MVA2005 IAPR Conference on Machine VIsion Applications, May 16-18, 2005 Tsukuba Science City, Japan
8-8

Thresholding Based Detection of Fine and Sparse Details

A. Drobchenko, J. Vartiainen, J.-K. Kamarainen, L. Lensu, H. Kälviäinen
Laboratory of Information Processing,
Department of Information Technology,
Lappeenranta University of Technology,
P.O.Box 20, FI-53851 Lappeenranta, Finland,
{drobchen,vartiain,jkamarai,ltl,kalviai}@lut.fi

Abstract

This study concentrates on locating fine sparse details from images. A statistical model for fine and sparse details was developed for the histogram and spatial representation. In experiments, artificial data was generated by using the statistical model and several thresholding methods were compared. The result was verified by using real images from IGT picking paper printability assessment, where small paper surface defects must be detected. Based on the experiments with artificial data and real images, it seems that the minimum error thresholding by Kittler and Illingworth outperforms the other methods.

1 Introduction

Binary thresholding is one of the most commonly used, and essential operations in digital image processing. In many image processing applications, thresholding is used at some point of the algorithm. Although thresholding operation itself is simple, it remains as a very important research topic [6] because new problem characteristics are continuously encountered in practical problems.

Most of the existing methods perform well when the image foreground and background constitute areas of sufficiently equal sizes, and the gray-level values have substantially non-overlapping distributions [6]. However, when either or both of the assumptions are not met, major difficulties can be encountered. This is the case in this study where the motivation comes from a problem where small paper surface defects must be automatically detected [1]. One such application is IGT picking assessment, which is a *de facto* standard for paper printability (runnability) evaluation in paper and printing industry. The assessment is performed on test printed paper samples. Number of defects in test images is typically very small making their gray-level histograms almost unimodal. Additionally, gray-level values of both defects and surface overlap significantly. Spatial distribution of the defects can be considered as random, and thus, there is motivation to apply general adaptive thresholding methods for detection of such fine and sparse details in images.

In this study, the problem of adaptive thresholding to segment fine and sparse details is considered. To find the most suitable method for the given task, well-known and well-performing general adaptive thresholding methods and methods specialized to unimodal histograms were compared. Based on these experiments, it is our goal to build a machine vision system that will automate the defects detection from IGT samples.

This work has been financially supported by European Union in the PAPVISION project (National Technology Agency of Finland Project No. 70049/03 and 70056/04) and by Academy of Finland (Project 204708)

2 Fine and sparse details on non-textured noisy background

Motivations and possible application areas for methods to detect fine and sparse details are explained first. In this particular case, the problem was to automatically perform the visual assessment of IGT picking samples. An IGT picking device prints a test pattern on a paper or a board sample. The number of visible defects, e.g., fiber puffing or coating tearing, provide information about printing properties of a particular paper type (printability and runnability) [1]. To acquire image data, strips of paper and board are digitally photographed under oblique lighting (Fig. 1) [1].

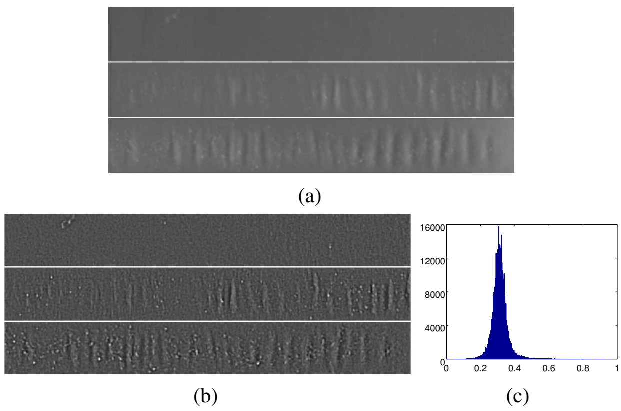


Figure 1: (a) IGT sample (coated board); (b) after preprocessing. Images (a) and (b) are divided into 3 pieces from top to bottom for better presentation; (b) gray-level histogram of preprocessed sample.

