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Robustness Assessment of Texture Features for the Segmentation of Ancient Documents

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***Abstract*—For the segmentation of ancient digitized document images, it has been shown that texture feature analysis is a consistent choice for meeting the need to segment a page layout under significant and various degradations. In addition, it has been proven that the texture-based approaches work effectively without hypothesis on the document structure, neither on the document model nor the typographical parameters. Thus, by investigating the use of texture as a tool for automatically segmenting images, we propose to search homogeneous and similar content regions by analyzing texture features based on a multiresolution analysis. The preliminary results show the effectiveness of the texture features extracted from the autocorrelation function, the Grey Level Co-occurrence Matrix (GLCM), and the Gabor filters. In order to assess the robustness of the proposed texture-based approaches, images under numerous degradation models are generated and two image enhancement algorithms (non-local means filtering and superpixel techniques) are evaluated by several accuracy metrics. This study shows the robustness of texture feature extraction for segmentation in the case of noise and the uselessness of a denoising step.**

***Keywords*—Ancient digitized document images, Texture, Multiresolution, Noise, Enhancement, Non-local means, Superpixel.**

I. INTRODUCTION

In the context of the DIGIDOC project (Document Image diGitisation with Interactive DescriptiOn Capability)[1], we are interested in simplifying and improving the archiving, processing, comparison, and indexing of ancient digitized books collected from the Gallica digital library[2]. Indeed, various and numerous problems may arise for automated analysis of ancient document images. Their segmentation and/or characterization has to be sophisticated due to their particularities, such as noise and degradation, and the great variability of the page layout: complicated layout, random alignment, overlapping object boundaries, and the superimposition of information layers (stamps, handwritten notes, noise, back-to-front interference, *etc.*). Due to the nature and specifications of such documents (*cf.* Figure 2(a)), existing approaches (*e.g.* XY-CUT [1]) based on *a priori* knowledge, such as the repetitiveness of document structure in a corpus, are not effective. Thus, in the context of ancient document images, various aspects of the texture features are investigated in order to assist the analysis of the images by characterizing a document image layout by a hierarchy of homogeneous regions and to conceive a model of similarities concerning the book structures.

During the two last decades, several studies [2], [3] have characterized and indexed images of ancient documents by their content by exploring textural analysis. In our previous work [3], a comparative study of three different well-known texture-based features (autocorrelation function, GLCM, and multiple channel Gabor filters), has been reported for segmentation of digitized ancient document images. The textural descriptors are extracted from only the foreground pixels of gray-level document images at four different sizes of sliding windows in order to adopt a multiscale approach. An adapted Hierarchical Ascendant Classification (HAC) [4] is performed subsequently on the normalized textural features by setting the maximum number of homogeneous and similar content regions equal to the one defined in our ground truth. Texture features are described and their effectiveness is assessed by only clustering accuracy metrics on simplified ancient document images. We have shown that the best performance for several internal and external clustering accuracies is obtained by analyzing the Gabor primitives.

In this paper, based on [3] a comparative study of robustness of texture descriptors (autocorrelation function, GLCM, and Gabor filters) for a pixel labeling system on semi-synthetic images is presented. The robustness is proven in the case of noise and degradation, and the uselessness of a denoising step is shown. This paper is organized as follows: Two preprocessing algorithms for enhancement/denoising are briefly described in Section II. The process of generating semi-synthetic simplified ancient document images under numerous degradation models is presented in Section III. Finally, Section IV details the qualitative results and the quantitative performance of the extracted textural features. Our conclusions and future work are presented in Section V.

II. DOCUMENT ENHANCEMENT

The issue of degraded document image enhancement is well studied. For instance, Likforman-Sulem *et al.* [5] compare and combine two image pre-processing techniques (non-local means filtering [6] and total variation [7]) for enhancement/denoising degraded printed documents. In this section, two pre-processing algorithms are presented which are used afterwards in the robustness study. Thus, we assess a well-used non-local means filtering technique as a pre-processing

[1]The DIGIDOC project is referenced under ANR-10-CORD-0020.

[2]http://gallica.bnf.fr

step. Then, we propose to perform the superpixel technique as enhancement/denoising step.

