Chapter 2
A Comprehensive Survey on Image Binarization Techniques

Abstract A detailed survey about the principles of image binarization techniques is introduced in this chapter. A comprehensive review is given. A number of classical methodologies together with the recent works are considered for comparison and study of the concept of binarization for both document and graphic images.

Keywords Review of binarization methods • Global binarization • Image thresholding • Adaptive local binarization

2.1 Foundations of Image Binarization Techniques

A number of methodologies have been proposed by several researchers on image segmentation using binarization and its applications toward moving object detection and human gait recognition. This section presents a review of the classical methodologies found in the literature. Over past four decades, several researchers have proposed a variety of thresholding techniques for binarization of document images [1–7] as well as graphic images [8, 9]. Processing of documents that are of very poor quality due to seeping of ink from the other side of the page or general degradation of the paper and ink, background noise or variation in contrast and illumination are also found in the literature [10]. All the reported thresholding methods have been demonstrated to be effective in constrained processing environments with predictable images. However, pictures taken in real-life situations may contain different artifacts such as shadow, non-uniform illumination. Proper binarization of these images is very important for separating the foreground object from the background. A good binarization will result in better recognition accuracy for any pattern recognition application.

Binarization can become a challenging job [10] under varying illumination and noise. A number of factors contribute to complicate the thresholding scheme including ambient illumination, variance of gray levels within the object and the

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background, inadequate contrast. A wrong selection of threshold value may misinterpret the background pixel and can classify it as object and vice versa, resulting in overall degradation of system performance. In document analysis, binarization is sensitive to noise, surrounding illumination, gray-level distribution, local shading effects, inadequate contrast, the presence of dense non-text components such as photographs. While at the same time, the merges, fractures, and other deformations in the character shapes affect the threshold value in OCR system.

The binarization methods can be categorized in different groups depending on which principal criteria they consider in calculating the threshold. The method proposed by Otsu [8] proposed a clustering analysis-based method based on image variance. Methods proposed by Johannsen et al. [11] and Kapur et al. [12] are entropy-based methods. Binarization methods based on image variance are proposed by Sauvola et al. [13] and Niblack [14]. Bernsen [9] proposed a thresholding approach based on image contrast. Kittler et al. [15] consider error measure in calculating the optimal threshold. Some of the methods are discussed below in brief.

Otsu's method [8] is the most successful global thresholding method. It automatically performs histogram shape-based image thresholding for the reduction of a gray-level image to a binary image. The algorithm assumes that the image for thresholding contains two classes of pixels (e.g., foreground and background) and then calculates the optimum threshold separating those two classes so that their combined spread (intra-class variance) is minimal. It exhaustively searches for the threshold that minimizes the intra-class variance, defined as the weighted sum of variances of the two classes. The weighted within-class variance is $\sigma_w^2(t) = q_1(t)\sigma_1^2(t) + q_2(t)\sigma_2^2(t)$ where the class probabilities of different gray-level pixels are estimated as:

$$q_1(t) = \sum_{i=0}^{t} P(i) \quad \text{and} \quad q_2(t) = \sum_{i=t+1}^{255} P(i)$$

And the class means are given by:

$$\mu_1(t) = \sum_{i=0}^{t} \frac{i * P(i)}{q_1(t)} \quad \text{and} \quad \mu_2(t) = \sum_{i=t+1}^{255} \frac{i * P(i)}{q_2(t)}$$

Total variance (σ^2) = Within-class variance ($\sigma_w^2(t)$) + Between-class Variance ($\sigma_b^2(t)$), where $\sigma_b^2(t) = q_1(t)[1 - q_1(t)][\mu_1(t) - \mu_2(t)]^2$

Since the total variance is constant and independent of t, the effect of changing the threshold is merely to move the contributions of the two terms back and forth. Between-class variance is $\sigma_b^2(t) = q_1(t)[1 - q_1(t)][\mu_1(t) - \mu_2(t)]^2$. Thus, minimizing the within-class variance is the same as maximizing the between-class variance. This method gives satisfactory results when the numbers of pixels in each class are close to each other.

In locally adaptive thresholding algorithms, a threshold is calculated at each pixel, which depends on some local statistics such as range, variance, or surface-fitting parameters of the pixel neighborhood. In what follows, the threshold $T(i, j)$ is indicated as a function of the coordinates (i, j) at each pixel, or if this is not possible, the object/background decisions are indicated by the logical variable $B(i, j)$. Niblack's method [14] calculates pixel-wise threshold by sliding a rectangular window over the gray-level image. This method adapts the threshold according to the local mean $m(i, j)$ and standard deviation $\sigma(i, j)$ and calculated a window size of $b \times b$. The threshold T is denoted as: $T(i,j) = m(i, j) + k \cdot \sigma(i, j)$.

