FOUNDATIONS OF COMPUTING AND DECISION SCIENCES
Vol. 38 (2013) No. 3

DOI: 10.2478/fcds-2013-0007 ISSN 0867-6356
e-ISSN 2300-3405

DATA MINING APPROACH TO IMAGE FEATURE EXTRACTION IN OLD PAINTING RESTORATION

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Abstract. In this paper a new approach to image segmentation was discussed. A model based on a data mining algorithm set on a pixel level of an image was introduced and implemented to solve the task of identification of craquelure and retouch traces in digital images of artworks. Both craquelure and retouch identification are important steps in art restoration process. Since the main goal is to classify and understand the cause of damage, as well as to forecast its further enlargement, a proper tool for a precise detection of the damaged area is needed. However, the complex nature of the pattern is a reason why a simple, universal detection algorithm is not always possible to be implemented. Algorithms presented in this work apply mining structures which depend of expandable set of attributes forming a feature vector, and thus offer an elastic structure for analysis. The result obtained by our method in craquelure segmentation was improved comparing to the results achieved by mathematical morphology methods, which was confirmed by a qualitative analysis.

Keywords: data mining application, image processing, k-means clustering, decision tree based image segmentation, virtual restoration of paintings

1 Introduction

As it was proved by increasing number of applications, image processing and analysis not only is a powerful tool for visualisation of a phenomena, but itself is a way of knowledge discovery in various disciplines. The analysis of artworks is only one of a broad spectrum of research areas, in which image analysis techniques are being intensively explored. An investigation based on image data is lead in medical diagnosis

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[41, 15], sonar and radar systems [37], automotive navigation, satellite and airborne multispectral image analysis [45] and others.

In art analysis the application of image processing techniques spreads from authorship verification [22, 20], through multispectral analysis of painted surfaces [36] and examination of the state of preservation [34], up to the simulation of a restoring process [7, 30]. In [39] Stork indicates brush stroke and craquelure identification, dewarping, perspective and lighting analysis as most explored and promising up to date fields of investigation. Other authors mention also research areas like recomposition of fragments, virtual restoration and lacuna filling (see [12, 6, 13] and [35] for summaries). A wide survey was performed on Vincent van Gogh works, concerning brush stroke identification [33], stylistic analysis [21], recognition of hidden layers [14] and analysis of complementary colours used by the artist [8]. Multispectral registration and enhancing of manuscript images was described in detail in [23, 24]. Stork in [38] discusses the use of optics and geometry in Renaissance paintings. Databases and data analysis tools appear in image analysis domain in the context of acquisition and storing a huge amount of data and in image retrieval systems: [31, 44] (fresco recomposition from fragments), [4] (searching for similar motives, integrated cross-collection searching). Clustering algorithms are mostly used in style and colour analysis, like in a pigment identification method given in [27].

Originally most of the tasks were resolved by means of well defined image processing operations like thresholding, filtering and mathematical morphology. In our model the image processing methods are combined with data mining techniques: clustering and classification, performed on a pixel level information represented in the image.

2 Virtual restoration, retouch and craquelure identification

Virtual restoration refers to a set of methods of non-invasive simulation of recovering an original shape of a destroyed artwork. Image processing techniques, as segmentation, feature detection, inpainting, noise removal and colour enhancement may serve the purpose of producing a digitally restored version of the work, or can be used as a guide for a physical restoration process.

Retouches (fragments of the surface covered with a new paint layer) and craquelure (a pattern of cracks in a paint layer, that appears during the process of aging) are both secondary objects of an artwork, in the meaning, they weren't intended by the artist in the original composition. Cracks appear as the canvas or wood support of the painting moves in response to changes of humidity and temperature. A detailed study of the pattern leads to a clearer understanding of the character, as well as a better recognition of the reason and seriousness of the injury [40, 46]. Thus, a precise segmentation of this objects from the background, as a preliminary step, is an important issue in a restoring process.

Multispectral analysis of an object is a good extension allowing a better estimation of the state of preservation. Images in the UV light reveal losses of the original painting and varnish layer, as well as their later filling, as darker areas, since the fluorescence of more recent interventions is weaker, related to previously put layers.