A. Non-local means filtering technique

The non-local means filtering technique [6] processes using a weighted average of the neighboring pixels of the analyzed pixel. The averaging weights are deduced from the similarities between a patch around the analyzed pixel and the neighboring patches located in a search window. Likforman-Sulem *et al.* [5] set the default parameters of the non-local means approach equal to 3 and 4 for patch and window sizes respectively for the enhancement of historical printed document images. By using the non-local means approach, the authors obtain an improvement of optical character recognition for a low level of degradation. As the non-local means has been proven to be efficient for historical document images, we adopt this approach here using the default parameters which are widely used in several applications. Figure 2(d) illustrates an example of enhanced image by the non-local means filtering technique and shows that the background is still noisy and there is no discernible difference to the naked eye with the original image (*cf.* Figure 2(c)).

B. Superpixel technique

The superpixel technique has recently been used in computer vision applications, such as segmentation [8], Gaussian noise estimation [9], *etc.* Many superpixel algorithms have been proposed in the literature [10] since the superpixel approach becomes a consistent alternative of using a rigid structure of pixel grid, *i.e.* it is faster, more memory efficient, and more interesting to compute image features on each superpixel center than on each image pixel. Achanta *et al.* [10] categorize the existing superpixel methods into three classes: graph-based, gradient-ascent-based and Simple Linear Iterative Clustering (SLIC). Indeed, the superpixel approach gathers pixels sharing similar characteristics (texture cues, contour, color, *etc.*) into a significant polygon-shaped region. Thus, this superpixel approach produces an over-segmented image representing a compact content map [10].

Cohen *et al.* [11] propose to separate drawings from background and noise of historical documents by using spatial and color features of superpixels. Liu *et al.* [12] propose an entropy rate superpixel segmentation algorithm based on a novel objective function. This objective function is based on entropy rate and balancing terms. The entropy rate ensures the classification of samples on homogeneous and compact clusters while the balancing term controls the size of clusters in order to obtain n superpixels with similar sizes. Firstly, the authors represent an over-segmented image by a weighted graph where each node corresponds to an image pixel, and each edge is weighted according to the similarity degree between the neighboring pixels. Then, the obtained graph is partitioned into n subgraphs maximizing the objective function using a greedy heuristic approach [13]. The authors prove that their proposed graph-based algorithm performs considerably better with a smaller number of superpixels than the state-of-the-art superpixel methods [12].

In order to obtain enhanced backgrounds of noisy ancient documents, we have developed a novel foreground-background segmentation algorithm based on entropy rate superpixel segmentation [12] and k-means clustering [14] algorithms. An entropy rate superpixel segmentation algorithm is performed in order to reduce the step complexity of a foreground-background segmentation of ancient documents. By setting the number of superpixels n equal to 5% of image pixels, the entropy rate superpixel segmentation algorithm is carried out on each grayscale image. Therefore, over-segmented images are generated. Then, a mean gray-level value is assigned to each superpixel, which is deduced by averaging over all the gray-level pixels contained in the superpixel region. Then, the k-means clustering algorithm is performed on the computed mean gray-level values of superpixels without taking into account the spatial coordinates for each image by setting the number of clusters k equal to 2, in order to segment the image into two layers: the foreground and background. Since the clustering algorithm is performed, the background superpixels are only retrieved. Thereby, the values of gray-level background superpixels and their pixels of the original image will be changed after the clustering step by assigning the value of a white pixel (*i.e.* a 255 gray-level value) in order to obtain an enhanced and non-noisy background, *i.e.* the noisy pixels will have 255 gray-level values. The values of the gray-level foreground superpixels and their pixels of the original image are remained unchangeable. Figure 2(e) illustrates an example of enhanced image by the superpixel technique with a clean background.

III. Document degradation model

Basically, the different degradations are generated synthetically for noise estimation or the assessment of image enhancement or restoration algorithms [9]. Contrarily, in this paper, several degradations are added to images with the goal of evaluating the robustness of the extracted texture features on semi-synthetic degraded images. The degradation models used in this paper simulate noise and corruption effects.

Firstly, the linear degradation model is introduced by adding a mixture uniform and Gaussian noise on images (*UGd*). By adding to each pixel a random value from a zero-mean and 35-standard deviation Gaussian distribution, semi-synthetic degraded images (*cf.* Figure 2(l)) are produced by convolving the original image (*cf.* Figure 2(c)) with the generated mixture of additive uniform and Gaussian noise.