In Fig. 1(a), the defects are not clearly visible, and the imaging suffers from distortions characteristic to board strips (e.g., curliness) and therefore it is necessary to enhance the original image by convolving a spot detector. The enhanced image can be seen in Fig. 1(b). The histogram of the enhanced image (Fig. 1(c)) is still unimodal thus making it hard to find a suitable threshold which separate small defects. Defects in the enhanced image appear as tiny spots having higher intensity than the surrounding non-textured noisy background.

For further processing, however, a suitable threshold value at which defects on paper surface begin to appear in the foreground must be selected. Based on a set of test samples, it was found out that the proportion of pixels representing defects was 0.5-3.0% of total imaging area, and they partly shared intensity values with background pixels. Thus, the background and foreground are scrambled into a nearly unimodal gray-level histogram making the selection of threshold value a very difficult problem.

The nature of the defects, and their presence in the given problem motivated us to introduce the notion of *fine and sparse defects*. It should be noted that the words details and defects are used interchangeably in this study. The fine and sparse defects are small (fine) and isolated (sparse) signal patches comprising only a minority of the total image size. Their intensities are close to or mixed with the background intensity range. To study the problem analytically, a statistical model of sparse defects was prepared first. Based on this statistical model, artificial data were generated for method comparisons, and a suitable thresholding method was selected. It was also necessary to visualize the statistical model to assure that the artificial data corresponds to the real data.

2.1 Model for fine and sparse details

If spatial relationships are neglected, image pixels can be considered as realizations of a random variable. For a sufficiently large image, it's gray-level histogram corresponds to a probability density function of the random variable. In this case, it is sufficient to model the probability density function (pdf) to model the fine and sparse details.

The noisy background can be modeled with a single probability density function, and foreground defects can be treated by a set of probability density functions. Finally, the pdf for fine and sparse details consists of a weighted sum of pdfs for both the foreground and background.

Intensities of background pixels can be modeled by values of a random variable having the normal distribution $N(\mu_b, \sigma_b)$ with the mean value μ_b, and standard deviation σ_b. Defects appear randomly in the spatial domain. Thus, each defect can be modeled by a low probability (low a priori) random variable which adheres to the normal distribution

$$P_d(i)\frac{1}{\sqrt{2\pi}\sigma_d(i)}e^{\dfrac{-(x-\mu_d(i))^2}{2\sigma_d(i)^2}} \tag{1}$$

where $\mu_d(i)$ and $\sigma_d(i)$ denote the intensity mean value and standard deviation for the i-th defect, and $P_d(i)$ corresponds to the a priori probability to encounter the defect. However, since a single defect is highly localized (concentrated near to a single spatial location), the $P_d(i)$ corresponds to a proportional spatial size of the defect rather than a true a priori probability. Correspondingly, the proportional spatial size of the background is

$$P_b = 1 - \sum_i P_d(i)\ . \tag{2}$$

Now, the resulting histogram of fine and sparse defects on a non-textured noisy background depends solely on the set of parameters $\{\mu_b, \sigma_b, \mu_d(i), \sigma_d(i), P_d(i)\}$. Finally, the composite probability density function which defines the expected shape of the histogram is

$$f(x) = P_b\frac{1}{\sqrt{2\pi}\sigma_b}e^{\dfrac{-(x-\mu_b)^2}{2\sigma_b^2}} + \sum_i P_d(i)\frac{1}{\sqrt{2\pi}\sigma_d(i)}e^{\dfrac{-(x-\mu_d(i))^2}{2\sigma_d(i)^2}}\ . \tag{3}$$

To compare existing thresholding methods, different types of histograms of sparse defects can be generated by varying the parameters μ_b, σ_b, $\mu_d(i)$, $\sigma_d(i)$ and $P_d(i)$. One more consideration is the distribution of $\mu_d(i)$ and $\sigma_d(i)$. Probably the simplest class of sparse defects, which is actually similar to the ones encountered in picking images, has a uniform distribution $\mu_d(i) \sim U(a,b)$, and standard deviation $\sigma_d(i) \sim N(\mu_{\sigma_d}, \sigma_{\sigma_d})$. The only difference is, that in real picking samples the distribution of defects is not actually uniform because the defects start to appear at higher running speeds as the printer accelerates. This is not a problem when generating the model since global processing is used to detect the defects. This way it does not matter when the defects start in the model or how they are distributed.

