A MULTISCALE OPERATOR FOR DOCUMENT IMAGE BINARIZATION

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Abstract: Basically, document image binarization consists on the segmentation of scanned gray level images into text and background, and is a basic preprocessing stage in many image analysis systems. It is essential to threshold the document image reliably in order to extract useful information and make further processing such as character recognition and feature extraction. The main difficulties arise when dealing with poor quality document images, containing nonuniform illumination, shadows and smudge, for example. This paper presents an efficient morphological-based document image binarization technique that is able to cope with these problems. We evaluate the proposed approach for different classes of images, such as historical and machine-printed documents, obtaining promising results.

1 INTRODUCTION

Document image binarization converts gray-scale images into binaries ones which are more appropriate to be used in several image analysis and understanding systems. Also, due to the increasing number of documents being digitalized, binarization has been used to facilitate data management and decrease storage space requirements.

Since the accuracy of the resulting images strongly affects the performance of subsequent high level tasks, such as optical character recognition (OCR) and feature extraction, it is essential to find thresholding methods that correctly keep all useful information while removing background and undesired details corresponding to noise.

The main difficulties in this sense arise from the fact that document images can be subjected to different degradation problems, which can significantly disturb the results if appropriate methods are not used. These problems may occur due to several reasons, like aging and environmental conditions. In historical document images, for example, it is very common to have seepage of ink, uneven illumination, smear and smudge. When working with scanned images, the main difficulties are related to poor printing/writing quality and low contrast due to shadows.

In this paper, we propose a multiscale binarization algorithm that explores the simplification properties of a scale-space toggle operator to define a dynamic thresholding operation. In contrast to other approaches, image maxima and minima interact at the same time, conducing to a region merging that simplifies the image in such a way that important image structures can be identified even in ill-illuminated images. The binarization rule depends on the local convergence of a pixel to a significative extrema, thus taking into account the whole image structure, and not only the local gray level. In a few words, if a pixel converges to a local minima, it is set to black. Otherwise, it is set to white.

To assess the robustness of our approach, we compare it against known threshold-based segmentation methods using images of different classes and subjected to different degradation problems. As we will se elsewhere, our approach is computationally efficient and conduce to better results for a wide range of experiments.

Section 2 briefly reviews some image thresholding techniques and Section 3 describes the proposed approach. Section 4 presents the experimental results and Section 5 draws some conclusions and future work perspectives.

2 RELATED WORK

Document image binarization approaches are typically classified into global and local methods. The former are based on histogram analysis, with the

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threshold value being determined based on the measure that best separate the histogram peaks. However, not necessarily all features of interest form prominent peaks. In a general way, global approaches yield good results only when there is a good separation between foreground and background, a limitation in document images with degradation problems like inhomogeneous backgrounds, smears and strains.

A well-known general purpose histogram-based global thresholding approach is the Otsu's algorithm (Otsu, 1979). Briefly, it selects as an optimal threshold the one which minimizes the ratio between the "between-class" and the total variance. The between-class variance is defined as the deviation of the mean values for each considered class (background and object) from the overall mean of the pixels.

On the other hand, local thresholding approaches provide an adaptive solution where the threshold value is determined pixelwise and depends on regional image characteristics. Due to the computational cost, it is important to define efficient transformations to be applied locally. We have compared our approach against some of these methods, described below.

The moving averages method considers a threshold based on the mean gray level of the last n pixels, and it is designed for images containing text. The image can be treated as a one-dimensional stream of pixels and the average can either be computed exactly or estimated via (Parker, 1996):

$$M_{i+1} = M_i - \frac{M_i}{n} + g_{i+1} \tag{1}$$

where M_{i+1} is the estimate of the moving average for pixel $i+1$ having gray level g_{i+1} and M_i is the previous moving average (i.e. for pixel i). Any pixel less than a fixed percentage of its moving average is set to black; otherwise it is set to white.