Here, k is a constant, which determines how much of the total print object edge is retained, and has a value between 0 and 1. The value of k and the size of the sliding window define the quality of binarization. Binarization gives thick and unclear strokes with a small k value, and slim and broken strokes with a large k value. As for many applications, a 25×25 size for the sliding window and 0.6 as the value of k have been found to be heuristically optimal. The size of the neighborhood should be small enough to reflect the local illumination level and large enough to include both objects and the background.

The method proposed by Sauvola et al. [13] is local-variance-based method. It is an improvement on the method proposed by Niblack [14], especially when the background contains light texture, big variations, stained and badly and unevenly illuminated documents. It adapts the contribution of the standard deviation. For example, in the case of text on a dirty or stained paper, the threshold is lowered. The threshold is calculated as follows:

$$T(i, j) = m(i, j) * \left[1 + k\left(\frac{\sigma(i,j)}{R} - 1\right)\right]$$

The typical values of $k = 0.5$ and $R = 128$ are suggested. Here, m and σ are again the mean and standard deviation of the whole window, and k is a fixed value. It was found that the value of R has a very small effect on the quality while the values of k and window size affect it significantly. The smaller the value of k, the thicker is the binarized stroke, and the more overlap exists between characters. A smaller window size will produce thinner strokes. An optimal combination of k and the sliding window will produce a good binary image.

Local adaptive method proposed by Bernsen [9] is based on contrast of an image. The threshold is set at the midrange value, which is the mean of the minimum $I_{\text{low}}(i, j)$ and maximum $I_{\text{high}}(i, j)$ gray values in a local window of suggested size $w = 31$. However, if the contrast $C(i, j) = I_{\text{high}}(i, j) - I_{\text{low}}(i, j)$ is below a certain contrast threshold k, the pixels within the window may be set to background or to foreground according to the class that most suitably describes the window. This algorithm is dependent on the value of k and also on the size of the window. $T(i, j) = 0.5\ \{\max_w[I(i + m, j + n)] + \min_w[I(i + m, j + n)]\}$, where $w = 31$, provided contrast $C(i, j) = I_{\text{high}}(i, j) - I_{\text{low}}(i, j) \geq 15$.

The method proposed by Kapur et al. [12] is an entropy-based method which considers the image foreground and background as two different signal sources, so that when the sum of the two class entropies reaches its maximum, the image is said to be under optimal thresholding.

In this method, two probability distributions (e.g., object distribution and background distribution) are derived from the original gray-level distribution of the image as follows:

$$\frac{p_0}{P_t}, \frac{p_1}{P_t}, \ldots \frac{p_t}{P_t} \quad \text{and} \quad \frac{p_{t+1}}{1-P_t}, \frac{p_{t+2}}{1-P_t}, \ldots \frac{p_l}{1-P_t}$$

where$t$ is the value of threshold and $P_t = \sum_{i=0}^{t} p_i$

$$H_b(t) = -\sum_{i=0}^{t} \frac{p_i}{P_t} \log_e \left(\frac{p_i}{P_t}\right) \quad \text{and} \quad H_w(t) = -\sum_{i=t+1}^{l} \frac{p_i}{1-P_t} \log_e \left(\frac{p_i}{1-P_t}\right)$$

The optimal threshold t^* is defined as the gray level which maximizes $H_b(t) + H_w(t)$, i.e. $t^* = \arg\mathrm{Max}\{H_b(t) + H_w(t)\}$ for all t belonging to the set of all gray values in the image.

Thresholding can be considered as a classification problem. If the gray-level distributions of the foreground object and background pixels are known or can be estimated, then the optimal, minimum error threshold can be obtained using statistical decision theory. This involves lots of computation. Therefore, it is realistic to assume that the respective populations are distributed normally with distinct means and standard deviations. Under this assumption, the parameters of the population can be inferred from the gray-level histogram by fitting. Afterward, the corresponding optimal threshold can be determined. A computationally efficient solution to the problem of minimum error thresholding has been derived by Kittler et al. [15] under the assumption of foreground object and background pixel gray-level values being normally distributed. The principal idea behind the method is to optimize the average pixel classification error rate directly, using either an exhaustive search or an iterative algorithm. The method is applicable in multi-threshold selection.