In the present work a UV photography of Rafal Hadziewicz's "The Holly Family" painting was analysed with regards to retouches and losses in painting layers (fig. 1).

Figure 1: UV fluorescence photography of Rafał Hadziewicz work "The Holly Family" with a highlighted fragment selected for further analysis

3 Segmentation by thresholding, filtering and mathematical morphology

Segmentation is a process of subdividing an image into a set of homogeneous, disjoined regions. The subdivision is complete in the meaning, that after the proces each pixel must belong to one of the separated regions [16].

The most intuitive and easy to implement group of operations that lead to the image segmentation is that based on point transformations. Global thresholding is a method of splitting pixels into subsets, defined by a single test related to the pixel value. In case there is only one threshold level, that defines the border between two resulting classes (the background and the object) the process is called binarization. The global threshold, though successfully applied in many cases, may fail due to non-uniform illumination, as the illuminated background may appear brighter, then shadowed object (fig. 2(b)). In that case a threshold may be applied parallelly in subsets of the image (an adaptive threshold).

More advanced segmentation methods are based on edge detection algorithms (Canny [11], watershed [9]), first derivative based filters (Prewitt, Sobel, Roberts) and second derivative based Laplace filter (fig. 3(i)) [16]. Regardless to the chosen method, pixels are classified as edge or non-edge according to the filter output. Then regions which are not separated by an edge are allocated to the same category. The problem of edge detection based segmentation is the discontinuity of the edges, which in worst cases implies, that all the image is flooded and annotated as one region.

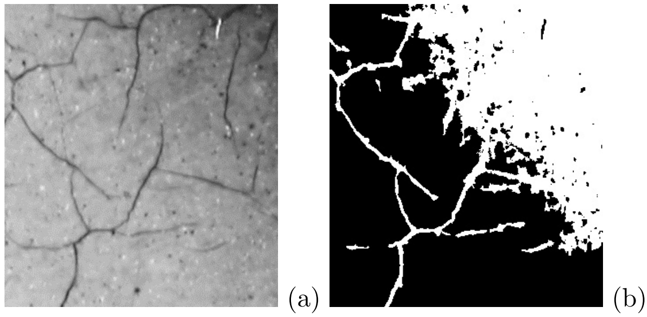


Figure 2: A grayscale fragment of a craquelure pattern in a painting (a), and the unsuccessful result of a segmentation by global threshold (b)

In opposite to the edge based segmentation methods, region growing algorithms do not require any border lines defined in advance. Instead, a starting point for each subset is needed and then an iterative process is run to expand the structure according to the gradient of pixel values [16]. Thus, the crucial factor of the method is a precise definition of the similarity condition. Too strong condition may result in omitting parts of a segmented object. On the other hand, too weekly defined parameters may cause an unexpected growth of the segmented structure, in worst case expanding to the whole image.

Mathematical morphology is a method of image analysis based on a set theory. The technique was originally developed by Matheron and Serra [32]. Most morphological operations are based on simple expanding (dilation) and shrinking (erosion) operations. Erosion and dilation can be used in a variety of combinations, thus leading to more advanced result like skeletonization, boundary detection and many pre- and post-processing techniques, especially edge thinning and pruning [16, 43, 42]. Two very important transformations are opening (dilation of the erosion of a set A by a structuring element B) and closing (erosion over dilation). Opening removes small objects from the foreground (usually taken as the dark pixels) of an image, placing them in the background, while closing removes small holes in the foreground. The primary application of morphology occurs in binary images, though it is also used on grey level images.

Grayscale erosion and dilation, considered in this domain minimal and maximal filters respectively, often are used to compute the morphological gradient of an image, denoted as a difference between dilation and erosion. The top-hat transformation, defined as a difference between the original image and its morphological opening, is useful for enhancing detail in case of shading in the background. As will be shown in following chapters, grayscale mathematical morphology play an important role in the image segmentation methods. The sample results of morphological operations may be referred to in fig. 3 (b)-(g).

