An ink texture descriptor for nir-imaged medieval documents.

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ABSTRACT

In this work we explore the task of authenticating and dating ancient manuscripts by capturing images of pages in near-infrared (NIR) and modelling and then comparing the ink appearance of segmented text. We present a texture feature descriptor to characterize and recognize semi-transparent materials such as the inks found in manuscripts. These textural patterns are different in nature from perceptual entities such as textons, tokens, frequency or repeatability of textural elements. Our ink texture descriptor relates a set of ink features from various first and second-order statistics to semi-liquid and viscous image-based properties of inks. In particular, we propose eigen features from the joint gray-level probabilities and off-diagonal sums of co-occurrence matrices. We test the qualities of the features with a classifier trained with the ink descriptor to show how well it recognizes eight different inks of known composition. Presented with the very same task the human visual system would fail to spot the ink composition difference given the inks inter-class and intra-class distances are extremely short.

***Index Terms*—** Image Analysis, feature extraction, document image processing

1. INTRODUCTION

Researchers in the area of art conservation and historians are in need of authenticating and dating ancient or medieval manuscripts. Such authentication or dating is usually possible through the study of manuscripts and the recovery of historical information such as the year the manuscript was written or facts described in the manuscripts. Computer vision techniques can be used as alternative diagnostic methods by computing models and interpreting the visual properties of the material used such as inks. In an early approach Kokla et al. studied techniques for image-based ink classification of historical documents using statistical modelling of ink intensity using Gaussian mixtures [1]. In a later work, the same authors consider co-occurrence matrices of ink intensities as models of the joint probability of adjacent ink pixels in order to represent the spreading behaviour of writing inks and classify eight specific ink compositions [2]. Dasari and Bhagvati used an 11-dimensional colour and texture vector to derive within-class and between-class distance distributions for text written with ball and gell/roller pens [3]. Another approach is to capture the physical characteristics of liquid inks. In forensics analysis Franke et al. employed Haralick texture features of co-occurrence matrices and Support Vector Machines classifier to discriminate among three classes of ink traces, solid, viscous, and fluid [4].

Visual properties of the inks captured in NIR spectrum (700 nm to 900 nm) provide valuable cues to the type of ink found in historical documents, such as Byzantine manuscripts. A crucial assumption is that these cues are not discernable to the naked eye, because of the perceptual limitations of the human visual system. Frequency, perceptual properties and repeatability of patterns are irrelevant to characterizing ink type texture. For this reason, texture features based on Gabor filter banks, wavelets, Fourier phase, autocorrelation, edge masks, and textons are not well suited for our purpose[5, 6, 7]. Some authors use MRF in old document to separate out and remove ink-bleed from foreground ink intended for reading [8]. However, our strategy differs in that it seeks to extract precious ink spreading information even from this areas of thinner ink spread. Our aim in this work is to describe textural features that address ink profiling, and in particular a texture descriptor that works well with the small inter-class distances of various ink compositions. The work is organized as follows: Section 2 describes the preprocessing, and introduces the first-order and second-order statistical feature to encode ink fluidity in descriptors of small inter-class distance, Section 3 details the experimental tests showing the descriptor performance, and Section 4 presents conclusions and future work.

2. TEXTURAL FEATURES FOR INK COMPOSITIONS IN IR SPECTRUM

Inks imaged in NIR spectrum have the advantage that light penetrates the ink outer surface without being excessively absorbed by the materials. This optical property provides valuable information to the image-based characterisation of the spreading behaviour of the inks, and its descriptor. Ink found on the manuscript must be correctly separated from the support (*e.g.* the background paper, parchment, or papyrus) before feature extraction. Image acquisition of manuscripts

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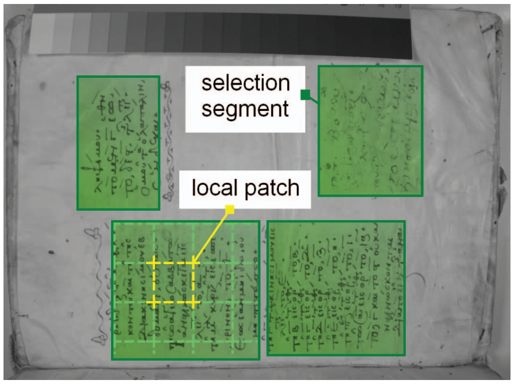

Fig. 1. Example of Byzantine manuscript image used to extract features from local patches.