$$p(g) = \sum_{i=1}^{2} P_i p(g|i), \quad \text{where, } p(g|i) = \frac{1}{\sqrt{2\Pi}\sigma_i} \exp\left(1 - \frac{(g-\mu_i)}{2\sigma_i^2}\right).$$

The threshold value can be selected by solving the quadratic equation

$$\frac{(g-\mu_1)^2}{\sigma_1^2} + \log_e \sigma_1^2 - 2\log_e P_1 = \frac{(g-\mu_2)^2}{\sigma_2^2} + \log_e \sigma_2^2 - 2\log_e P_2$$

However, the parameters $\mu_{i,}\sigma_i^2$ and $P_i (i = 1, 2)$ of the mixture density $p(g)$ associated with an image for thresholding are not usually known. In order to overcome the difficulty of estimating these unknown parameters, Kittler et al. introduced a criterion function $J(t)$ given by

$$\begin{aligned} J(t) = 1 + 2\big\{P_1(t)\log_e \sigma_1(t) + P_2(t)\log_e \sigma_2(t)\big\} \\ - 2\big\{P_1(t)\log_e P_1(t) + P_2(t)\log_e P_2(t)\big\} \end{aligned}$$

where

$$P_1(t) = \sum_{g=0}^{t} h(g), \quad P_2(t) = \sum_{g=t+1}^{l} h(g)$$

$$\mu_1(t) = \frac{\left\{\sum_{g=0}^{t} h(g)g\right\}}{P_1(t)}, \quad \mu_2(t) = \frac{\left\{\sum_{g=t+1}^{l} h(g)g\right\}}{P_2(t)},$$

$$\sigma_1^2(t) = \frac{\left\{\sum_{g=0}^{t} (g-\mu_1(t))^2 h(g)\right\}}{P_1(t)}, \quad \sigma_2^2(t) = \frac{\left\{\sum_{g=t+1}^{l} (g-\mu_2(t))^2 h(g)\right\}}{P_2(t)}.$$

The optimal threshold is obtained by minimizing $J(t)$, i.e., by finding $t^* = \arg\mathrm{Min}\{J(t)\}$ for all gray levels t belonging to the image.

The method proposed by Johannsen et al. [11] uses the entropy of the gray-level histogram of the digital image as a measure of information. Essentially, it divides the set of gray levels into two parts so as to minimize the interdependence between them. This method chooses the threshold value t^* from the relation, $t^* = \arg\mathrm{Min}\{S(t) + S'(t)\}$ for all possible gray levels t in the image. Here,

$$S(t) = \log_e\left(\sum_{i=0}^{t} p_i\right) - \frac{1}{\sum_{i=0}^{t} p_i}\left[p_t \log_e(p_t) + \left(\sum_{i=0}^{t-1} p_i\right)\log_e\left(\sum_{i=0}^{t-1} p_i\right)\right]$$

$$S'(t) = \log_e\left(\sum_{i=t}^{l-1} p_i\right) - \frac{1}{\sum_{i=t}^{l-1} p_i}\left[p_t \log_e(p_t) + \left(\sum_{i=t+1}^{l-1} p_i\right)\log_e\left(\sum_{i=t+1}^{l-1} p_i\right)\right]$$

A technique for determining a threshold for binarization of an image is presented in [16]. The method follows an iterative process and assumes that the image contains an object and background occupying different average gray levels. The iterative method provides a simple automatic selection of the optimum threshold. Assuming an object is located within a square region of the image; without any prior knowledge of the exact location of the objects, it is considered as a first approximation that the four corners of the scene contain only background pixels and the remainder contains the object. Thresholding is done to come up with a path image. This patch may then be used as a switching function $f(s)$ to route a digitized image into one of two integrators.

In [17] a multi-scale binarization, framework is introduced, which can be used along with any adaptive threshold-based binarization method. This framework is able to improve the binarization results and to restore weak connections and strokes, especially in the case of degraded historical documents. The framework requires several binarization methods on different scales, which is addressed by introduction of fast grid-based models. This enables to explore high scales which are usually unreachable to the traditional approaches. In order to expand the set of adaptive methods, an adaptive modification of Otsu's method, called AdOtsu, is introduced. In addition, in order to restore document images suffering from bleed-through degradation, the authors combine the framework with recursive adaptive methods. The framework shows promising performance in subjective and objective evaluations performed on available datasets.

