Unsupervised colour image segmentation applied to printing quality assessment

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Received 26 October 2002; received in revised form 13 August 2003; accepted 8 November 2004

Abstract

We present an option for colour image segmentation applied to printing quality assessment in offset lithographic printing by measuring an average ink dot size in halftone pictures. The segmentation is accomplished in two stages through classification of image pixels. In the first stage, rough image segmentation is performed. The results of the first segmentation stage are then utilized to collect a balanced training data set for learning refined parameters of the decision rules. The developed software is successfully used in a printing shop to assess the ink dot size on paper and printing plates.

Keywords: Colour image segmentation; Fuzzy clustering; Quality inspection; Colour printing

1. Introduction

The motivation for this work comes from the printing industry. Offset lithographic printing is the most widely used commercial printing process. It is used to produce high quality pictures in the production of magazines, catalogs, newspapers, etc. The pictures are created by printing cyan (C), magenta (M), yellow (Y), and black (K) dots of varying sizes upon each other through screens having different raster angles [1]. Fig. 1 (left) illustrates an example of an enlarged view of a small area of a newspaper picture that contains dots of all the four inks.

Colour observed in a local area of such pictures depends on proportions of the four inks deployed on that local area of paper [2]. To obtain high quality prints a relatively high precision of determining the proportions of inks is required. Therefore, there is a great need to accurately measure the percentage of area covered by inks of different colours. Since four separate printing plates—one for each ink—are used to print such pictures, the expected and the actual percentages of an area covered by the different inks can be measured separately for each ink. Fig. 1 (right) presents an example of a halftone cyan area, on which the percentage of cyan needs to be accurately determined. Thus, to measure the percentage, we need to solve an image segmentation task. Though only a bi-level segmentation is required, colour information needs to be taken into consideration, since yellow ink is used and, moreover, the four inks can be printed on coloured backgrounds.

Various colour image segmentation techniques have been proposed. The most commonly used approaches include: histogram thresholding [3–5], feature/colour space clustering [6,7], edge detection approaches [8,9], neural network based approaches [10–14], region-based approaches [15,16], Markov random field [17] and mixture-of-Gaussians modelling [18], physics-based approaches [19], and combinations of above [20–23]. A recent survey of colour image segmentation methods can be found in [24].

All the existing colour image segmentation approaches are strongly application dependent and suffer from different characteristic drawbacks. For example, histogram thresholding does not consider spatial details and does not work well for images without obvious peaks and valleys. Feature space clustering based methods do not utilize spatial
information too. How to select features for obtaining satisfactory segmentation results remains unclear. Region-based approaches are quite expensive in computation time and sensitive to the examination order of regions and pixels. Edge detection approaches are quite sensitive to noise and do not work well for images containing ill-defined edges. Neural network based approaches usually require long training time and initialization may affect the results. Markov random field modelling is quite expensive in computation time.

In this work, our objectives are a relatively high segmentation speed and accuracy and low sensitivity to noise. Observe that the relatively high segmentation accuracy needs to be obtained even for the images containing very small areas of one colour and large areas of other colour. Fig. 1 (Right) provides an example of such an image.

The approach we adopted in this work consists of three phases. In the first phase, we cluster a relatively small number of randomly selected pixels represented by a 3-dimensional colour vector. Parameters of the clusters found are then used for rough image segmentation. In the second phase, the segmented image is preprocessed and based on the segmentation results a new set of pixels is selected. An equal number of pixels from the different colour clusters is included in this new data set used for a refined estimation of parameters of the clusters. In addition to the 3-dimensional colour vector, information from a local neighbourhood is also used to represent pixels in this new data set. In the third phase, the Minimum Fuzzy Cluster Volume clustering algorithm is applied to the data set. Then, by assigning image pixels to the clusters found the final image segmentation is obtained.

The remainder of the paper is organized as follows. In Section 2 we briefly describe the colour space used. Section 3 presents the approach proposed. Section 4 describes the results of the experimental investigations. Finally, Section 5 presents conclusions of the work.

