Teeth Segmentation on Dental Panoramic Radiographs Using Decimation-Free Directional Filter Bank Thresholding and Multistage Adaptive Thresholding

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***Abstract*— Dental utilization typically associated with tooth shape features which are extracted from dental panoramic radiograph image. However, because dental panoramic radiograph images usually have low contrast, we need a segmentation method that can work well on low contrast images and make the tooth shape is evident. In this paper, we propose a system to do teeth segmentation using Decimation-Free Directional Filter Bank Thresholding (DDFBT) and Multistage Adaptive Thresholding (MAT). The system is built with three main steps, which are formation of vertical and horizontal directional images using DDFBT, enhancement on directional images for teeth edge reinforcement and noise removal, and segmentation using MAT with Sauvola Local Thresholding. The experimental result on 40 teeth images shows that this system has a better performance than Otsu Thresholding, Sauvola Local Thresholding, and MAT with Niblack Local Thresholding with misclassification error (ME) and relative foreground area error (RAE) values are 17.0% and 9.7%.**

Keywords—Decimation-Free Directional Filter Bank Thresholding, dental panoramic radiograph, directional filtering, Multistage Adaptive Thresholding, Sauvola Local Thresholding

I. INTRODUCTION

The teeth is the most resilient and durable part of skeleton. It plays an important role on Forensic Medicine because it can be used for identification of badly burned, traumatized, decomposed, and skeletonised remains [1]. Furthermore, dental panoramic radiographs can also be used to do age estimation and detection of certain disease [2]. There have been many algorithms which are developed to accommodate those needs. Those algorithms are using features which are extracted from dental panoramic radiograph image, such as tooth shape features. To extract tooth shape features from dental panoramic radiographs, there are prior processes that needed to be done on the image. Those processes include the image enhancement and segmentation. Segmentation is performed to separate the object (foreground), which in this case is the teeth, from its background.

In general, the image segmentation process uses global thresholding method, e.g. Otsu Thresholding. However, because dental panoramic radiograph images usually have a low contrast, segmentation with global thresholding method usually has unsatisfactory results. Meanwhile, if using local thresholding method, the low contrast can lead to an over segmentation [3]. So we need a segmentation method that using both advantages of global and local thresholding. Multistage Adaptive Thresholding (MAT) is a segmentation method that use two global thresholds and statistic information which is gained from local thresholding process. So this segmentation method can not only use the advantages from local thresholding, but also prevent from over segmentation because there is global image information which is provided by global thresholding process [3].

To obtain good segmentation results, image quality should be enhanced first. Image enhancement processes are including noise removal, contrast enhancement, and edge reinforcement. Because of the features that are often taken from the teeth image usually associated with tooth shape, image enhancement that will be done should highlight the shape of the teeth.

Most of the teeth images have two dominant directions, which are vertical and horizontal, so that the edges of the teeth are mostly consisted of those two directions. Vertical edges mark the vertical border of the teeth. Horizontal edges mark the horizontal border of the teeth and the horizontal border of the gum. Because the purpose of segmentation process is to separate the teeth with its background, such as the gum, we need to do different enhancement scheme for vertical and horizontal edges so that we can reinforce the edges of the teeth without reinforce the edges of the background.

To separate the vertical edges with the horizontal edges, we can use directional filtering, which is extracted the edges in image based on their direction in its spectrum frequency [4]. The relationship between the presence of an edge in an image and its contribution to its spectrum frequency is used in directional filtering method to extract directional information in an image. There are several directional filtering methods, i.e. Directional Filter Bank (DFB), Decimation-Free Directional Filter Bank (DDFB), and Non-Uniform Decimation-Free Directional Filter Bank (NUDDFB) [5]. DFB and DDFB separate images into four fixed directions, while NUDDFB separate images into several directions adaptively [5]. However, two dominant directions on teeth images can be separated using NUDDFB with segmentation principal.