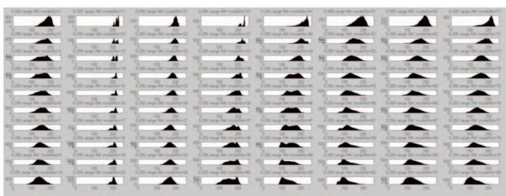

Fig. 2. Intensity histograms of various ink types and densities. Columns represent different ink composition, and rows different level of density of the ink. As can be noted in the figure, intensity distributions vary with different ink types and to some degree even with physical density.

consistently took place in controlled lab conditions at similar colour temperature (tungsten light), position and orientation of the illuminants. Light intensity in images was normalised with a simple piece-wise linear interpolation using a Kodak Gray Card, so to correct gradients introduced by illuminants. A local adaptive thresholding similar to the document binarization algorithm proposed by Sauvola et al. [9] was employed to segment the low-contrast NIR images.

2.1. First and Second-Order Gray-Level Statistics

The intensity distributions vary with different ink types and to some degree even with physical density (Figure 2).We employ first-order statistics such as moments up to the third order, smoothness, and entropy of the histogram (Table 1). The first moment statistic is notoriously variant to lighting conditions, as it shifts with illuminant direction. And yet, after imposing some constraints on the capture conditions (camera, and illuminant position, scale, and orientation), this feature is rather rich in information.

Second-order statistics (table2) allow to capture the spreading structure of textures such as ink. Typically, these are hard for the preattentive part of the visual system to perceive, as shown in a well known study by Julesz in [10]. Our

Feature	Description
$\mu = \sum_{l=0}^{L-1}(b_l)p(b_l)$	histogram mean
$\sigma^2 = \sum_{l=0}^{L-1}(b_l - \hat{b})^2 p(b_l)$	histogram second moment
$\gamma = \sum_{l=0}^{L-1}(b_l - \hat{b})^3 p(b_l)$	skewness
$\beta = \sum_{l=0}^{L-1} 1 - \frac{1}{1+\sigma^2}$	smoothness
$H_1 = -\sum_{k=1}^{L} p(b_l)\log_2 p(b_l)$	histogram entropy

Table 1. First Order Textural Features

hypothesis is that second-order statistics of NIR imaged inks help capturing patterns invisible to the naked eye. We use co-occurrence matrices of gray-level intensities (GLCM) to model these second-order statistics [11]. Contrast is a measure of the clearness of ink regions, and of the amount of local variation. A low value of contrast results from images of uniform ink. Entropy quantifies the amount of different image intensity value pairs in the GLCM. For example, minimum entropy relates to the highly peaked distributrion of a smooth and liquid ink texture, and maximum entropy to flat distribution due to the generous amount of differently shaded details in a viscous ink texture.

2.2. Weighted Sums Of Off-Diagonal Bands

The co-occurrence matrix has the property that off-diagonal entries represent pair of intensities of a specific difference. For example, the off-diagonal of rows i and columns $i+2$ are all intensities pairs with a relative difference of two gray-levels, regardless of the absolute intensity values. Groups of off-diagonals (i.e. matrix bands) are the basis for the first of the feature categories proposed in this paper.

The proposed set of four features are from the statistics of different bands of joint gray-level intensities $P_{i,j}$ is,

$$\bigcup_{b=1}^{4}\left\{\sum_{w=b}^{2^{(b-1)}}\sum_{i=1}^{L-w} P_{i,i+w}\right\} \tag{1}$$

where b represents the number of bands, dummy variable w is the width of the band in off-diagonal units, and L are the maximum intensity levels. Adding up entries of the same off-diagonal band is equivalent to create a texture statistic that is partially invariant to illumination intensity changes.

2.3. Co-occurrence Spectrum

For the second category of proposed features, we view the co-occurrence matrix as a collection of L-dimensional row vectors p_k, that is $P_d = P_d^T = [p1, ..., p_L]^T$. Then, the covariance matrix $Cov(P_d)$ of the symmetric matrix P_d provides information on the covariance of gray-level intensities with respect to all other neighbouring intensities. The eigen decomposition of the covariance matrix provides a compact

Feature	Description
$\gamma_{\Phi_c} = \sum_{i,j} \{p(i,j)(i-j)^2\}$	Contrast (Φ_c rads)
$H_{\Phi_c} = -\sum_{i,j} \{p(i,j) \log_2 p(i,j)\}$	Entropy (Φ_c rads)
$\lambda_{\Phi_c}^{(i)} \in \Lambda_{\Phi_c} \Leftarrow Cov(GLCM_{\Phi_c})$	eigenvalues
$S_{\Phi_c} = \bigcup_{B=0}^{4} \left\{ \sum_{\delta=2^B}^{2^{(B+1)-1}} \sum_{i,j} p(i,j) \right\}$	Bands Sums