2. Colour space used

Colour image acquisition equipment such as a CCD colour camera obtains the RGB values, which can be directly used for representing colours in the RGB colour space

\[ \{R, G, B\} = \int [E(\lambda)O(\lambda)F(\lambda)] d\lambda \]

where \(E(\lambda)\) expresses spectral properties of the illumination source, \(O(\lambda)\) is spectral reflectance function of an object, and \(F(\lambda)\) stands for three spectral sensitivity functions of the colour camera. However, different acquisition equipment give us different RGB values for the same incident light. One more drawback of the RGB colour space is that the metrics does not represent colour differences in a uniform scale, making it difficult to evaluate the similarity of two colours from their distance in the space.

To meet the requirement of uniformity of distribution of colours the Commission Internationale de l’Eclairage (CIE) has recommended using one of two alternative colour spaces: \(L^*a^*b^*\) or \(L^*u^*v^*\) colour space [25,26]. It is a common practice to use the \(L^*a^*b^*\) colour space for describing absorbing materials such as pigments and dyes [1]. Therefore, we used the \(L^*a^*b^*\) colour space in this work.

To map the RGB values into the \(L^*a^*b^*\) colour space, the RGB values are first transformed to the XYZ tristimulus values as follows:

\[ X = a_1 R + a_{12} G + a_{13} B \]

\[ Y = a_2 R + a_{22} G + a_{23} B \]

\[ Z = a_3 R + a_{32} G + a_{33} B \]

with the coefficients \(a_{ij}\) being determined by a colourimetric characterization of the hardware used. XYZ tristimulus values can describe any colour. It is often convenient to discuss ‘pure’ colour in the absence of luminance. For that purpose, the CIE defines \(x\) and \(y\) chromaticity co-ordinates:

\[ x = X/(X + Y + Z) \]

\[ y = Y/(X + Y + Z) \]

A colour plots as a point in an \((x,y)\) chromaticity diagram. However, the distribution of colours observed in the chromaticity diagram is also non-uniform. A dominant wavelength correlates very non-uniformly with the perception of hue and excitation purity with the perception of saturation.

Having XYZ tristimulus values the \(L^*a^*b^*\) colour space is defined as follows [26]:

\[ L^* = 116(Y/Y_n)^{1/3} - 16, \quad \text{if } Y/Y_n > 0.008856 \]

\[ L^* = 903.3(Y/Y_n), \quad \text{if } Y/Y_n \leq 0.008856 \]

\[ a^* = 500[(X/X_n)^{1/3} - (Y/Y_n)^{1/3}] \]

\[ b^* = 200[(Y/Y_n)^{1/3} - (Z/Z_n)^{1/3}] \]

where \(X_n, Y_n, Z_n\) are the tristimulus values of \(X, Y,\) and \(Z\) for the appropriately chosen reference white. If any of the ratios \(X/X_n, Y/Y_n,\) and \(Z/Z_n\) is equal to or less than 0.008856, it is
replaced in the above formulae by:
\[ 7.787f + 16/116 \]
where \( f \) is \( X/X_n \), \( Y/Y_n \), or \( Z/Z_n \), as the case may be [26]. New measures are provided in the colour space which correlate with hue and saturation more uniformly. For example, CIE hue-angle: \( H_{ab} = \arctan(b^*/a^*) \) [26].

The Euclidean distance measure can be used to measure the distance \( (\Delta E) \) between the two points representing the colours in the colour space:
\[ \Delta E = [(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2]^{1/2} \]

3. The approach

The technique developed consists of three steps. In the first step, rough image segmentation is performed. Then, in the second step, the binary erosion operation is applied to the segmented image. Finally, refined image segmentation based on the data collected from the eroded image is accomplished. We adopted the Fuzzy Kohonen Clustering algorithm [27] to learn parameters of the clusters utilized for accomplishing the rough image segmentation and the Minimum Fuzzy Cluster Volume algorithm [28] to learn parameters of the clusters for the refined image segmentation phase. Next, we describe the proposed image segmentation procedure and the main topics of it.

3.1. Segmentation procedure

The image segmentation procedure is encapsulated in the following eight steps.