Secondly, six local noise regions defined by different degradation models (three noise kinds and three noise levels) are also added to images in order to generate semi-synthetic degraded images. Three kinds of local degradation models have been proposed in [15]: independent spots (*Is*), overlapping spots (*Os*), and disconnected spots (*Ds*). The *Is* noise is generated by adding dark/bright spots located inside/outside characters as in Figure 1(b). The *Os* noise is generated by adding dark/bright spots connected with the character edges as in Figure 1(c). Finally, *Ds* noise is generated when bright spots totally break the connectivity of characters as shown in Figure 1(d). To generate these local degradation models, seed-points (*i.e.* centre of noise regions) are selected from the binarized original image. Then, an elliptic-shaped noise region is defined around each seed-point according to the degradation model. Three other local degradation models: low (*Ld*), medium (*Md*), and high (*Hd*), are generated by combining the first three models (*i.e.* *Is*, *Os*, and *Ds*) after fixing the number of seed-points and the size of noisy regions. The last three local degradation models are defined for three different levels of noise. For each level, the proportion of each type of local degradation model is randomly chosen. Two sets for each of the six degradation models are generated with distinct parameters for each set (*i.e.* 12 sets of semi-synthetic degraded images are generated by adding local noise to images). The degradation model characteristics are presented in Table I.

(a) Original (b) *Is* (c) *Os* (d) *Ds*

Fig. 1. Examples of three types of noise in semi-synthetic documents: (a) a non-noisy image, (b) two independent dark/bright spots, (c) two overlapping dark/bright spots, and (d) disconnection bright spot.

TABLE I. LOCAL NOISE MODELS.

	Number of seed-points	Model/Size of noisy regions
Is1	2000	Independent spots
Is2	2500	Independent spots
Os1	1500	Overlapping spots
Os2	2000	Overlapping spots
Ds1	1000	Disconnection spots
Ds2	1500	Disconnection spots
Ld1	1000	Low/5
Ld2	1000	Low/8
Md1	1500	Medium/7
Md2	1500	Medium/9,5
Hd1	2500	High/10
Hd2	2500	High/12

Finally, a mixture of *Md2*, uniform, and Gaussian (35-standard deviation) noise (*UGMd2*) is added to images in order to evaluate the robustness of the proposed approach in the case of a mixture of linear and local degradation models noise.

IV. Evaluation and Results

A. Experimental protocol

Since the task of real historical document image analysis and characterization (*c.f* Figure 2(a)) is tricky, a subset of simplified ancient document images was created, as a first stage of validation and analysis of the pros and cons of each texture feature (autocorrelation function, GLCM, and Gabor filter). By adding few occlusions in the document image (*c.f* Figure 2(a)), the real document layout is simplified and its complexity is reduced (*c.f* Figure 2(b)). From four real ancient document images, containing graphics and text with different fonts (*c.f* Figure 2(a)), a subset of 25 simplified ancient document images (*c.f* Figure 2(b)) was generated. Then, from the 25 simplified ancient document images:

- 50 enhanced images by the non-local means filtering and superpixel techniques
- 350 degraded images are generated synthetically by adding different degradation models:
  - 25 degraded images under a mixture of additive uniform and Gaussian noise
  - 300 damaged images under local degradation models
  - 25 corrupted images using a mixture of *Md2*, additive uniform and Gaussian noise.

To assess the noise robustness of the extracted texture features on synthetically enhanced and corrupted document images, each image is segmented by analyzing the three texture primitives based on a multiresolution analysis. Extracting the three texture descriptors from the enhanced images gives a total of 150 analyzed images (50 enhanced images $\times$ 3 texture approaches). Then, performing the three texture-based approaches from the degraded images gives a total of 1050 analyzed images (350 degraded images $\times$ 3 texture approaches). The segmented results are compared to a specified ground-truth. Then, several clustering accuracy (silhouette width *SW* and purity per block *PPB*) and classification metrics (precision *P*, recall *R*, and classification accuracy *CA*) are computed for performance evaluation. The higher the values are, the better the results.