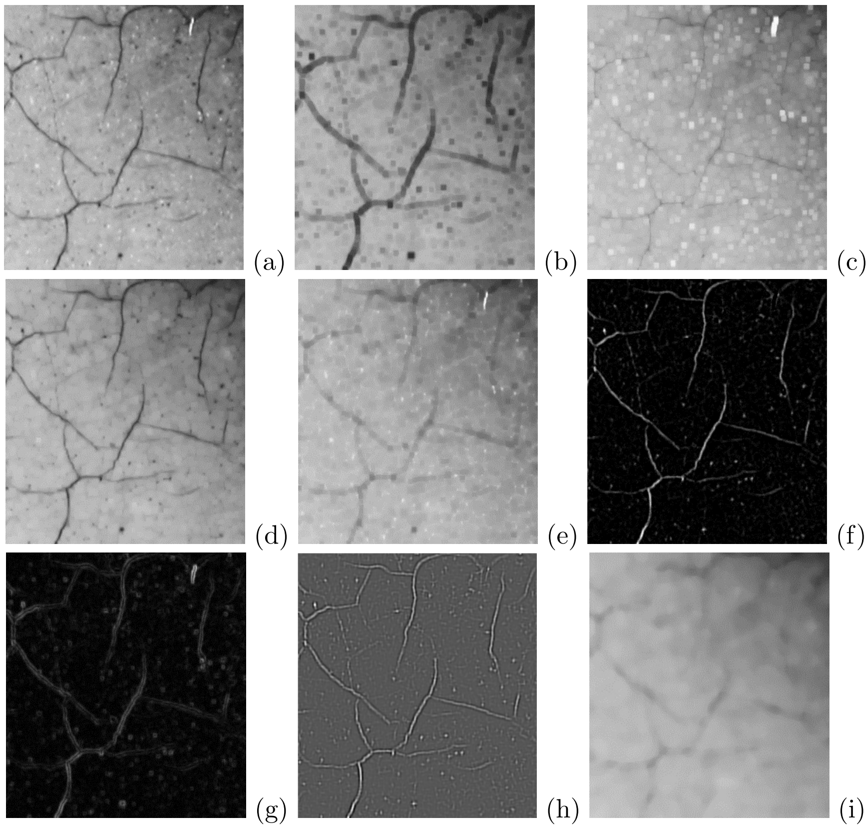


Figure 3: Original grayscale fragment of an investigated artwork (a) and the results of performed morphological erosion (b), dilation (c), opening (d), closing (e), top-hat operation (f), morphological gradient (g), Laplace filter with Gaussian smoothing (h) and median filtering (i)

4 Data mining based image segmentation

4.1 The model

Though widely used and stable in their performance morphological operations not always produce satisfactory results as a method of feature extraction. The main difficulties in processing and segmentation of artwork images is the fine structure of the details and very frequent mistakes in separating original brushstroke pattern from destroy traces appearing during the process of aging. What is clearly distinguishable for an experienced art restorer is usually a challenging task for an algorithm.

The data mining approach is based on observing the manual work done by the restorer on selected examples and then defining splitting rules for feature extraction to be applied when given a new image. It means the algorithm should learn the restorer's technique and then apply it automatically to a new task. One of the crucial steps in the data minig method is to define a training set and a suitable feature vector to find out a group of attributes and rules that best classifies pixels to the object and the background. For each pixel we define an n-argument feature vector V

$$V(x, y) = [a_1, a_2, ..., a_n]$$

, where (x, y) are the coordinates of a pixel and $a_1, ..., a_n$ are the original and transformed intensity values for the pixel.

The methodology of image segmentation proposed in this paper might be defined as *image segmentation based on pixel level data mining* (fig. 4, upper part). Assuming the segmentation would be performed on a series of images, retrieving an image according to a given pattern should be defined as *content based image retrieval* (based on pixel level data mining). A task of forecasting further degradation of the painting due to enlargement of the injury area, based on a series of segmented images and with respect to additional information, like physical measurements, would be referred to as an *image mining* problem (fig. 4, lower part).