1) Randomly select \( N \ll P \times Q \) training pixels, where \( P \) and \( Q \) are the image sizes in the vertical and horizontal directions, respectively.
2) Run the Fuzzy Kohonen clustering algorithm for the selected pixels using the Euclidian distance measure.
3) Segment the image by assigning each pixel into one of the clusters found. Use the minimum distance classifier with the Euclidian distance measure for the classification.
4) Perform the binary erosion operation on all parts of the segmented image.
5) Using the eroded image, randomly select a new set of \( N \) pixels subject to the constraint that each cluster obtained in Step 1 is represented by an equal number \( N/K (K=2 \text{ in our case}) \) of pixels. If \( N/K > \beta N_{\min} \), where \( N_{\min} \) is the number of pixels left in the smallest cluster after the erosion and \( \beta \) is a constant, set the number of pixels selected from each cluster to \( \beta N_{\min} \).
6) For each selected pixel, calculate the local information, as described in Section 3.4, and append this value as an extra component to the colour vector representing the pixel.
7) Run the Minimum Fuzzy Cluster Volume clustering algorithm for the selected pixels.
8) Segment the image by assigning each pixel into one of the clusters found. Use the minimum distance classifier with the Mahalanobis distance measure [29] for the classification.

The rationale for executing the erosion operation is to prevent the training data collecting process from selecting pixels of uncertain colour-pixels located on colour edges.

To speed up the whole image segmentation process, the phase of rough segmentation is based on colour information only. However, to obtain an accurate image segmentation, the local spatial information is also utilized in the final segmentation stage. The rough image segmentation phase is required for collecting a balanced training data set utilized to estimate parameters on which the stage of refined image segmentation is based.

3.2. Fuzzy Kohonen clustering

The clustering algorithm used is summarized in the following four steps.

1) Initialize the weight vectors \( w_i(0) \)—centres of the clusters—of all the \( K \) (2 in our case) nodes with small random values. Choose the distance \([x - w_i]\) measure between two vectors, where \( x=[L^*, a^*, b^*]^T \), the maximum number of learning iterations \( I_{\text{max}} \), a small positive constant \( \epsilon > 0 \), and a constant \( m > 1 \) (the degree of fuzziness).
2) Compute all the \( K \times N \) learning rates \( \alpha_{ki,t}, \) \( k=1,...,K, \) \( i=1,...,N \), where \( N \) is the number of pixels used in the learning process, according to the following formulas:
\[ \alpha_{ki,t} = (\mu_{ki,t})^{\eta_t} \]
\[ \mu_{ki,t} = \left( \frac{\sum_j \left( \frac{||x_j - w_k||_S}{||x_j - w_i||_S} \right)^{2/(m - 1)}}{1} \right)^{-1} \]
where
\[ ||x_i - w_k||_S = (x_i - w_k)^T S^{-1} (x_i - w_k) \]
where \( S \) is the input data covariance matrix.
\[ w_k = \frac{\sum_{t} (\mu_{ki})^{\eta_t} x_j}{\sum_{t} (\mu_{ki})^{\eta_t}}, \quad k = 1, 2, ..., K \]
\[ m_t = m - t \Delta m \]
\[ \Delta m = (m - 1)\epsilon_{\text{max}} \]  
(16)

(3) Update all the \( K \) vectors \( \{w_{k,t}\} \) according to the rule:

\[
w_{k,t} = w_{k,t-1} + \frac{\sum_{i=1}^{N} \alpha_{ki}(x_i - w_{k,t-1})}{\sum_{i=1}^{N} \alpha_{ki}}
\]
(17)

(4) Compute the difference between the weight vectors in two subsequent cycles:

\[
E_t = \|w_t - w_{t-1}\|^2 = \sum_{k=1}^{K} \|w_{k,t} - w_{k,t-1}\|^2
\]
(18)

If \( E_t < \epsilon \) Stop; Else iterate steps 2–4.

3.3. Erosion

For an image \( I \) and a structural element \( W \) the erosion of \( I \) by \( W \), denoted \( I \ominus W \), is defined as

\[
I \ominus W = \{x | (W)_x \subseteq I\}
\]
(19)

where

\[
(W)_x = \{c | c = w + x, \ \text{for} \ w \in W\}
\]
(20)

is the translation of \( W \) by \( x = (x_1, x_2) \).

3.4. Local information

The local information \( g(x, y) \) at the pixel \((x, y)\) is given by the local average in a small square window \( w \) centred at the pixel \((x, y)\):

\[
g(x,y) = \frac{1}{(2w + 1)^2} \sum_{i=-w}^{w} \sum_{j=-w}^{w} d(x+i, y+j),
\]
(21)

where \( d(x,y) \) is a distance image. The distance image is obtained by calculating the Euclidian distance, given by Eq. (10), between the colour of the pixel being considered and the mean colour of the largest cluster found in the first clustering phase. The mean colour is given by the average \( L^*, a^*, \) and \( b^* \) values calculated over the pixels assigned to the largest cluster.