The Niblack's algorithm defines a local threshold based on the mean and standard deviation values calculated over a rectangular window around the pixel according to the following formula (Niblack, 1986):

$$T = m + k * s \tag{2}$$

where m is the mean and s the standard deviation of the pixels in the window. The variable k determines how much of the object is retained, and assumes a value between -1 and 1. As drawbacks, we have the low thresholding speed, the sensitivity to the size of the window and the occurrence of noise in the background.

In order to minimize the background noise in images with uneven illumination, Sauvola proposed an extension to Niblack's algorithm where the threshold value is computed with the dynamic range of the standard deviation, R, according to the equation (Sauvola and Pietikainen, 2000):

$$T = m * \left(1 + k\left(\frac{s}{R} - 1\right)\right) \tag{3}$$

where, again, m and s are mean and standard deviation of the window. Here, k takes a positive value between 0 and 1. To properly determine the R value, it is necessary to know the document contrast. The influence of the window size and the threshold speed still remain a problem.

Gatos et al. (Gatos et al., 2006) proposed a locally adaptative binarization scheme that can deal with degraded document images. The method consists in five basic steps, starting from a rough estimation of the foreground, obtained using the Sauvola's algorithm, that is improved using local image analysis. More complete reviews of image thresholding techniques can be found in (Trier and Jain, 1995) (Gatos et al., 2006) (Sahoo et al., 1988) (Sezgin and Sankur, 2004).

3 SCALE-SPACE TOGGLE OPERATOR FOR IMAGE SIMPLIFICATION

Multiscale approaches have been largely considered, playing an important role when designing automatic methods to cope with real world measurements where, in most of the cases, there is no prior information about which would be the appropriate scale.

Here, we use an operator based on the scale-space approach (Witkin, 1984), in which the inherent multiscale nature of real-world images is represented by embedding the original signal into a family of simplified signals, created by successively removing image structures across scales while preserving the essential features. Since the representation of an interest signal feature describes a continuous path through the scales, it is possible to relate information obtained in different representation levels, a drawback in many multiscale approaches.

Due to the problems inherent to the linear approaches (Witkin, 1984), non-linear scale-space operators based on mathematical morphology have been frequently used (Bosworth and Acton, 2003). In this context, scale-spaces are generated by filtering gray-scale signals with specific combinations of the scaled erosion and dilation operations, defined as follows (Jackway and Deriche, 1996).

Definition (Dilation). The dilation of the function $f(\mathbf{x})$ by the structuring function $g_\sigma(\mathbf{x})$, $(f \oplus g_\sigma)(\mathbf{x})$, is given by:

$$(f \oplus g_\sigma)(\mathbf{x}) = \sup_{\mathbf{t} \in \mathcal{G} \cap \mathcal{D}_x} \{f(\mathbf{x}-\mathbf{t}) + g_\sigma(\mathbf{t})\} \qquad (4)$$

Definition (Erosion). The erosion of the function $f(\mathbf{x})$ by the structuring function $g_\sigma(\mathbf{x})$, $(f \ominus g)(\mathbf{x})$, is given by:

$$(f \ominus g_\sigma)(\mathbf{x}) = \inf_{\mathbf{t} \in \mathcal{G} \cap \mathcal{D}_x} \{f(\mathbf{x}+\mathbf{t}) - g_\sigma(\mathbf{t})\} \qquad (5)$$

where $f : \mathcal{D} \subset \mathbb{R}^n \to \mathbb{R}$ is the image function, $\mathcal{D}_x$ is the translate of $\mathcal{D}$, $\mathcal{D}_x = \{\mathbf{x}+\mathbf{t} : \mathbf{t} \in \mathcal{D}\}$, and $g_\sigma : \mathcal{G}_\sigma \subset \mathbb{R}^2 \to \mathbb{R}$ is the scaled structuring function

$$g_\sigma(\mathbf{x}) = |\sigma| g(|\sigma|^{-1}\mathbf{x}) \quad \mathbf{x} \in \mathcal{G}_\sigma, \forall\, \sigma \neq 0. \qquad (6)$$