An automatic histogram threshold approach based on a fuzziness measure is presented in [18]. Using the concepts of fuzzy logic, the problems involved in finding the minimum of a criterion function are avoided. Similarity between gray levels is the key to find an optimal threshold. Two initial regions of gray levels are defined at the boundaries of the histogram. After that using an index of fuzziness, a similarity process is started to find the threshold point. A significant contrast between objects and background is assumed. Histogram equalization is used in images having small contrast difference.

Paper [19] presents an adaptive algorithm for efficient document image binarization with low computational complexity and high performance. This is particularly suitable for use in portable devices such as PDA, mobile phones which are marked by their limited memory space and low computational capability. This method divides the document image into several blocks by integrating the concept of global and local methods. After that a threshold surface is constructed based on the diversity and the intensity of each region to derive the binary image. Experimental results show the effectiveness of the proposed method.

A binarization method is presented in [20] based on edge information for video text images. It attempts to handle images with complex background with low contrast. The contour of the text is detected, after that local thresholding method is used to look for the inner side of the contour; subsequently, the contours of the characters are filled up to form characters that are recognizable to OCR software.

A new document image binarization technique is presented in [21], as an improved version of the adaptive logical-level technique (ALLT). The original ALLT makes use of fixed windows for extracting essential features (e.g., the character stroke width). However, there are possibilities of characters with several different stroke widths within a region. This may lead to erroneous results. In [21], local adaptive binarization is used as a guide to adaptive stroke width detection. The skeleton and the contour points of the binarization output are combined to identify the stroke width locally. In addition, an adaptive local parameter is defined that enhances the characters and improves the overall performance achieving more accurate binarization results for both handwritten and printed documents with a particular focus on degraded historical documents.

In [22], the authors proposed a new technique for the validation of document binarization algorithms. Authors claim that the proposed method is simple in its implementation and can be performed on any binarization algorithm since it does not require anything more than the binarization stage. As a demonstration of the proposed technique, we use the case of degraded historical documents. The proposed technique is evaluated with 30 binarization algorithms for performance comparison.

Images with two dominant intensity levels are subjected to manual thresholding a ease. For automatic image thresholding, most of the effective techniques are either too complex or too eager of computer resources.

The balanced histogram thresholding method [23] is a very simple method used for automatic image thresholding. Like Otsu's method [8], this is a histogram-based thresholding method. Assuming that the image is divided into two main classes: the background and the foreground, this method tries to find the optimum threshold level that divides the histogram in two classes. This method weighs the histogram, checks which of the two sides is heavier, and removes weight from the heavier side until it becomes the lighter. It repeats the same operation until the edges of the weighing scale meet. This method may have problems when dealing with very noisy images, because the weighing scale may be misplaced. The problem can be minimized by ignoring the extremities of the histogram.

Evaluation of document image binarization techniques is a tedious task that is mainly performed by human experts or by involving an OCR engine. Paper [24] presents a methodology for objective evaluation of document image binarization algorithms. The methodology aims at reducing the human interference in the construction of the ground truth and testing. A skeletonized ground truth image is created by the user following a semiautomatic procedure. The estimated ground truth image can aid in evaluating the binarization result in terms of recall and precision as well as to further analyze the result by calculating broken and missing text, deformations, and false alarms.

Paper [25] presents a real-time adaptive using the integral image of the input. The technique proposed is robust to illumination changes in the image suitable for processing live video streams at a real-time frame-rate which makes it suitable for the interactive applications.

2.2 Recent Works

In Sect. 2.1, we have discussed the broad area of our research by citing some of the most significant works that have shaped the evolution in the relevant areas. In this section, the state-of-the-art for image binarization methods is discussed for all the areas considered in this work.

Binarization is an essential step for document image analysis. In general, different available binarization techniques are implemented for different types of binarization problems.

In [26], a learning framework for the optimization of the binarization methods is introduced, which is designed to determine the optimal parameter values for a document image. The framework works with any binarization method performs three main steps: extracts features, estimates optimal parameters, and learns the relationship between features and optimal parameters. An approach is proposed to generate numerical feature vectors from 2D data. The statistics of various maps are extracted and then combined into a final feature vector, in a nonlinear way. The optimal behavior is learned using support vector regression (SVR). The experiments are done using grid-based Sauvola's method and Lu's method on the DIBCO2009 and DIBCO2010 datasets.