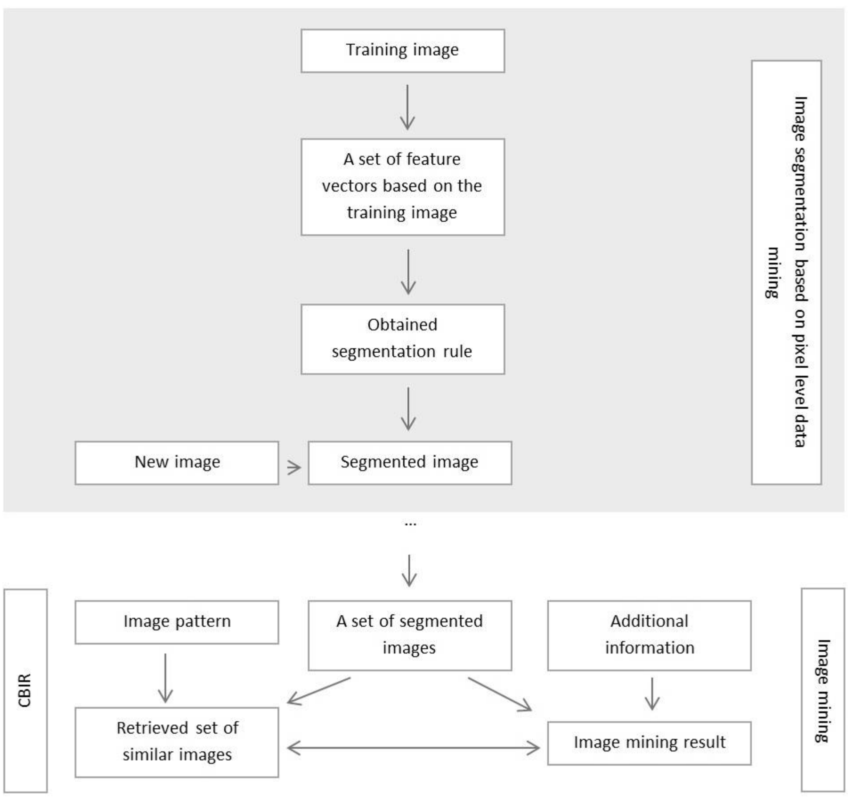


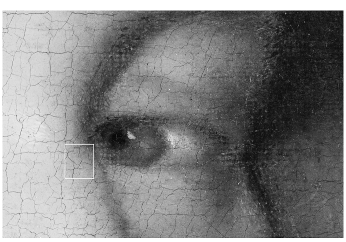
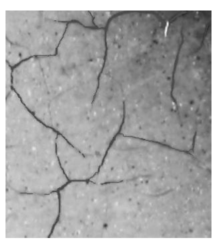
Figure 4: A model of the proposed research structure

In image retrieval task, the feature vector might consist of general information about the image, like average luminosity, entropy, dominating colour. Then, the vector is added as metadata to the image and may be stored in a database. In painting restoration however, the feature vector is annotated directly to each pixel, thus representing particular values like colour, brightness, and might be extended by adding values computed according to its neighbourhood.

4.2 Craquelure identification

The semi-automatic method of craquelure identification described by Barni et al. in [5] and then recalled by Capellini et al. in [12] is based on a manual selection of at least one starting point for each separated piece of a craquelure pattern. Then a region growing process is run constrained by a similarity condition defined for the pattern. This approach is adequate due to the character of a craquelure pattern which is formed of linear, continuous shapes, however, the manual work input is often too high. In automatic selection model cracks are identified by means of a proper filter [35] or morphological operation, like a top-hat transform [1, 2, 3]. However, with this approach not only cracks, but also brush strokes or other texture, like a canvas pattern, might be detected.

In our method the manual step is not omitted completely, since it remains the most precise way to define craquelure pixels in a training set. However, the ratio of manual work applied by the restorer to the obtained result might be acceptable, and in many cases more adequate then in the region growing method. A training area, which contains the future training set, is defined on a small fragment of an artwork, selected as a representative region of the whole image. Since, according to the specification of the selected decision tree implementation, the number of training set entries annotated to the output classes should be similar, in our case only a small subset of background pixels was chosen to the training set. See fig. 5 to observe the training set definition for an analysed fragment of 19th century Rafal Hadziewicz painting "Portrait of Antoni Wentzl". In case the painting is not consistent, that means the parts differ from one another significantly, a few training areas may be chosen concurrently, according to the colour, brightness and texture.