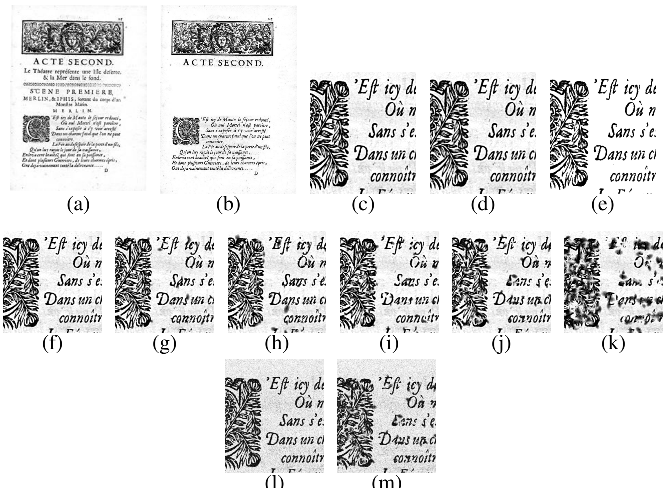

Fig. 2. Example of original, enhanced and degraded images: (a) a real ancient document image, (b) an simplified image, (c) a zoomed region of (b). Figures (d) and (e) show enhanced regions using non-local means filtering and superpixel techniques respectively. Figures (f), (g), (h), (i), (j), and (k) depict respectively degraded regions of (b) using a*Is2*, *Os2*, *Ds2*, *Ld2*, *Md2*, and *Hd2* degradation models respectively. Figures (l) and (m) show a degraded region using a mixture of additive uniform and Gaussian noise and a mixture of *Md2*, additive uniform and Gaussian noise respectively.

B. Texture features

Figures 5(a), 5(f), and 5(k) illustrate qualitatively the effectiveness of the extracted texture features in discrimination of the foreground layers of an ancient simplified document image, particularly of two classes: text and graphics. By visual inspection of the segmented images, we note that the autocorrelation and GLCM approaches (*c.f* Figures 5(a) and 5(f)) provide satisfying results particularly in distinguishing the textual regions from the graphical ones. Nevertheless, the Gabor approach (*c.f* Figure 5(k)) confuses the uppercase text and the graphical components. This confusion can be explained by the limitations of the Gabor approach to separate close distinct kinds of information, *i.e.* the vertical spacing is too small. Indeed, the Gabor indices are extracted for a specified range of frequency and direction values. Thus, the performance of the Gabor approach depends directly on the layout document. However, by analyzing the Gabor primitives, we can see that distinct kinds of graphics can be discriminated in Figure 5(k). For the same document image, each cluster (identified by a given color) represents a similar or homogeneous region.

The results of the different accuracy measures for the set of 25 simplified ancient document images are presented in Figure 3 (*cf.* blue bar). The best performance is obtained using the Gabor approach for almost all evaluation metrics with 0.33%(*SW*), 96%(*PPB*), 93%(*P*), 90%(*R*), and 93%(*CA*) without taking into consideration the topographical relationships of pixels. However, when the numerical complexity is taken into account, the Gabor approach is the highest resource-consuming (memory and computational time) approach. The time required to process a page (1965*2750 pixels) using the autocorrelation and the Gabor approaches is 2 and 6 minutes respectively while using the co-occurrence descriptors is reduced to only 14 seconds. The obtained values of the computed classification accuracy metrics are in concordance with the various internal and external clustering evaluation indices presented previously in [3].

C. Document enhancement

In the first experiments, we compare qualitatively the performance of the segmented images using the three texture-based approaches detailed in [3] (autocorrelation, GLCM, and Gabor), without adding a pre-processing step (*cf.* Figures 5(a), 5(f), and 5(k)), with the results by integrating the non-local means filtering technique (*cf.* Figures 5(b), 5(g), and 5(l)) and the superpixel technique (*cf.* Figures 5(c), 5(h), and 5(m)). By visual inspection of the segmented images, the obtained results for the three approaches by introducing a pre-processing step (the non-linear filtering and superpixel techniques) are relatively similar to those obtained without a pre-processing phase. Although, we note a slight deterioration for the Gabor approach (*cf.* Figure 5(m)) by introducing the superpixel algorithm as a pre-processing step and for the co-occurrence approach (*cf.* Figure 5(g)) by using the non-local means filtering technique. Contrarily, an improvement is obtained for the the GLCM approach (*cf.* Figure 5(h)) by using the superpixel technique. This improvement is due to the fact that the GLCM approach depends on the probability of occurrence of pixel pairs according to their gray levels and distance by considering the spatial relationship of pixels in the image. Then, by enhancing images, the foreground pixel pair properties change and the GLCM-based approach results improve.

Figure 3 (*cf.* left column) illustrates the quantitative performance obtained on original and enhanced images by non-local means filtering and superpixel techniques. We note a slight gain in the average performance of the GLCM approach equal to 1%(SW), 0%(PPB), 2%(P), 1%(R), and 3%(CA) when using the superpixel technique. Therefore, we confirm our hypothesis that this gain is due to the changes in pixel pair properties when using the superpixel technique as a pre-processing step. However, similar performance is obtained according to the most computed accuracy metrics when comparing the segmentation results on simplified and enhanced images. Therefore, we conclude that a denoising step in our approach can be neglected.