2.2 Model visualization

For the visualization, a model in the spatial domain that corresponds to the model in the domain of gray-level histograms must be defined. First, the image background is generated using a random variable with the same distribution and parameters, μ_b and σ_b, as described. Next, the defects are randomly seeded on the noisy background. For each defect, the area is derived in accordance with the total image size and the proportional defect size $P_d(i)$. Finally, each defect area is altered with values of the corresponding random variable, $N(\mu_d(i), \sigma_d(i))$. To vary also the sizes of defects, the proportational area can be derived from $P_d(i) = N(\mu_{P_d}, \sigma_{P_d})$. It should be noted, however, that if a certain foreground/background ratio is required, the proportational sizes $P_d(i)$ must be normalized to achieve the requested ratio. Shapes of defects is generated randomly, but the defect shape does not matter since images are processed based on their gray-level statistics.

Now, using the histogram model and the visualisation method, artificial images with fine and sparse details can be generated. An example of an artificial image is shown in Fig. 2.

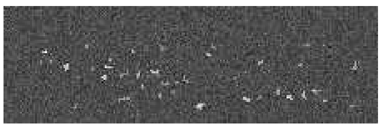


Figure 2: An artificial image ($\mu_b = 0.3$, $\sigma_b = 0.055$, $i = 1, \ldots, 100$, $\mu_{\sigma_d} = 0.01$, $\sigma_{\sigma_d} = 0.002$, foreground/background ratio $= 0.015$, $\mu_{P_d} = 5$, $\sigma_{P_d} = 3$).

3 Candidate thresholding methods

Image segmentation is an important step in image analysis for recognition of objects or details. The aim is to separate different objects from each other. Segmentation can be performed by using different gray-level thresholding techniques.

First, the most popular and well-performing general-purpose thresholding methods were applied, and secondly, two methods designed esspecially for unimodal histograms were studied.

3.1 General gray-level thresholding methods

General thresholding methods should perform well when (i) the foreground objects and background constitute proportionally same sizes in an image, and (ii) the gray-level values of objects and background possess substantially distant and non-overlapping distributions. When these restrictions can be met, one of the most popular methods is Otsu's method [4], and furthermore, methods by Kittler and Illingworth [3] and Kapur et al. [2] have been shown to outperform many others in comparisons [6]. Thus, these methods are good candidates as general thresholding methods for the given problem. Next, these three methods will be briefly reviewed.

3.1.1 Kittler's method

Kittler and Illingworth have proposed a thresholding algorithm which is based on optimizing a Bayesian rule cost function. In this method, it is assumed that the foreground and background class conditional probability density fuctions in an image are normally distributed. [3]

3.1.2 Otsu's method

Otsu's thresholding method is based on the idea of finding a threshold value that minimizes the within-class variance of resulting foreground and background classes [4]. Otsu's thresholding is one of the most widely used and cited threshold estimation method.

3.1.3 Kapur's method

A thresholding method based on entropy has been proposed by Kapur et al. The method maximises class entropies, which can be interpreted as measures of class compactness and separability. When the sum of the two class entropies reaches maximum the image is said to be optimally thresholded. [2]

3.2 Unimodal histogram thresholding methods

Unimodal distributions are typically obtained when an image consists mostly of large background area with small, but significant foreground regions. The thresholding is more difficult the more similar the objects and the background gray-level values are, as is the case in fine and sparse details. Next, two unimodal thresholding methods are briefly reviewed.

3.2.1 Tsai's method

Tsai has introduced two similar approaches to image thresholding using smoothed histograms [7]. The first approach looks for peaks and valleys in the histogram smoothed with a Gaussian kernel. The smoothing level is adjusted to make the smoothed histogram to contain exactly the same number of peaks as the desired number of thresholding levels. The valleys between the peaks are selected as the threshold values. In the case where the number of peaks is less than the desired number after using the smallest possible Gaussian kernel for smoothing, additional threshold values are selected as the maximums of curvature of the histogram.