(a)

(b)

(c)

Figure 5: Training set definition: original training area (a), craquelure mask (b), selected background pixels (c)

The Microsoft Decision Trees algorithm was applied as the mining structure in the presented research. The algorithm uses different methods to compute the best tree and the method used depends on the task, which can be linear regression, classification, or association analysis. Here, as the investigated problem was a classification task, a method based on Bayesian approach to learning causal interaction models with a uniform Dirichlet distribution of priors was chosen (default method) [29, 19]. A mining source was defined as a table containing feature vectors of each pixel in the training set. There are two class labels: 1 and 0, for craquelure and non-craquelure pixels respectively. Attributes of the feature vectors contain values computed as a grayscale transformation of the original image, R, G, B values of the original image, morphological transformation: erosion, dilation, opening, closing, top-hat and smoothing filters (median, 1st and 3rd quartile). Figure 6 presents the root and two main levels of the inducted decision tree.

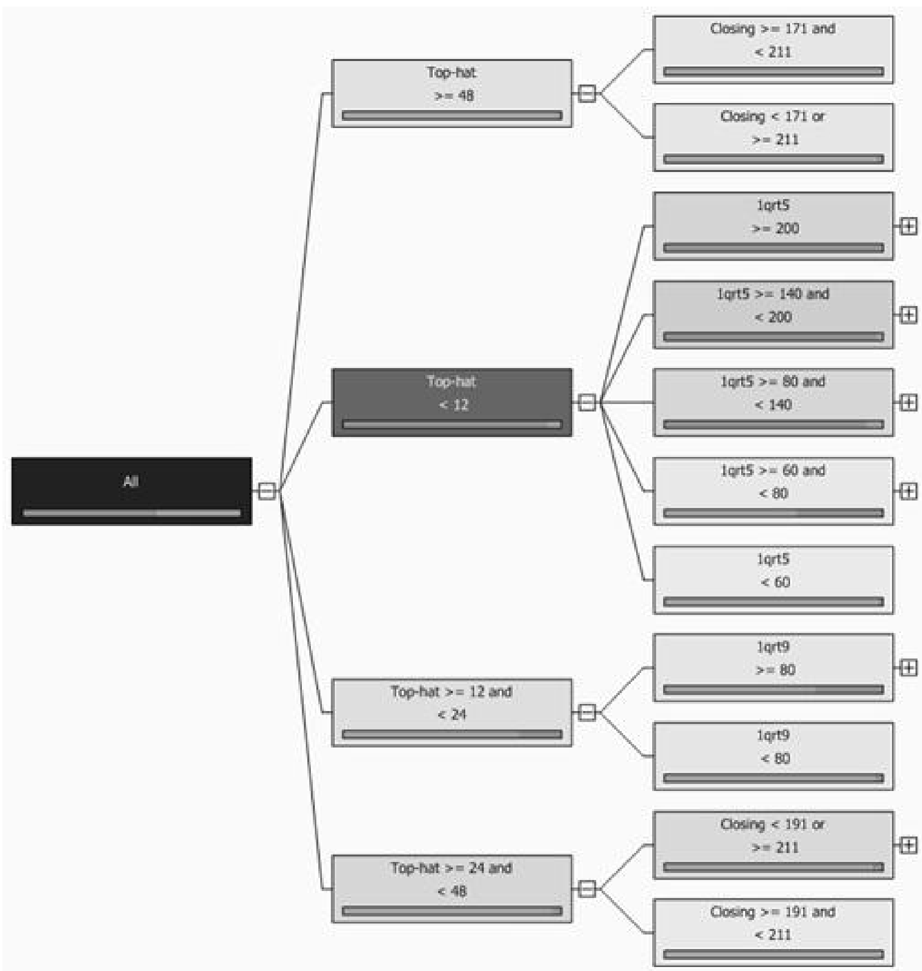


Figure 6: Decision tree diagram generated by the algorithm

As might be seen, the main splitting rule is defined upon the top-hat transformation of the image, which is in agreement with the already set statement, that frequently top-hat operation is itself assumed a segmentation criteria in similar problems. Here, we obtained some additional classification criteria. According to the shape and characteristics of the tree inducted by processing of the mining model, three decision rules might be highlighted that define a craquelure pixels. They are as follows:

1. pixels with top-hat value greater than or equal to 24

2. pixels with top-hat value between 12 and 24, and 1st quartile lower than 80 (with 5x5 mask)

3. pixels with top-hat value lower than 12 and 1st quartile lower than 60 (with 9x9 mask).