D. Document degradation models

In order to assess the noise robustness of the three texture-based approaches, degraded images are generated as detailed in section III. Firstly, each degradation model is evaluated in isolation. Secondly, we compare their respective performance. By visual inspection of the segmented degraded images (*cf.* Figures 5(d), 5(i), 5(n), 5(e), 5(j), and 5(i)), similar performance can be observed as the non-noisy image, *i.e.* the original images (*cf.* Figures 5(a), 5(f), and 5(k)). The result of the segmented degraded image represents the case when the clustering is performed by setting the number of types of content regions equal to 3 (*i.e.* the defined one on the ground-truth) +1 (*i.e.* the noisy foreground cluster has been taken into account). We can see that the texture feature can discriminate the noise cluster (*i.e.* the mixture of uniform and Gaussian noise) from the text/graphic clusters. In Figure 5(o), by degrading the image under a mixture of additive *Md2*, uniform, and Gaussian noise, the Gabor approach can to some extent distinguish different text fonts and graphics kinds. The clustering results on the noisy images (*cf.* Figure 5(o)) using the Gabor approach are better than the results obtained without noise (*cf.* Figure 5(k)). This can be justified by the fact that we specify a range of frequency and direction values specified *a priori* when extracting the Gabor indices and due to the random values of noise, the foreground pixels are correctly classified and the noise cluster is also identified.

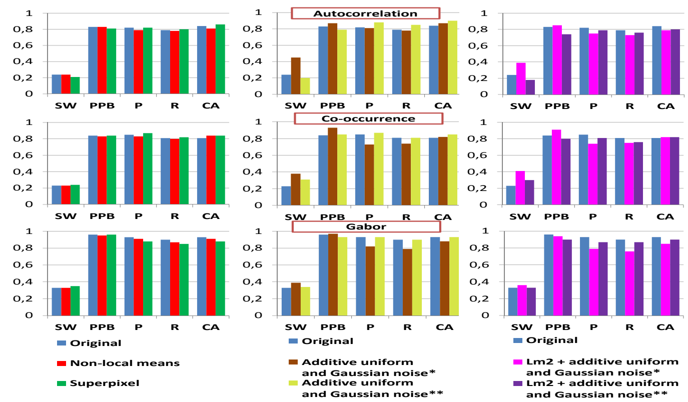

Fig. 3. Evaluation of the extracted textural features using different accuracy metrics on enhanced images (non-local means filtering and superpixel techniques) and degraded images: silhouette width (SW), purity per block (PPB), precision (P), recall (R), and classification accuracy (CA). The "*" and "**" represent the case when the clustering is performed by setting the number of types of content regions equal to the defined one on the ground-truth, and to the defined one on the ground-truth +1 (*i.e.* the noisy foreground cluster has been taken into account) respectively.

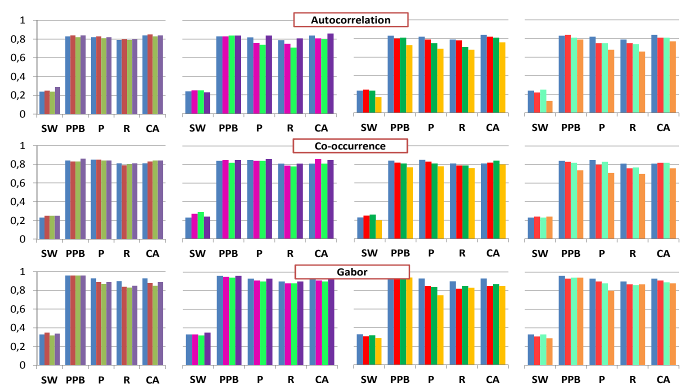

Fig. 4. Evaluation of the extracted features on degraded images under different degradation models: silhouette width (SW), purity per block (PPB), precision (P), recall (R), and classification accuracy (CA).

Figures 3 and 4 show the quantitative performance obtained on original and degraded images under different types and levels of noise. We note that by adding a mixture of uniform and Gaussian noise and with taking in consideration the noisy cluster, similar performance is obtained. By comparing the quantitative performance obtained of the autocorrelation-based approach on original and degraded images under a mixture of uniform and Gaussian noise, we observe a slight drop in performance (*SW* and *PPB* metrics) and a gain in the average performance of *P*, *R*, and *CA* accuracies. This gain is due to the fact that the noise pixels are correctly classified, *i.e.* they are labeled as their neighboring pixels and our ground-truth is not-pixel-based, *i.e.* it is defined by spatial boundaries of regions with labels. This highlights the need for a pixel-based ground-truth. A slight drop in the average performance for the three texture-based approaches can be observed when adding the six levels of degradation models: *Ld1*, *Ld2*, *Md1*, *Md2*, *Hd1*, and *Hd2*.