To ensure reasonable scaling behavior, g_σ must be a monotonic decreasing function along any radial direction from the origin (i.e., anti-convex). To avoid level-shifting and horizontal translation effects, respectively, one must also observe the conditions

$$\sup_{\mathbf{t} \in \mathcal{G}_\sigma} \{g_\sigma(\mathbf{t})\} = 0 \text{ and } g_\sigma(\mathbf{0}) = 0. \qquad (7)$$

We use a scale-space toggle operator, named Self-dual Multiscale Morphological Toggle (SMMT) (Dorini and Leite, 2008), which uses as primitives iterated versions of an extensive and an anti-extensive transformation, namely, the scale dependent dilation and erosion defined above. The decision rule is based on which primitive value is closer to the original one.

Definition (Self-dual Multiscale Morphological Toggle Operator). Let the primitives be defined as $\phi_1^n(\mathbf{x}) = (f \oplus g_\sigma)^n(\mathbf{x})$ and $\phi_2^n(\mathbf{x}) = (f \ominus g_\sigma)^n(\mathbf{x})$, that is, the dilation and erosion, respectively, of $f(\mathbf{x})$ with the scaled structuring function g_σ n times. The Self-dual Multiscale Morphological Toggle (SMMT) operator is defined as (Dorini and Leite, 2008):

$$(f \oslash g_\sigma)^n(\mathbf{x}) =$$

$$\begin{cases} \phi_1^n(\mathbf{x}), & \text{if } \phi_1^n(\mathbf{x}) - f(\mathbf{x}) < f(\mathbf{x}) - \phi_2^n(\mathbf{x}), \\ f(\mathbf{x}), & \text{if } \phi_1^n(\mathbf{x}) - f(\mathbf{x}) = f(\mathbf{x}) - \phi_2^n(\mathbf{x}), \\ \phi_2^n(\mathbf{x}), & \text{otherwise.} \end{cases} \qquad (8)$$

Idempotence is usually desired when dealing with toggle-like transformations to avoid undesirable effects, such as oscillations (Serra and Vicent, 1992). Since the previously defined operator is not idempotent, it is important to ensure that it has a well-controlled behavior for any parameter set.

It has been proved that the operator obeys the necessary conditions to constitute a scale-space operator for varying scale (Dorini and Leite, 2007). The monotonicity property (requiring that the number of features must necessarily be a monotonic decreasing function of scale) holds when using as features image extrema (there is no need to consider image maxima and minima separately as in previous approaches (Jackway and Deriche, 1996)). The SMMT operator has interesting characteristics, such as self-duality, i.e., there is a symmetric treatment of foreground and background, thus reducing the gray-level bias. Also, it leads to an image simplification that does not displace the boundaries.

On the other hand, when considering iterative applications of the operator, a stronger simplification is obtained and regions are merged as discussed below. To make calculations easier and more intuitive, let us consider the pyramid structuring function given by

$$g_\sigma(x,y) = -|\sigma|^{-1} \max\{|x|,|y|\} \qquad (9)$$

in its scaled version. Under these conditions, we have the following equivalence for the SMMT operator (for a fixed scale σ):

$$(f \oslash g_{\sigma_3})^n(\mathbf{x}) == (f \oslash g_{\sigma_{2n+1}})^1(\mathbf{x}) \qquad (10)$$