All the highlighted rules were selected with respect to the condition of at least 90 per cent confidence of the node. Figure 7 presents the mask defined manualy in the training set definition process compared with a craquelure pattern obtained by application of the decision rules. Although several missclassification may be observed in the picture, the result, compared to the simple top-hat generated pattern is more accurate. Owing to the additional classification criteria, in this case based on the 1st quartile value, less noise appear in the final result, when at the same time the satisfying part of the craquelure pattern is identified.

Figure 8 presents the result of applying the obtained decision rules to the whole investigated image (for better appearance shown in negative).

As might be expected, the proposed method gives best result in all of the area structurally similar to the training set. For more complex images additional training sets could be defined to obtain decision rules more accurate to the particular fragments.

Although not suitable for a quantitative tracking a state of preservation of an artwork (due to the manual, not repeatable step), the data mining based method of craquelure identification, at the current stage of research, should be acceptable for a rough analysis of size, shape and density of the craquelure pattern. Despite the observable missclassifications, the result is promising and in many cases the method is more suitable than traditionally applied top-hat (because of the accuracy of the classification) or region growing method (because of the amount of manual work necessary to indicate all the starting points of the pattern). Moreover, the decision tree based image segmentation may be applied in other research areas, like digital maps and satellite image analysis.

4.3 Retouch and loss segmentation

There are two situations in which manually defining an initial set of points for region growing based retouch identification is not suitable. One is when the cardinality of separated retouched fragments is too high, and the ratio of work put by the restorer

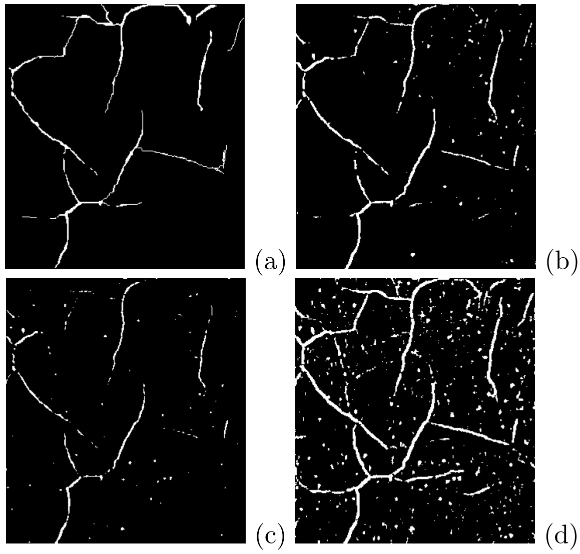


Figure 7: The mask (a) and the set of craquelure pixels generated by the obtained decision rules (b) compared with the top-hat operation result thresholded with higher (c) and lower (d) threshold level; it might be observed, that lowering the threshold level lets more craquelure pixels to be detected, but also allows more noise

to the final result is not adequate. Second is, if not only does the shape have a meaning, but also the shade of the retouch pattern. That is, when there are retouches originating from different periods and performed in different techniques, and all of them must be classified according to their characteristics.

The image clustering method presented in this work lets the restorer apply a fast algorithm and get satisfactory result automatically for the beginning, then letting him achieve final separation result by thresholding the clustered image with a chosen threshold level. The case presented in fig. 9 is based on colour and brightness analysis of a selected fragment of the UV image of a painting. Feature vectors are related to each pixel and built of its red, green and blue channel values. Methodology of the proposed solution is based on three steps: (1) reading the matrix of image pixel values, (2) generating feature vectors for a data mining model, (3) analysing the achieved splitting rules, (4) thresholding the initial image with respect to the rules. This path should be supplemented in further research by additional image processing step, based on filtering and mathematical morphology tools, so that the feature vector would be completed with another independent attributes to improve the results.