Table 2. Second-Order Textural Features

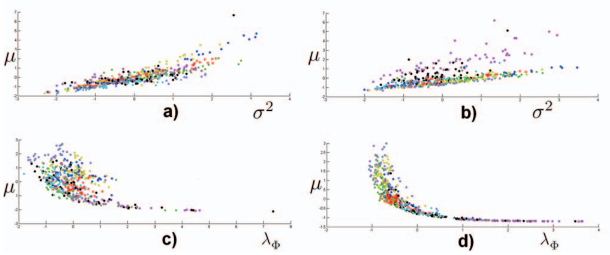

Fig. 3. Ink descriptor distribution in feature space. Figures 3a,3c show different dimensions of the feature space in the visible spectrum, where the first histogram statistic is plotted against second moment of histogram, covariance eigenvalues. Figures 3b,3d show corresponding plots in NIR spectrum.

description of the intensity spread spectrum in terms of eigenvalues, one for each gray-level.

$$Cov(P_d)\Sigma = \Sigma\Lambda \qquad (2)$$

where Σ is an orthonormal matrix of eigenvectors, and Λ is an LxL diagonal matrix of eigenvalues. The first six largest eigenvalues are then retained as features.

2.4. Ink Descriptor Space

The first and second order statistical features previously described are extracted from samples of different image local patches containing ink (see Figure 1). A sliding window breaks up the patches in smaller and slightly overlapping sub-patches, which makes the features invariant to mild image rotations and translations. The intensity histogram statistics and co-occurrence statistics are concatenated into high-dimensional ink descriptors ink_n, and normalised to zero-mean and unit standard deviation.

$$ink_n = \left\{ \mu, \sigma^2, \gamma, \beta, H_1, \gamma_0, H_0, \lambda_0^{(i)}, S_0, \gamma_{\frac{\pi}{4}}, H_{\frac{\pi}{4}}, ... \right\} \quad (3)$$

Ink descriptors form clusters that are non-linearly distributed, besides forming a manifold embedded in higher-dimensional feature space (see Figures 3c and d).

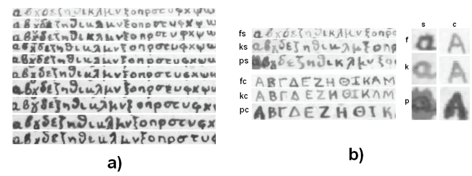

Fig. 4. Test images. a) the same ink was used to write ten layers of the Greek alphabet at ten different densities. b) test images capture the writing behaviour of an author as it is influenced by pen type and letter size. Penna type (p) often results in accidental ink spills and larger spread areas, as opposed to the terser kalamus (k) and feather (f).

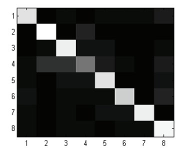

Fig. 5. Results of MLP ink classifiers trained with ink texture descriptors. Confusion matrix for test data.

3. EXPERIMENTS

3.1. Dataset of Manufactured Inks

We test the ink descriptor performance with the ink dataset used in [2]. A total of 480 writings on paper were captured with a NIR (Near Infrared) camera. Hereafter we refer to these as the model images. Each model image was generated with different ink types[1] and under various writing conditions(see figure 4b). From figure 4a the reader can observe how each of the ten layers increases in ink density from top to bottom. All images were captured with same optics, and under consistent capturing conditions. Unlike carbon-based inks, metal salts absorb less light, especially in NIR spectrum.

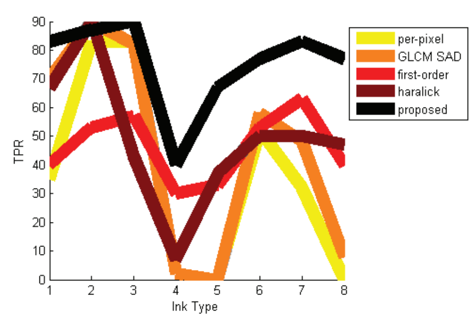

Fig. 6. Comparison of ink texture descriptors against true positive rates (TPR). Co-Occurrence SAD, First-order, and Haralick descriptors are more discriminative than Per-Pixel Intensities. The proposed descriptor combines eigen features, off-diagonal bands, first and second order statistics outperforming all others.