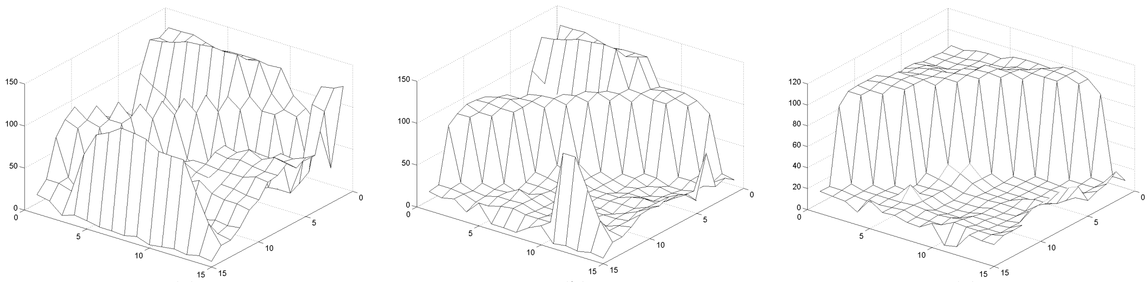
where the subscript on σ denotes the structuring element size. In a few words, n iterations of the primitives using a 3×3 structuring element is equivalent to one iteration using a structuring element of size $2n+1$. Since the transformed value of a pixel depends on the dominant extrema in the region being considered, the increasing on the number of iterations simplifies the image so that these extrema create wider "attraction zones", leading to a homogenization of the gray levels. The defined operator can be seen as a *quasi-connected* operator, in the sense that it simplifies the image by creating quasi-flat zones as explained next.

Definition (Maragos and Meyer, 2000) (R-flat-zone). Two pixels x, y belong to the same R-flat zone of a function f if and only if there exists an n-tuple of pixels $(p_1, p_2, \ldots, p_n)$ such that $p_1 = x$ and $p_n = y$, and for all i, (p_i, p_{i+1}) are neighbors and satisfy the symmetrical relation $f_{p_i} R\, f_{p_{i+1}}$.

In this paper, R corresponds to the relation $|p_i - p_{i+1}| \leq \lambda$. When R is the equality, we are dealing with flat zones, which consist on connected components where the pixel value is constant. In Figure 1, we show the transformation of the gray levels of a small portion of an image when applying successive iterations of the defined operator, $n = 1 \ldots 5$, with $\sigma = 1$. Observe that quasi-flat zones are created.

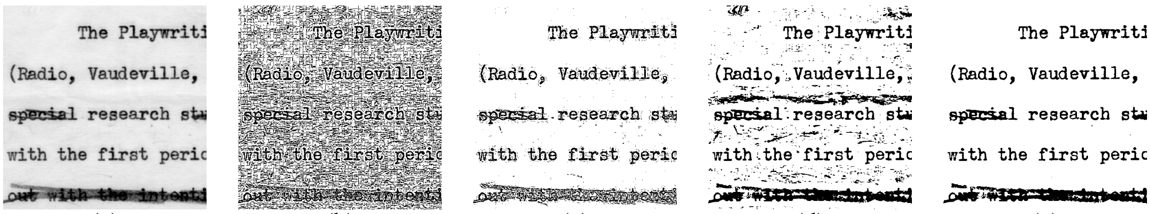
Here, we explore these properties to define a dynamic local thresholding operator as follows:

Definition (Binary Self-dual Multiscale Morphological Toggle Operator). Let the primitives be defined as $\phi_1^n(\mathbf{x}) = (f \oplus g_\sigma)^n(\mathbf{x})$ and $\phi_2^n(\mathbf{x}) = (f \ominus g_\sigma)^n(\mathbf{x})$, that is, the dilation and erosion, respectively,



(a) (b) (c)

Figure 1: Simplification obtained by considering successive iterations (1, 3 and 5) of the operator at scale $\sigma = 1$.



(a) (b) (c) (d) (e)

Figure 2: Influence of the scale and number of iterations parameters in the binarization. (a) original image and images processed by the BSSMT operator using the parameters (b) $\sigma^{-1} = 1$ and $n = 1$, (c) $\sigma^{-1} = 10$ and $n = 1$, (d) $\sigma^{-1} = 1$ and $n = 10$ and (e) $\sigma^{-1} = 5$ and $n = 10$.

of $f(\mathbf{x})$ with the scaled structuring function g_σ n times. We call Binary Self-dual Multiscale Morphological Toggle (BSMMT) operator:

$$(f \oslash g_\sigma)^n(\mathbf{x}) = \begin{cases} 255, & \text{if } \phi_1^n(\mathbf{x}) - f(\mathbf{x}) <= f(\mathbf{x}) - \phi_2^n(\mathbf{x}), \\ 0, & \text{otherwise,} \end{cases} \quad (11)$$

Basically, if a pixel converges to a local maxima, it is set to white. Otherwise, it is set to black. In such a way, the thresholding depends on the the image structures, and not only on the gray level in a predefined region.

