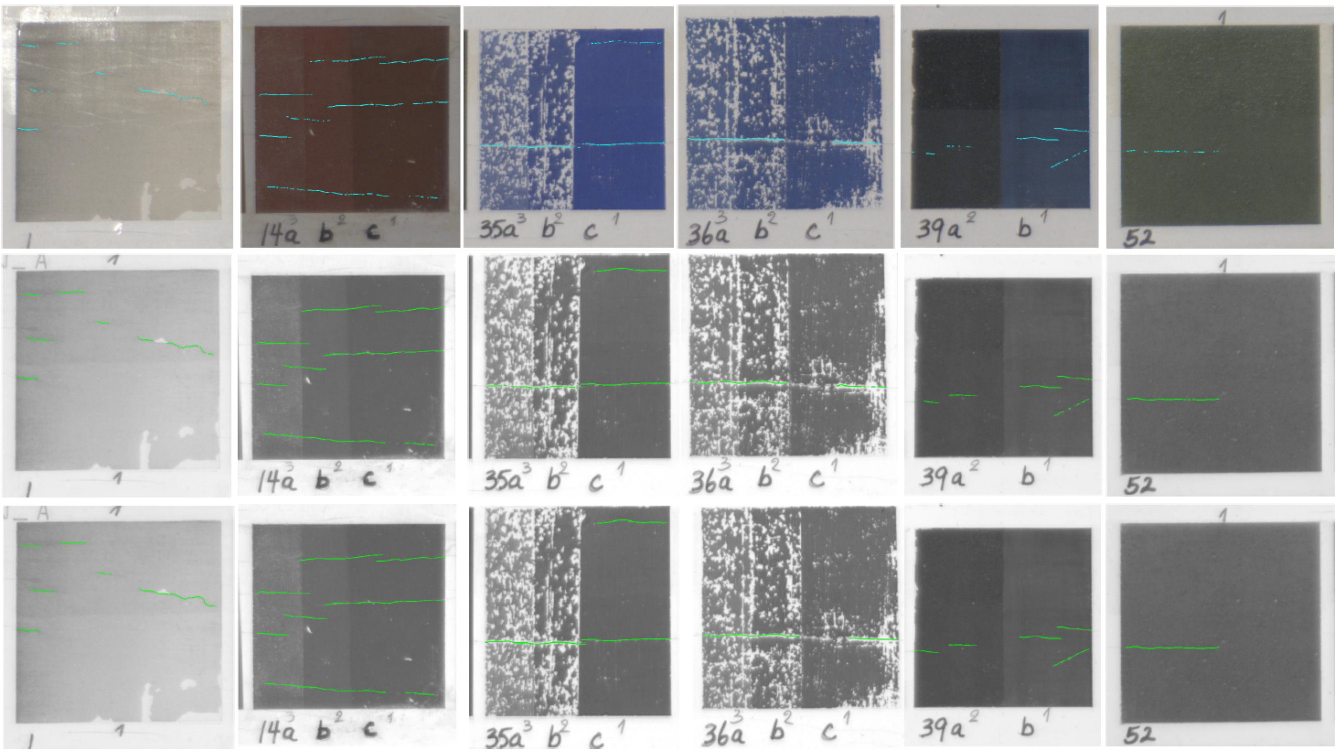

Figure 6: *Cracks detection on test painted squares. Top row: corresponding cracks detected on a single image after CNN classification superimposed on images (cyan points). Middle row: corresponding cracks detected on MLIC after CNN classification, superimposed on albedo image (green points). Third row: ground truth crack points superimposed on albedo image (green points).*

method can extract reasonably well the cracks neglecting most of the other image edges not corresponding to cracked painting.

5. Conclusion

The automatic identification of specific painting features like cracks can be extremely useful for conservators to monitor the aging of the items, highlighting possibly critical regions of the surface.

The use of machine learning tools coupled with multi-light imaging is surely a good way to address the problem of automatic crack detection, but it is not widely studied in the literature. We proposed a specifically designed pipeline that can be used to detect cracks (but also other critical features with specific training). Results are encouraging, even if they could be certainly improved and tested on more data with heterogeneous features.

One problem related to the use of machine learning for the automatic interpretation of CH data is the lack of large annotated databases specifically designed to solve practical problems for analysis and conservation applications.

We plan therefore to collect novel datasets to evaluate the proposed approach on larger collections of MLIC data.

Acknowledgments. This work was supported by the Scan4Reco project (EU H2020 grant 665091), the DSURF (PRIN 2015) project funded by the Italian Ministry of University and Research, and the VIGECLAB project funded by Sardinian Regional Authorities.

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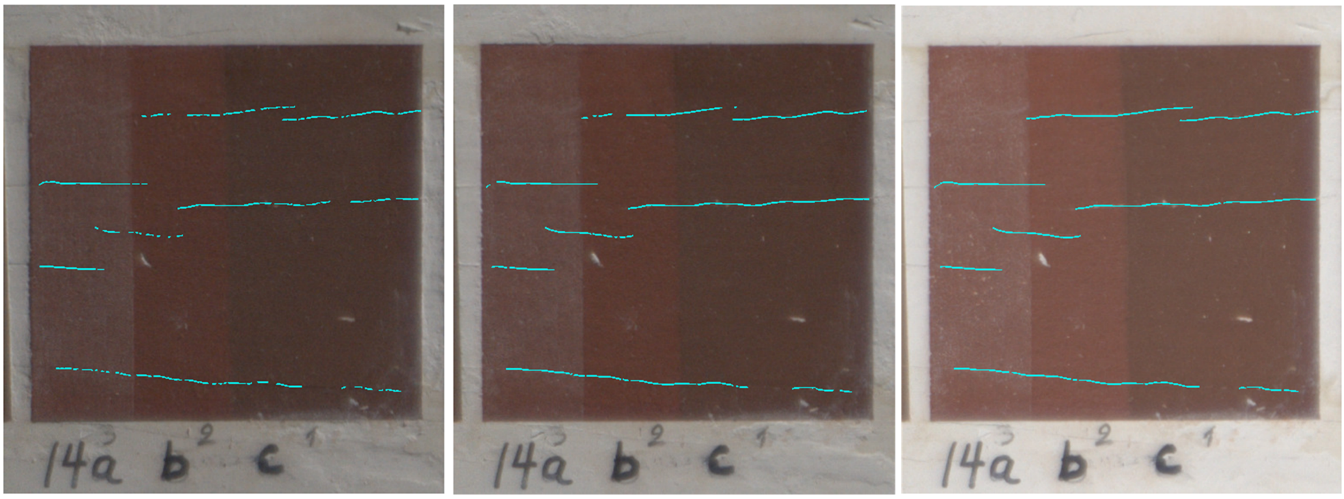

Figure 7: *Crack points detected on a single image at various elevation angles superimposed on the corresponding images. Left to right crack detected from an image captured at elevation angles of 18, 44 and 66 respectively. As we can see, on the left image the lines which represent a crack edge are disconnected. Whereas in the middle and mainly on the right one they are connected. This tells us that on the high elevation almost all the crack points are detected precisely and on the low elevation not.*

Figure 8: *Crack points detected on real images. Left: example image chosen from the Multi-light image collection, one of the few where cracks are visible. Middle: grayscale albedo. Right: corresponding cracks detected on MLIC after CNN classification, superimposed on the grayscale albedo image (green points).*

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