In this paper we proposed a new method for the teeth segmentation on dental panoramic radiographs, based on NUDDFB. We call this method as Decimation-Free Directional Filter Bank Thresholding (DDFBT) and combine it with Multistage Adaptive Thresholding (MAT) to get a better segmentation result. DDFBT has an important advantage compared with other directional filtering methods, that DDFBT is adaptive to the input images. It can make two directional filters with various size, depend on the spectrum frequency of input image, to create vertical dan horizontal directional images.

II. Literature Review

A. Non-Uniform Decimation-Free Directional Filter Bank

In 1992, one of directional filtering methods, called Directional Filter Bank (DFB), was introduced by Bamberger and Smith [7]. Bamberger's DFB also has decimation process to provide compression effect which can make the result maximally decimated but still allows the original image to be exactly reconstructed. In 2005, Khan et al. introduced new DFB without decimation process for enhancement purpose which is called as Decimation-Free Directional Filter Bank (DDFB) [5]. Khan said that decimation process in Bamberger's DFB uses interpolation that can produce false artifact in the output image, so that it is not suitable to be used in enhancement of medical image.

However, DDFB can not give an adaptive directional decomposition based on each input image. It gives fixed uniform portion frequency in every filter in each stage for every input image, so that Jawas et al. introduced Non-Uniform Decimation-Free Directional Filtering (NUDDFB) in 2014. NUDDFB using Histogram Cluster Analysis to create non-uniform filter bank to separate input images into several directional images adaptively, depends on the spectrum of input image [5].

B. Multistage Adaptive Thresholding

In 2005, Yan et al. proposed a new method to do two-level thresholding, or binarization, which was called as Multistage Adaptive Thresholding (MAT) method. This method combines global and local thresholding method to take advantages from both thresholding methods.

MAT based on both the global intensity distribution and local image statistics within a variable neighborhood [3]. Global intensity distribution can be obtained using Multilevel Otsu Thresholding, or using percentile. And the local image statistics are obtained using Niblack Local Thresholding method. From the experiment, MAT is capable of thresholding images that have been degraded from noise and poor illumination. MAT in general can be used on the other type of images with superior performance [3].

C. Sauvola Local Thresholding

Sauvola Local Thresholding method was introduced in 2000 and firstly used for text binarization. This method is the modified version of Niblack Local Thresholding method. Niblack's method does not work well for cases in which the background contains light textures as the gray values of these unwanted details exceed the threshold values.

Sauvola Local Thresholding amplifying the contribution of local standard deviation in an adaptive manner so that it gives a good adaptation into different defect types such as illumination, noise, and resolution changes. This method showed a robust behavior in most situations in degradation and performed well against the comparison techniques, such as Niblack, Bernsen, Eikvil, and Parker algorithm [6].

III. Proposed Method

There are three main steps in this system that is shown in Figure 1. The steps are formation of directional images, enhancement of directional images, and segmentation.

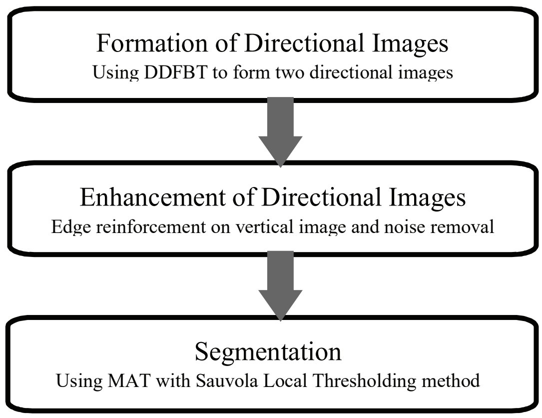


Figure 1. Main steps of the system.

A. Formation of Directional Images

The aim of this step is to decompose input image, which is teeth image, into two directional images so that enhancement process on the next step can be done to specific edge direction. We use Decimation-Free Directional Filter Bank Thresholding (DDFBT) method because it can make vertical and horizontal directional filters which have various size, depend on the spectrum frequency of input image.