3.5. Minimum Fuzzy Cluster Volume Clustering

We initialize the Minimum Fuzzy Cluster Volume clustering algorithm with the cluster centres \( w_k, k=1,\ldots,K \) and the memberships \( \mu_{kj} \) obtained from the Fuzzy Kohonen clustering algorithm.

In each iteration of the Fuzzy Volume algorithm, the memberships \( \mu_{ki} \) and the cluster centres \( w_k \) are updated according to the following rules:

\[
\mu_{kj} = \begin{cases} 
\frac{[d_2(x_j, w_k)]^{\frac{1}{1-m}}}{\sum_{i=1}^{K} [d_2(x_i, w_k)]^{\frac{1}{1-m}}}, & \text{if } d_M(x_j, w_k) - n > 0 \ \forall \ k \\
0/1, & \text{if } d_M(x_j, w_k) - n \leq 0 \ \exists \ k
\end{cases}
\]
(22)

where \( n \) is the dimensionality of \( x \), \( m \) is the degree of fuzziness, \( d_M(x_j, w_k) \) is the Mahalanobis distance given by

\[
d_M(x_j, w_k) = (x_j - w_k)S_k^{-1}(x_j - w_k)^T
\]
(23)

\[
d_2(x_j, w_k) = |S_k|^{\frac{1}{2}} [d_M(x_j, w_k) - n] \\
\sum_{i=1}^{N} \mu_{ki}^{m}
\]
(24)

where \( S_k^{-1} \) is the inverse of the fuzzy covariance matrix \( S_k \)

\[
S_k = \frac{\sum_{j=1}^{N} \mu_{kj}^{m}(x_j - w_k)(x_j - w_k)^T}{\sum_{i=1}^{N} \mu_{ki}^{m}}
\]
(25)

and \( |S_k| \) is the determinant of the matrix.

In (22), \( \mu_{kj} = 1 \), if \( k = \arg \min_{i=1,\ldots,K} d_2(x_j, w_i) \)

(26)

and \( \mu_{kj} = 0 \), otherwise.

\[
w_k = \frac{\sum_{i=1}^{K} \mu_{ki} x_i}{\sum_{i=1}^{K} \mu_{ki}}, \quad k = 1, \ldots, K
\]
(27)

The same rule (18), as in the Fuzzy Kohonen clustering algorithm, is used to terminate the learning process.

4. Experimental investigations

A one-chip CCD colour camera has been used to capture colour images. The resolution used was such that an image consisting of 768 \( \times \) 576 pixels was recorded from an area of approximately 8 \( \times \) 6 mm\(^2\). In all the experiments, the data used were normalized to zero mean and variance one.

To compare segmentation results obtained from the technique developed, we have chosen the Stochastic Expectation Maximization (SEM) algorithm [30]. The SEM algorithm is a contextual adaptation of the traditional EM algorithm. Based on the observation that adjacent pixels are likely to possess the same labels, priors in the SEM algorithm are modelled as a second-order Markov random field.

As in all image segmentation tasks, there is no objective method to assess segmentation results. An independent evaluation against correct ink coverage values is quite difficult, since these values remain unknown. Therefore, in our tests, we mainly resorted to a careful inspection by a human eye. Additionally, to assess the results obtained from the technique proposed, we employed the particle induced X-ray emission (PIXE) [31] at a nuclear microprobe
technique [32]. Using the non-optical PIXE based technique a very accurate estimate of the amount of ink pigment on paper can be obtained [32]. However, the PIXE measurements are very expensive and time consuming. Therefore, in [32], only six screen dots have been analysed. To assess our technique, we used the data provided by the authors of [32].