The Microsoft Clustering algorithm, which was applied during the research, provides two methods of creating clusters and assigning data points to the clusters. The first, K-means algorithm, is a hard clustering method. This means that a data point can belong to only one cluster, and that a single probability is calculated for the membership of each data point in that cluster. The second method, the Expectation Maximization (EM) method, is a soft clustering method. This means that a data

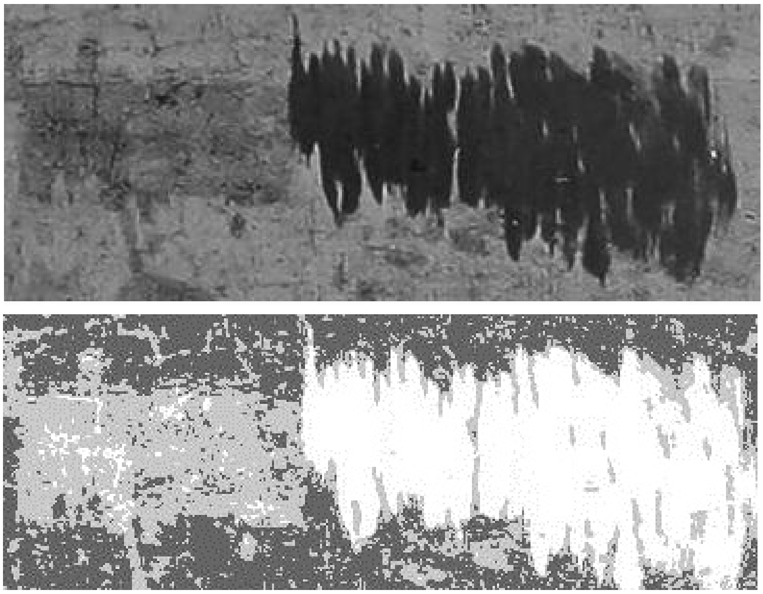
Figure 8: A final set of craquelure pixels generated by applying the obtained decision rules

point always belongs to multiple clusters, and that a probability is calculated for each combination of data point and cluster [28]. In the presented example the default EM method was used with the expected number of clusters manually set to three. This value was chosen by a subjective, visual judgement.

The number of classes given as input parameters to the mining model refers to the two retouch areas seen on the investigated fragment and the background. The number of missclassified pixels is acceptable for a rough analysis of size and shape of the retouch. Further improvement of the result might be achieved by another pre- and post-processing of the image, including denoising, smoothening, sharpening and edge detection. Furthermore, different clustering algorithms should be investigated, including hierarchical clustering model, to search for the optimal segmentation method.

5 Conclusions and further work

A new technique of craquelure and retouch identification in old paintings was presented. The novel approach is based on application of mining models to the analysis. Though none of these methods can replace the restorer's work completely, a significant help is obtained, thus letting more caution to be paid to further steps of the investigation and restoration of an artwork. The proposed method provide some improvement of the results when considering the missclassified pixels, and regarding the rate of manual preprocessing. Further work may concern better adjustment of the feature vector as well as optimization of the mining model, to obtain more accurate segmentation.



(a)

(b)

Figure 9: Original fragment of the UV image (a) and two retouch classes recognized by the clustering algorithm (b)

6 Acknowledgements

The study was based on a research material from the collection of the National Museum in Krakow, the results were presented on two Rafal Hadziewicz paintings: "The Holly Family" (sketch of the painting), 1844, oil on canvas, 41x49,5 cm and "Portrait of Antoni Wentzl", 1837-1839, oil on canvas, 75,7x61,3cm.

Authors would like to thank Mr Janusz Czop, Chief Conservator of the National Museum in Krakow, Mrs Elzbieta Zygier, Head of the Painting and Sculpture Conservation Studio in the Sukiennice and Mr Piotr Fraczek, conservator in the Laboratory of Analysis and Non-Destructive Investigation of Heritage Objects and author of the pictures for sharing materials for this research.

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Presented at the 16th East-European Conference on Advances in Databases and Information Systems, September 17-20, 2012, Poznań, Poland