Directional filtering use the relationship between presence of an edge in an image and its contribution to image spectrum frequency. An edge introduces in the spectrum high spatial frequencies along the direction which is orthogonal to its own direction [5]. In frequency domain image, a line from the center of the image to the certain point on the outer side of the image is a representation of some edges with a certain direction in the input images. So if we want to get, for example, edges with horizontal direction, firstly we must group every edges on the input image based on their directions. The process is called creation of spectrum frequency histogram.

Secondly, we must determine which directions can we categorized as vertical direction and horizontal direction. Each input image has two different dominant directions. It could be an image has perpendicular horintal and vertical direction, while another image has a slightly tilted vertical and horizontal direction. The process to categorized the two directions is called histogram thresholding.

The last processes are creation of directional filter bank and directional filtering. So that in DDFBT there are four processes to be done, which are creation of spectrum frequency histogram, histogram thresholding, formation of directional filter bank, and directional filtering.

Creation of Spectrum Frequency Histogram

Firstly, the input image, that is grayscale image with size m x m pixels, is transformed to frequency domain using 2D Fast Fourier Transform, which are shown in Figure 2(a) and Figure 2(b). And then the spectrum frequency is mapped radially to form a histogram in Cartesian diagram. This Cartesian diagram is analogized as a histogram which reaches 0 to 180 degrees of spectrum frequency which each bins shows the sum of grayscale value of pixels in spectrum image from the center of the spectrum image (m/2, m/2), straight to the outer point of the image in its direction. This mapping is done to the outer points of frequency domain image from coordinate (1, 1) until coordinate (1, m) to create bin 1 until m, and coordinate (2, m) until coordinate (m, m) to create bin (m+1) until (m+m) in histogram. This mapping is run clock-wisely from 0 to 180 degree and only done to the half of the image because the spectrum frequency on the other half is the repetition of the spectrum frequency on the first half of the image.

Histogram Thresholding

We separate the frequency domain image into vertical and horizontal directional images using between-cluster analysis introduced by Otsu (1979) by dividing the histogram into two clusters that its threshold value (t) is determined by the following equation

$$\sigma_b^2(t) = \omega_1(t)\,\omega_2(t)\,[\mu_1(t) - \mu_2(t)]^2 \qquad (1)$$

where $\sigma_b^2(t)$ is between-class variance, $\omega_i(t)$ is the probability of class i, and $\mu_i(t)$ is the mean of class i. We choose the optimal threshold value to divide the histogram into two cluster. If in the Otsu's method the clusters is related to background and object, in this DDFBT method the clusters is related to vertical and horizontal images, because in this method the thresholding is done to spectrum frequency histogram of the image, while in Otsu's method the thresholding is done to the gray level histogram of the image. The example of histogram of spectrum frequency with its threshold is shown in Figure 2(c).