Figure 2 illustrates how the parameters influence the binarization results. When using $\sigma = 1$ and $n = 1$, Figure 2(b), a great amount of noise remains in the background. In a different scale, Figure 2(c), less features persist, but the letters are noisy because the most significative image extrema influence only a small region. When considering more iterations, Figure 2(d), we have the opposite situation (undesired features but good letters' definition). With an appropriate combination of the parameters a satisfactory segmentation is obtained (Figure 2(e)).

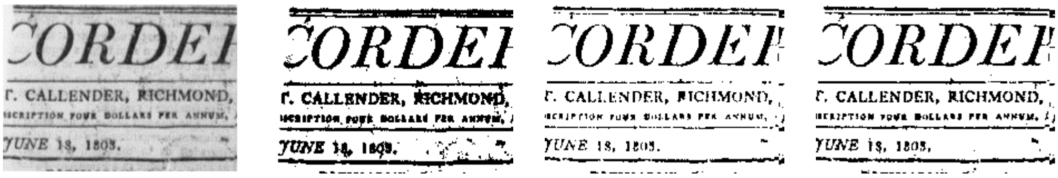
4 EXPERIMENTAL RESULTS

We compare our approach against the binarization methods discussed in Section 2 using degraded images of three different categories: historical handwritten documents, old newspapers and poor quality modern documents. In the following, we show an example of each class and discuss the overall conclusions about each method.

In a general way, the historical handwritten document images of our test set have non-uniform illumination, seepage of ink, shadows, smear and strain. Additionally, old newspaper images have extra noise mainly due to the old printing matrix precision. Finally, the modern documents have shadows that difficult the separation between background and text. Since no ground truth was available, we evaluate the binarization results according to visual criteria such as image quality and preservation of meaningful textual information.

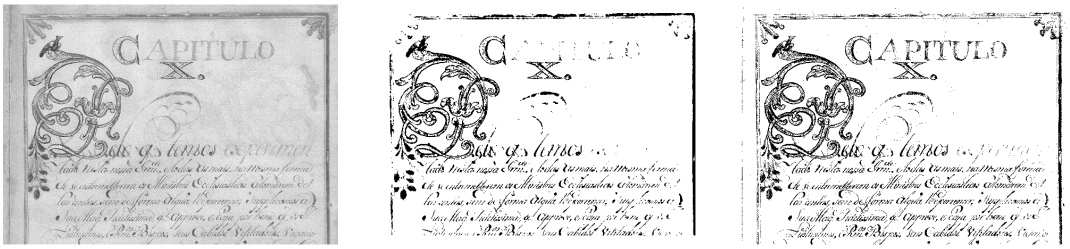
Figure 3 illustrates the binarization of an old newspaper image. We compare our results against the ones obtained by Niblack's and Sauvola's algorithms, which has been implemented taking $k = -0.2$ and $k = 0.5$, respectively, as suggested in (Niblack, 1986) and (Sauvola and Pietikainen, 2000). We use a 60×60 window (covering 1-2 characters) in both cases. For Niblack's algorithm, there is too much noise in the background region, while Sauvola's method yields thin and broken characters in several examples. Our approach presents accurate results.