The second approach utilizing curvature is intended especially for unimodal histograms, and represents a custom case of the first approach. In the case where only one peak can be found in a histogram, the threshold value is selected as intensity value at which the histogram reaches its maximum curvature.

3.2.2 Rosin's method

Rosin's thresholding is another method for the bilevel thresholding in the case of unimodal histograms [5]. The method assumes that there is one dominant population in the image that produces one main peak located at the lower end of the gray-level histogram relative to the second population. A straight line is drawn from the highest bin in the histogram to the high end of the histogram. High end means that the line finishes at the first empty bin following the last filled bin, a threshold point is selected as a histogram index that maximises the perpendicular distance between the line and the point in the gray-level histogram.

This method lacks intuitive motivation. The theoretical mathematical analysis shows that the method is almost insensitive to foreground pixels, and it actually determines the threshold value using only information about the dominating background [5].

4 Experiments

The experiments were conducted using both artificial data derived from the statistical model and real data of IGT picking images. Using the artificial data, it was possible to produce quantitative results by computing proportions of details not detected, and falsely detected background. For the real data, the comparison was done by visually comparing the result images.

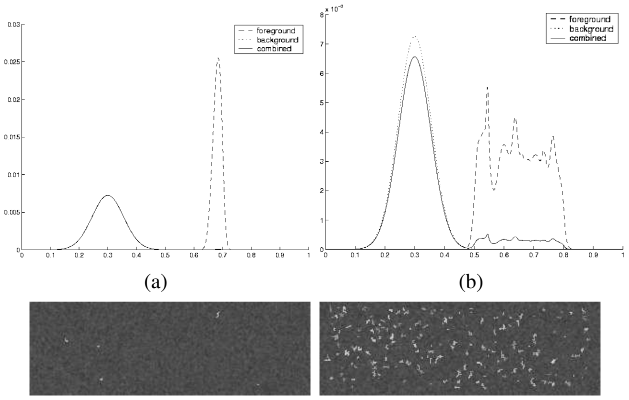
4.1 Artificial data derived from the model

With artificial data generated from the model in Section 2.1, it was possible to evaluate how methods would perform in separating details from background. Since the distributions of both foreground and background were known, it was possible to calculate proportions of both distributions that fall into the incorrect side of a given threshold value. The proportions were computed as functions of the foreground/background ratio which was selected to correspond to the ratios of IGT picking images ($0.1\% - 5.0\%$).

The statistical model parameters used in the experiment were $\mu_b = 0.30$, $\sigma_b = 0.055$, $i = 1, \ldots, 50$, $\mu_d(i) \sim U(0.50, 0.80)$, $\sigma_d(i) = N(\mu_{\sigma_d}, \sigma_{\sigma_d}) = N(0.01, 0.002)$, Examples of artificial histograms and images for two extreme foreground/background ratios are shown in Fig. 3. In Figs. 3(a) and 3(c) the number of defects was 5 and in Figs. 3(b) and 3(d) number of defects was 200.

4.2 Results for different methods

With the artificial data, Otsu's method completely failed because it detected most of the background as foreground (Fig. 4(b)), and Kapur's method failed by missing a significant amount of foreground defects (Fig. 4(a)). Tsai's method performed well for small amounts of defects but became unstable when the foreground/background ratio approached to 0.05 (Figs. 4(a) and 4(b)). The selection between Kittler's method and Rosin's method would depend on whether a large number of correct detections (sensitivity), or a small number of false detections (selectivity) is

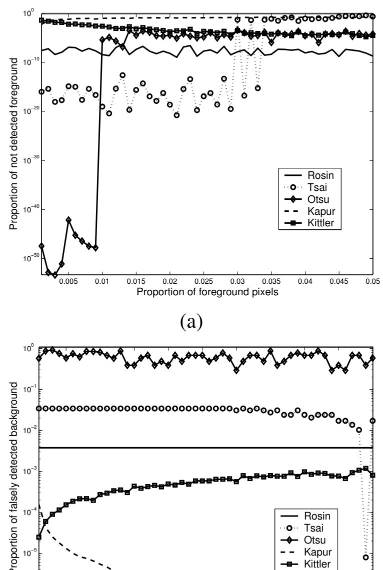


(a) (b)

(c) (d)

Figure 3: Model-generated histograms and the corresponding artificial images: (a),(c) Foreground/background ratio 0.001; (b),(d) 0.05.

preferred. In the latter case, which tends to be a more beneficial for this application, Kittler's method should be used. Kittler's method is a general thresholding method, but it seems to work also with nearly unimodal histograms.