4.1. Parameter settings

There are several parameters to be chosen, namely the degree of fuzziness $m$, the small constant $\varepsilon$ used to stop the learning process, the number of training pixels $N$, the size of the window $w$ for calculating local information, the size of the structural element $W$ to fulfill the erosion operation, and the parameter $\beta$ controlling the number of pixels selected for the second learning phase. The values of $m=1.8$, $\varepsilon=0.001$, $N=10,000$, $w=1$, $W=3$, and $\beta=0.8$ worked well in all the tests performed. The segmentation results were quite insensitive to the choice of the parameter values, except the size of the local window $w$. The use of $w>2$ deteriorated the segmentation accuracy of the images containing very small areas of one colour and large areas of other colour. An example of such an image is shown in Fig. 2.

4.2. Segmentation results

Fig. 2 presents a typical example of an image, in which the percentage of the area covered by a printing ink needs to be determined. Figs. 3–5 display intensity histograms of the Red, Green, and Blue bands of the image, respectively. As can be seen from the figures, the histograms contain only one peak. Thus we cannot expect obtaining an accurate estimate of the area by simple histogram thresholding.

Fig. 6 exemplifies an image of an enlarged view of a small printing plate area made aiming to get a halftone with 5% ink coverage—a nominal ink dot size of 5%. However, due to inaccuracies and some unavoidable factors occurring in the printing process, the actual ink dot size may significantly differ from the nominal one. The actual ink dot size in the halftone area shown in Fig. 6 is much larger than 5%. To estimate the actual ink dot size the image was segmented into ‘dots’ and ‘background’ parts. In Fig. 6, the segmentation result, obtained employing only the first phase of the segmentation procedure, is provided for the left part of the image. By contrasting the left—segmented and the right—unsegmented parts of the image we can easily notice that the estimated ink dot size is too high. This estimation error occurs due to the fact that the clustering algorithm favours equally populated clusters, while the background area happens to be much more densely represented in the randomly selected training set.

Fig. 7 illustrates the segmentation result of the image shown in Fig. 6 when both phases of the segmentation procedure developed are utilized. One can easily notice that this segmentation result is much closer to the ‘ground truth’ than the one shown in Fig. 6.
Three factors—equalization of the number of pixels representing the ‘dots’ and ‘background’ parts of the image in the training set, the use of local information, and elimination of pixels of ‘uncertain colour’ from the training set—contribute to improving the accuracy of the estimate of the ink dot size. Amongst them, the first factor is the most significant one.

We experimented with images taken from halftone areas of different nominal ink dot sizes. Images of different colours, including yellow, taken from both printing plates and paper have been used in the experiments.

Table 1 summarizes the results of the experiments when images taken from a printing plate were utilized. The halftone areas used were manufactured in cyan on grey background. For each nominal ink area—column NA % in Table 1—10 images from different physical areas were recorded. In the table, the estimated mean ink dot size—the average percentage of the area covered by ink—and the standard deviation, calculated from these 10 trials are provided. The standard deviations are shown in parentheses.

<table>
<thead>
<tr>
<th>NA (%)</th>
<th>SEM</th>
<th>Phase 1</th>
<th>Phase 1+LI</th>
<th>Phases 1&amp;2+LI</th>
<th>Phases 1&amp;2+LI</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>14.34 (0.31)</td>
<td>12.94 (0.46)</td>
<td>11.76 (0.43)</td>
<td>09.38 (0.32)</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>25.15 (1.01)</td>
<td>24.63 (0.98)</td>
<td>23.56 (0.92)</td>
<td>22.64 (0.75)</td>
<td></td>
</tr>
<tr>
<td>45</td>
<td>45.17 (0.93)</td>
<td>45.27 (1.23)</td>
<td>45.31 (1.13)</td>
<td>44.92 (1.02)</td>
<td></td>
</tr>
<tr>
<td>80</td>
<td>78.14 (0.64)</td>
<td>78.84 (0.75)</td>
<td>79.65 (0.67)</td>
<td>81.92 (0.59)</td>
<td></td>
</tr>
<tr>
<td>95</td>
<td>91.12 (0.29)</td>
<td>92.07 (0.35)</td>
<td>93.11 (0.31)</td>
<td>95.21 (0.18)</td>
<td></td>
</tr>
</tbody>
</table>

As can be seen from the table, the four alternatives give comparable results when segmenting images with approximately equal number of pixels in the ‘dots’ and

Four segmentation alternatives have been examined:

(1) segmentation by the SEM algorithm;
(2) segmentation using only the first phase of the procedure proposed—column ‘Phase 1’ in Table 1;
(3) segmentation using the first phase of the segmentation procedure when the colour vector representing a pixel is augmented with the local information term—column ‘Phase 1+LI’
(4) Segmentation using both phases of the procedure and the local information term—column ‘Phases 1&2+LI’.