A pixel-based binarization evaluation methodology for historical handwritten/machine-printed document images is presented in [3]. In the evaluation scheme in [3], the recall and precision evaluation measures are properly modified using a weighting scheme that diminishes any potential evaluation bias. Additional performance metrics of the proposed evaluation scheme consist of the percentage rates of broken and missed text, false alarms, background noise, character enlargement, and merging. The validity of the method is justified by several experiments conducted in comparison with other pixel-based evaluation measures.

An image binarization technique is proposed in [27] for degraded document images that takes into consideration the adaptive image contrast. The adaptive image contrast is a combination of the local image contrast and the local image gradient that is tolerant to text and background variation caused by different types of document degradations. An adaptive contrast map is first constructed for an input-degraded document image. The contrast map is then binarized and combined with Canny's edge map to identify the text stroke edge pixels. The document text is further segmented by a local threshold that is estimated based on the intensities of detected text stroke edge pixels within a local window. It has been tested on three public datasets achieving accuracies of around 90 %.

There are many challenges addressed in handwritten document image binarization, such as faint characters, bleed-through, and large background ink stains. Usually, binarization methods cannot deal with all the degradation types effectively. Motivated by the low detection rate of faint characters in binarization of handwritten document images, a combination of a global and a local adaptive binarization method at connected component level is proposed in [4] that aims in an improved overall performance. Initially, background estimation is applied along with image normalization based on background compensation. Afterward, global binarization is performed on the normalized image. In the binarized image, very small components are discarded and representative characteristics of a document image such as the stroke width and the contrast are computed. Furthermore, local adaptive binarization is performed on the normalized image taking into account the aforementioned characteristics. Finally, the two binarization outputs are combined at connected component level. Authors report good performance after extensive testing on the DIBCO series datasets which include a variety of degraded handwritten document images.

An adaptive binarization method inspired by Otsu's method is introduced in [1]. The method, called AdOtsu, uses the estimated background (EB) as a priori information to differentiate between text and non-text regions. The estimated background values are calculated in a boot-strap process implicitly incorporating the proposed binarization method. Also, a priori structural information, including the average stroke width and the average text height, is used to adapt the method on the input document image and to make it parameter-less. The method is generalized to a multi-scale binarization, which enables it to separate interfering patterns from the true text using higher scales. Postprocessing corrections, both topological and clustering, are considered to improve the final output.

Paper [5] proposes another algorithm for the binarization of degraded document images. The image is mapped into a 2D feature space in which the text and background pixels are separable, and then this feature space is partitioned into small regions. These regions are labeled as text or background using the result of a basic binarization algorithm applied on the original image. Finally, each pixel of the image is classified as either text or background based on the label of its corresponding region in the feature space.

An adaptive binarization method for historical manuscripts and degraded document images is reported in [6]. The method is based on maximum likelihood (ML) classification using a priori information and the spatial relationship on the image domain. The method performs a decision of thresholding based on a probabilistic model. It recovers the main text in the document image, including low intensity and weak strokes from an initialization map (under-binarization) containing only the darkest part of the text. Fast and robust local estimation of text and background features is obtained using grid-based modeling and in-painting techniques; afterward, the ML classification is performed to classify pixels into two classes (black and white). This method preserves weak connections and provides smooth and continuous strokes due to its correlation-based nature. Performance is evaluated both subjectively and objectively against standard databases. The method produces competitive results with state-of-the-art methods presented in the DIBCO2009 binarization contest.

The majority of binarization techniques are complex and are compounded from filters and existing operations. However, the few simple thresholding methods available cannot be applied to many binarization problems. In [7], a local binarization method is presented based on a simple, novel thresholding method with dynamic and flexible windows. The method is tested on selected samples of DIBCO 2009 benchmark dataset.

An adaptive water flow model for the binarization of degraded document images is presented in [28]. In this approach, the image surface is regarded as a three-dimensional terrain and water is poured on it. The water finds the valleys and fills them. The algorithm controls the rainfall process, pouring the water, in such a way that the water fills up to half of the valley depth. After stopping the rainfall, each wet region represents one character or a noisy component. To segment each character, the wet regions are labeled and regarded as blobs. Some of the blobs represent noisy components. A multilayer perceptron is trained to label each blob as either text or non-text. The algorithm is shown to preserve stroke connectivity. Experimental verification shows superior performance against six well-known algorithms on three sets of degraded document images with uneven illumination.

It is evident from the discussion in this chapter that there is a need of a binarization algorithm that would work well for both document and graphic images. In addition to this, we need a methodology for generating the reference image for quantitative evaluation among different image binarization methods. In Chap. 3 of this text, we have documented works that addresses these issues.

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