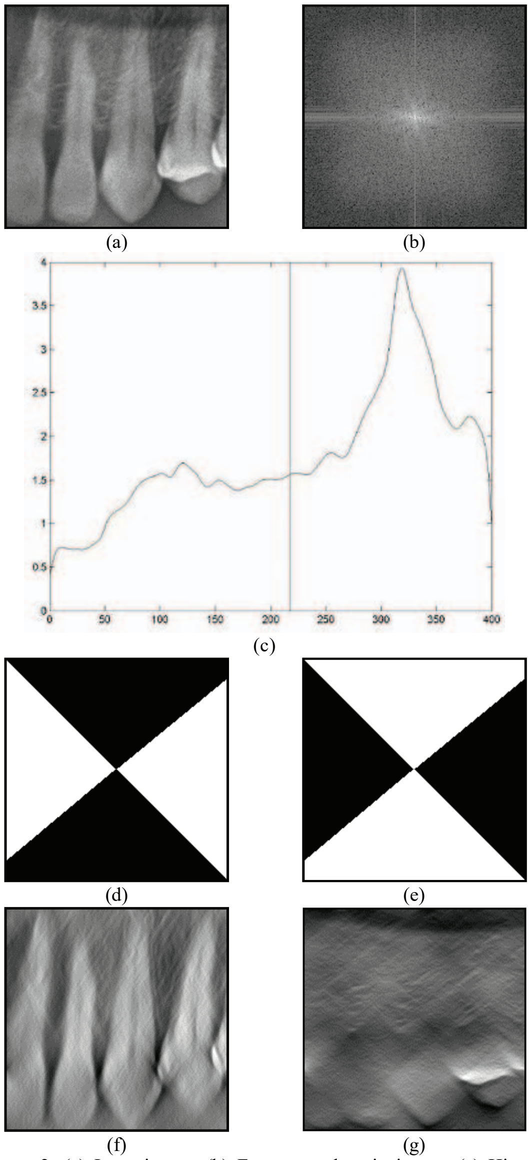


Figure 2. (a) Input image; (b) Frequency domain image; (c) Histogram of frequency domain image with its threshold; (d) Filter for first cluster; (e) Filter for second cluster; (f) Vertical directional image; (g) Horizontal directional image.

Formation of Directional Filter Bank

After get the threshold value (t) that divided the histogram into two clusters, two directional filters are made to create vertical and horizontal directional images. We created a black image (the values of all its pixels are 0) with size of frequency domain image. And then we created white lines from the center point of the black image to a certain outer point of the black image.

The outer points that used to create filter for vertical directional image are point with coordinate (t-m, m) until point with coordinate (m, m), and point with coordinate (1,1) until point with coordinate (m+m-t, m). The filter for horizontal directional image is created by doing invers to the filter for the vertical directional images. The example of the filter for vertical and horizontal directional images are shown in Figure 2(d) and Figure 2(e).

Directional Filtering

We do a filtering process by multiplying the frequency domain image with the two filters which had been created. The filtered frequency domain images are transformed to the spatial domain using 2D Invers Fast Fourier Transform to get two directional images which have vertical and horizontal direction as shown in Figure 2(f) and Figure 2(g).

With DDFBT, we can get two directional images which is adaptive to its input image, because the directional filtering processes in DDFBT are using filters with various size. Otsu's method in histogram thresholding process defines the best threshold that will separate the vertical and horizontal images using frequency domain approachment.

After we get two directional images, we enhanced the images separately. The motivation of separating directional images is to consider proper enhancement scheme for a specific directional image. Enhancing in specific direction leads to well-separated appropriate objects. We consider that edge reinforcement using Laplacian operator to the vertical directional image will enhance the root of each tooth as described in section B.

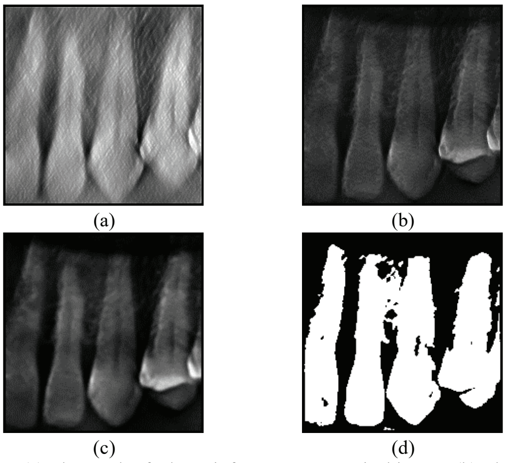


Figure 3. (a) The result of edge reinforcement at vertical image; (b) The result of unification of vertical and horizontal image; (c) The result of median and mean filtering; (d) The result of segmentation process.

B. *Enhancement of Directional Images*

One of the advantages using directional filtering in image enhancement process is that we can separate images into several directional images so that we can do specific enhancement scheme to each of the directional images, which can lead to a better segmentation result. Using DDFBT in the previous step, we get vertical and horizontal directional images, and we will do an edge reinforcement to the vertical directional image because the dominant edge direction at the teeth image is vertical. Edge reinforcement is done by a convolution with the Laplacian operator to the vertical image. The result of edge reinforcement on vertical image is shown in Figure 3(a). The advantage of Laplacian operator is this operator does not make an excessive edge thickening effect.