	1	2	3	4	5	6	7	8
recall(TPR)	.77	.87	.80	.40	.77	.70	.80	.83
TNR	.97	.97	.95	.95	.96	.98	.99	.94
precision	.79	.81	.69	.55	.72	.81	.92	.66

Table 3. Performance of ink descriptor classifier. The horizontal axis represent ink compositions, and the vertical axis the corresponding true positive rate (TPR)and true negative response (TNR) using the test classifier. 1,2,3=incomplete irrongal, 4=fourna, 5=carbon, 6=irongall, 7=metalgall, and 8=mixed inks. Notice that recall percentage for ink 4 (Carbon) is only 40% due to its high level of NIR absorbance.

3.2. Descriptor Performance

The ink descriptor is tested with a MLP neural network classifier trained on features from 240 images and tested on the remaining 240 images. Table 3 shows the recall, and precision rates for ink images recognized by the classifier trained on the ink descriptors.

Trained images are classified correctly most of the times, and test images 74% of the times on average across ink type recipes. The confusion matrix in Figure 5 shows that descriptors for carbon ink are the most difficult to discriminate, even in NIR spectrum. Figure 6 shows results of comparisons among the descriptors. Notice how all descriptors perform poorly against ink type 4 (i.e. carbon ink) due to its high light absorbance.

4. CONCLUSIONS AND FUTURE WORK

We have introduced a statistically-based texture descriptor for material of different ink compositions to cope with short interclass distance. The descriptor is enriched by first-order and second-order statistics, with a new feature based on weighed off-diagonal bands and eigen decomposition of the covariant matrix of local joint intensity co-occurrences. The resulting texture descriptor has the disadvantage of being high-dimensional, and in future work we plan to reduce redundant dimensions. The advantage of the proposed ink texture descriptor is that is suited to discriminate among ink compositions in the NIR part of electromagnetic spectrum as the comparison tests show. We also demonstrated that the second-order statistical nature of the features allows the descriptor to discriminate among ink texture of different chemical composition, a task the human visual system finds extremely challenging to accomplish given the minuscule inter-class variance, which results in different ink composition surfaces to be perceived as identical.

5. REFERENCES

[1] V. Kokla, A. Psarrou, and V. Konstantinou, "Probabilistic image-based characterization of manuscript inks," in *Proceedings of SPIE: optical methods for arts and archaeology. International Society for Optical Engineering,*, 2005, pp. 299–310, ISBN 0819458570.

[2] V. Kokla, Psarrou A., Alexopoulou A., and Konstantinou V., "Ink discrimination based on co-occurrence analysis of visible and infrared images," in *In: Proceedings of the Ninth International Conference on Document Analysis and Recognition, IEEE (ICDAR'07)*, Curitiba, Brazil, 2007.

[3] H. Dasari and C. Bhagvati, "Identification of non-black inks using hsv colour space," in *Ninth International Conference on Document Analysis and Recognition (ICDAR 2007)*, 2007, vol. 1, pp. 486–490.

[4] K. Franke, O. Bunnemeyer, and T. Sy, "Ink texture analysis for writer identification," in *Eighth International Workshop on Frontiers in Handwriting Recognition*, 2002, pp. 268– 273.

[5] J.M. Coggins and A.K. Jain, "A spatial filtering approach to texture analysis," *Pattern Recognition Letters*, vol. 3, pp. 195–203, 1985.

[6] F. Farrokhnia, *Multi-channel filtering techniques for texture segmentation and surface quality inspection*, Ph.D. thesis, Computer Science Department, Michigan State University, 1990.

[7] M. Varma and A. Zisserman., "A statistical approach to texture classification from single images.," *International Journal of Computer Vision: Special Issue on Texture Analysis and Synthesis,*, vol. 62(1–2), pp. 6–81, 2005.

[8] Huang Y., Brown M., and Xu D., "A framework for reducing ink-bleed in old documents," in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'08)*, 2008, pp. 1–7.

[9] J. Sauvola and M. Pietikainen, "Adaptive document image binarization," *Pattern Recognition 33(2)*, 2000.

[10] B. Julesz., E. N. Gilbert, L. A. Shepp, and H. L. Frisch, "Inability of humans to discriminate between visual textures that agree in second-order statistics - revisited," *Perception*, vol. 2, pp. 391–405, 1973.

[11] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. SMC-3, pp. 610–621, 1973.