(a)

(b)

Figure 4: Detection results for artificial data: (a) proportion of not detected foreground pixels, and (b) proportion of falsely detected background pixels.

In the second experiment, a set of 22 IGT picking images were used to test the candidate methods. As a preceding step to thresholding, image enhancement was applied to the image. In Fig. 5 are shown an IGT picking image, its enhanced version, and the images obtained by using the thresholding methods. Validation of results was based on visual inspection of sample images. Thresholding results were comparable with the results obtained when the methods were used to threshold artificial data. Kittler's method seemed to work well with the real data also.

5 Conclusions

In this study a model for images with fine and sparse details was given. The model was based on the statistics in the image gray-level histogram domain. Artificial data were derived from the model and several well-known and widely used thresholding methods were studied to experimentally evaluate which methods are the most promising to be used in the detection of fine and sparse details.

The proposed model was aimed to explain characteristics of the real problem where surface defects must be detected from digital images taken from IGT picking assessment samples. Based on the conducted experiments, Kittler's and Illingworth's minimum error thresholding was selected as the most suitable method for the given task.

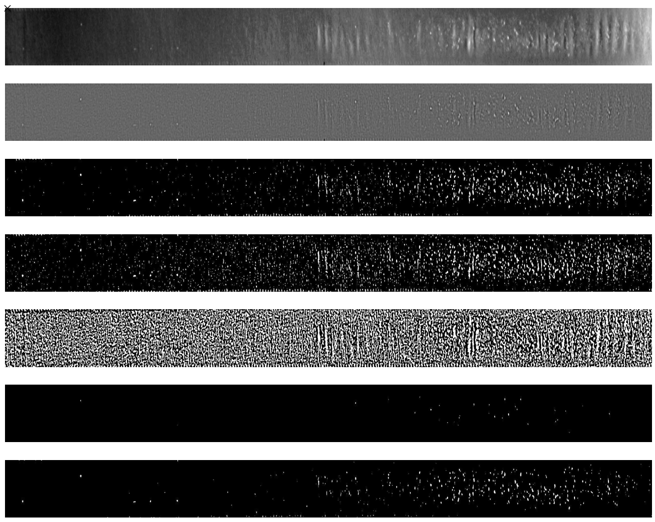


Figure 5: Example of IGT picking image, and the thresholding results. Images from the top are the original image (top), enhanced image, result after Rosin's, Tsai's, Otsu's, Kapur's, and Kittler's method (bottom).

References

[1] Alexander Drobchenko. Automated picking assessment using machine vision. Master's thesis, Lappeenranta University of Technology, 2004.

[2] J.N. Kapur, P.K. Sahoo, and A.K.C. Wong. A new method for gray-level picture thresholding using the entropy of the histogram. *Computer Vision Graphics and Image Processing*, 29:273–285, 1985.

[3] J. Kittler and J. Illingworth. Minimum error thresholding. *Pattern Recognition*, 19:41–47, 1986.

[4] N. Otsu. A threshold selection method from gray-level histograms. *IEEE Transactions on Systems, Man, and Cybernetics*, 9(1):62–66, 1979.

[5] P.L. Rosin. Unimodal thresholding. *Pattern Recognition*, 34(11):2083–2096, 2001.

[6] M. Sezgin and B. Sankur. Survey over image thresholding techniques and quantitative performance evaluation. *Journal of Electronical Imaging*, 13(1):146–165, 2004.

[7] Du-Ming Tsai. A fast thresholding selection procedure for multimodal and unimodal histograms. *Pattern Recognition Letters*, 16:653–666, 1995.