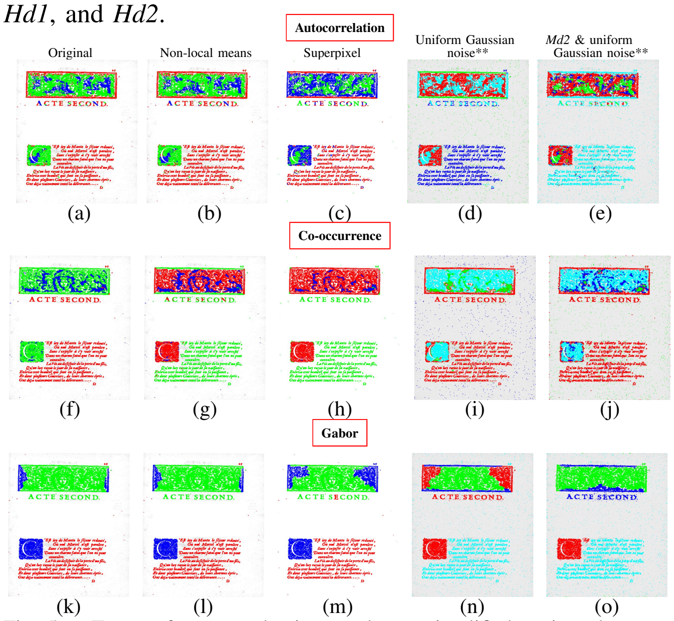

Fig. 5. Texture feature evaluation results on simplified ancient document images (*cf.* Figures 5(a), 5(f), and 5(k)), enhanced images by non-local means (*cf.* Figures 5(b), 5(g), and 5(l)) and superpixel (*cf.* Figures 5(c), 5(h), and 5(m)) techniques, and degraded images by adding a mixture of uniform and Gaussian noise (*cf.* Figures 5(d), 5(i), and 5(n)). Figures 5(e), 5(j), and 5(o) illustrate the clustering result obtained from degraded images by adding a mixture of *Md2*, uniform, and Gaussian noise). Because the process is unsupervised, the colors attributed to text or graphics may differ from one document image to another.

Some performance difference rates between the obtained results on simplified and degraded images are presented in Table II. On average, the three texture-based approach performance drops when adding noise at the high levels *Hd1* and *Hd2*. The performance of the three features decreases slightly and progressively from the low level to the high level noise. We also observe a slight gain in GLCM-based approach performance of the average when adding the *Is2* degradation model. This confirms our assumption that the noise pixels are correctly classified. By adding *UGMd2* noise, the performance difference is relatively slight for the autocorrelation, GLCM, and Gabor approaches respectively. We conclude that the texture feature extraction for segmentation is robust in the case of different kinds and levels of noise since we note only a slight performance drop.

TABLE II. PERFORMANCE DIFFERENCE RATES.

	Feature	*SW*	*PPB*	*P*	*R*	*CA*
UGd	Gabor	1	-3	0	0	0
UGd	Autocorrelation	-4	-4	6	6	6
Hd1	Gabor	-4	-2	-18	-7	-8
Hd2	Gabor	-4	-2	-13	-3	-5
Is2	Co-occurrence	1	1	1	0	4
UGMd2	Autocorrelation	-6	-9	-3	-3	-4
UGMd2	Co-occurrence	-7	-4	-4	-5	1
UGMd2	Gabor	0	-6	-6	-3	-3

V. Conclusions and Further Work

This article studies the robustness of texture-based segmentation of ancient digitized document images in the case of noise. Three different texture-based features, autocorrelation function, GLCM, and multiple channel Gabor filters are assessed. Firstly, we conducted a comparative study of two image pre-processing algorithms: the non-local means filtering and superpixel techniques. Based on the computation of several clustering and classification accuracy metrics, we conclude the uselessness of a denoising step for three different texture-based segmentation approaches. In addition, another analysis is presented by evaluating the performance of texture feature classification on degraded images under numerous degradation models. Quantitative performance has also shown that the three texture-based features are robust to different kinds and levels of noise. The first aspect of future work will be to analyze the robustness of other texture descriptors such as the wavelets. Further work also needs to be done by combining various texture descriptors in order to construct an optimal texture feature set.

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