Figure 4 shows an example of historical handwritten image. The approach suggested in (Gatos et al., 2006) yields regular results, but the use of Sauvola's



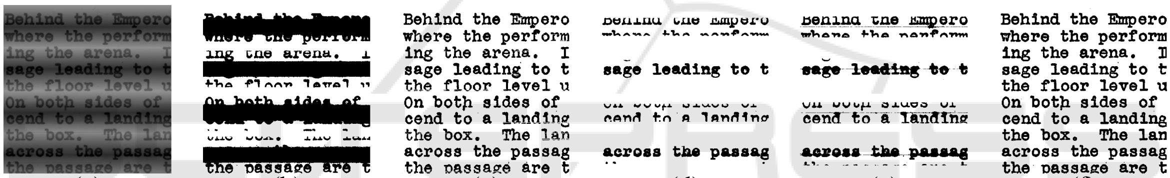
(a) (b) (c) (d)

Figure 3: Binarization results. (a) original image, (b) Niblack, (c) Sauvola and (d) Our approach.



(a) (b) (c)

Figure 4: Binarization results. (a) original image, (b) Gatos et al. and (c) Our approach.



(a) (b) (c) (d) (e) (f)

Figure 5: Binarization results. (a) original image, (b) Otsu, (c) Moving Averages, (d) Niblack, (e) Sauvola and (f) Our approach.

algorithm to obtain a first rough approximation of the foreground implies on a resulting image with broken or even discarded characters. On the other hand, our approach has shown to produce more reliable results, presenting a superior performance even when the input images are noisy and highly degraded.

The example of Figure 5 illustrates the robustness of the BSSMT operator to images with uneven illumination (Figure 5(a)). Observe in Figure 5(b) how a global threshold method, such as Otsu's, fails when choosing a unique threshold for the whole image. For the Niblack's (Figure 5(d)) and Sauvola's (Figure 5(e)) algorithms, the letters in the regions with a brighter illumination were wrongly classified as background. The moving averages algorithm (Figure 5(c)) is less sensitive to the noise, but the resulting image presents some white stripes in the letters, illustrated in Figure 6(b), which can disturb the results when performing an OCR system (Figure 7). As you can see from Figures 5(f) and 7(c), the proposed approach yields accurate results that can be properly used in the same OCR software.

5 CONCLUSIONS

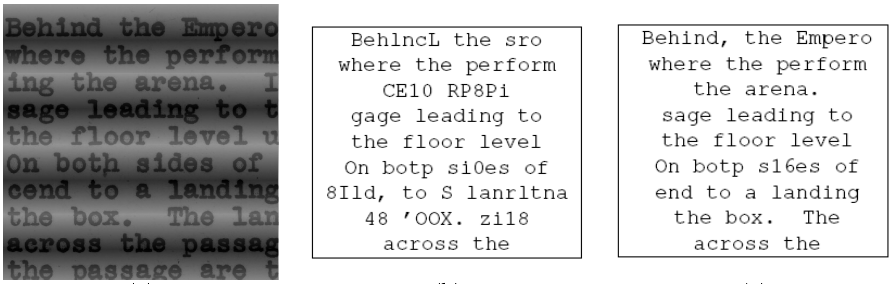
We have presented an adaptative document binarization technique for segmenting text from degraded document images. We explore the scale-space properties of a toggle operator to define a new thresholding operation that is robust to non-uniform illumination. When using appropriate parameters, the SMMT operator leads to a meaningful region merging that simplifies the image, thus eliminating undesired details such as noise. The binarization rule takes into account the way image maxima and minima interact in this merging process to determine the value of each pixel.

When compared to other well-known approaches, the proposed operator has shown to be robust to a wide range of degradation problems, without yielding extremely thinned and broken characters.

Since most document processing systems analyze a large number of documents, having different styles and layouts, it is important to develop automatic techniques that do not require user intervention to set parameters each time it is applied. Thus, we will ex-

(a) (b)

Figure 6: (a) Our approach result and (b) The moving averages algorithm yields stripes that disturb the OCR results.



(a) (b) (c)

Figure 7: Results of an automatic OCR system using Abby software (ABBYY, 2008). (a) Original image, (b) using the moving averages result (Figure 5(c)) and (c) using the result of our approach (Figure 5(f)).

tend our approach to use different representation levels (scales) to extract the interest characters automatically. Future work also includes the validation of the method using quantitative measures.

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