As can be seen from the table, the four alternatives give comparable results when segmenting images with approximately equal number of pixels in the ‘dots’ and
background areas of the images. However, when the number of pixels in these areas significantly differ, the procedure proposed is much more accurate than the other segmentation alternatives tested. The equalization of the number of pixels representing the 'dots' and 'background' parts of the image in the training set plays the major role in gaining the segmentation accuracy. We recall that the Nominal Area (NA) provided is not the 'ground truth', on the contrary, we attempt to determine the 'ground truth' through image segmentation.

Figs. 8–10 present one more image segmentation example. The left part of the image shown in Fig. 8 is segmented by the SEM algorithm. The result presented in Fig. 9 is obtained from the third image segmentation alternative. The result obtained using the fourth image segmentation alternative is presented in Fig. 10. Again, by contrasting the left and the right parts of the images, one can clearly see the superiority of the fourth image segmentation alternative.

The developed software was installed in a newspaper printing shop in Sweden and is successfully used on production line to assess the ink dot size on both paper and printing plates.

4.3. Tests using the ‘PIXE data’

Six screen dots printed in cyan ink on ordinary newsprint have been used in this experiment. The dots were scanned using both a CCD colour camera and the non-optical PIXE-based method. The same resolution of 2 μm/pixel has been applied in both techniques. A 3-CCD colour camera was used in this experiment [32]. While the CCD colour camera records a 3-band intensity image, the use on the PIXE-based technique results in an image of the amount of ink pigment. The data obtained from the two techniques were preprocessed to bring them into the same coordinate system [32]. The pigment images were thresholded based on knowledge on the composition of the ink and paper used [32]. The thresholding technique is known to be very accurate and robust.

Fig. 11 illustrates a pair of binary images of the same screen dot. The left-hand side image is the thresholded pigment image obtained from the PIXE-based technique. The right-hand side image is the 'optical' image obtained from the technique proposed. One can easily notice that the optical image does not contain small holes and small isolated 'islands'. The holes and islands disappear due to light scattering in paper. The dot detected by the image
analysis based approach is 2.28% larger than the one identified by the \textit{PIXE}-based technique. The same range of discrepancy between the optical and non-optical measurements was observed for the other five screen dots. Bearing in mind the light scattering phenomenon in paper, the obtained estimate of the dot size can be considered as very accurate.

5. Conclusions

We presented an option for colour image segmentation applied to printing quality assessment. The segmentation is based on classification of image pixels. Parameters of the decision classes are obtained by clustering a small number of randomly selected pixels—a training data set—represented by a colour vector augmented with one additional component providing information from a local neighbourhood of a pixel being considered. The segmentation is accomplished in two stages. In the first stage, rough image segmentation is performed. The results of the first segmentation stage are then utilized to collect a balanced training data set for learning refined parameters of the decision classes. The final segmentation is obtained by assigning image pixels to the decision classes represented by a set of the refined parameters.

The use of balanced training data sets and the local information significantly improved the image segmentation accuracy if compared to the results obtained when using ‘pure’ randomly selected training data sets. Small training data sets utilized allowed to significantly seed up the whole image segmentation process. The developed software is successfully used in a printing shop to assess the ink dot size on paper and printing plates.

Acknowledgements

We gratefully acknowledge the support we have received from the Foundation for Knowledge and Competence Development and the TTF research program.

References

[28] R. Krishnapuram, J. Kim, Clustering algorithms based on volume
236.

[29] R.O. Duda, P.E. Hart, D.G. Stork, Pattern Classification, Second ed,

907–923.

[31] S.A.E. Johansson, J.L. Campbell, PIXE—a novel technique for

[32] P. Kristiansson, C.M. Nilsson, H. Busk, L. Malmqvist, M. Elfman,
K.G. Malmqvist, R.J.U.J. Pallon, K.A. Sjoland, C. Yang, Optical dot
gain on newsprint determined with the lund nuclear microprobe,
Nuclear Instruments and Methods in Physics Research Section B:
Beam Interactions with Materials and Atoms 130 (1–4) (1997) 303–
307.