After that, the vertical directional image that had been convoluted is multiplied by the horizontal directional image to get back the horizontal edges of the teeth image. The result is teeth image with reinforced vertical edges as shown in Figure 3(b). And then, we do noise removal process using median filtering to remove outlier noises and mean filtering to remove Gaussian noises. The last result of this step is shown in Figure 3(c).

C. *Segmentation*

The enhanced teeth image, which is the result of the previous step, is segmented using Multistage Adaptive Thresholding (MAT) to separate the object, which in this case is the teeth, from its background. It was called 'multistage' because this method have two thresholding processes, those are global thresholding process to classified pixels which are too bright or too dark, and the local thresholding process to classified pixels which have not been classified by the global thresholding process.

Multilevel Otsu Thresholding

Firstly, we do multilevel thresholding that is thresholding process which use more than one threshold value. We use Multilevel Otsu Thresholding to determine two global thresholds, namely lower global threshold (t_1) and upper global threshold (t_2) using Equation 2

$$(\sigma_B')^2(t_1, t_2) = H(1, t_1) + H(t_1 + 1, t_2) + H(t_2 + 1, L) \qquad (2)$$

where $(\sigma_B')^2$ (t_1, t_2) is between-class variance of the three classes that are formed and H $(t_{i-1} + 1, t_i)$ is between-class variance of class which has graylevel value $t_{i-1} + 1$ until t_i. Pixels that have graylevel value less than lower global threshold will be classified as background and pixels that have graylevel value more than upper global threshold will be classified as object.

Sauvola Local Thresholding

After global thresholding, we do local thresholding using Sauvola Local Thresholding method towards pixels which have graylevel value between lower and upper global threshold by the following equation

$$t(x) = \mu_s(x)\left(1 + k\left(\frac{\sigma_s(x)}{R} - 1\right)\right) \qquad (3)$$

where μ_s (x) is the local mean of pixel x, σ_s (x) is the local standard deviation of pixel x, R is the maximal global standard deviation, and k is the ratio between the number of pixels which are classified as object and background.

To get value k, we do Otsu Thresholding, and then we calculate the ratio of pixels which are classified as background

(ρ). We assumed that value k has normal distribution so that it can be calculated using Equation 4.

$$k = \left(\left(\frac{x}{\mu} \right) - 1 \right) / \left(\frac{\sigma}{R} - 1 \right) \quad (4)$$

which x is the upper bound from Z-table which produce value ρ, μ is mean of normal distribution , σ is standard deviation of normal distribution, and R is maximum value of global standard deviation.

Local thresholding that we done is adaptive, which the size of neighborhood b will be increased with $0.5b$ if the local variance is less than two times of minimal global variance, because the neighborhood which local variance is less than two times of minimal global variance is regarded as noise. In this system, the optimal value of b is 3. After the local variance is greater than two times of minimal global variance, local mean and local standard deviation will be put in Equation 3 to do local thresholding with Sauvola method. The result of this step is teeth image that had been segmented as shown in Figure 3(d).

In local thresholding method, each pixel has a threshold value which can be different with another pixel, because the mean and the standard deviation of pixels are various. So that the advantage of local thresholding is we can classify a pixel based on its local image statistics. But in MAT, the local thresholding is limited by global image information, such as the lower and upper global threshold and the maximal global standard deviation (R) so that it will not lead to excessive segmentation, which is the problem of local thresholding methods.

IV. EXPERIMENTAL RESULT

A. Data

Input data that is used is the region of interest (ROI) which is image teeth from dataset dental panoramic radiograph. There are 40 ROIs with size of 200 x 200 pixels. Dental panoramic radiograph dataset is obtained from UNAIR Hospital with the patients's age are between 49 until 82 years old.

B. Experiment on Neigborhood Size Parameter

Neighborhood size b affects the result of adaptive local thresholding that is the part of segmentation process. We do an experiment to determine the optimal value of b with the values that be evaluated are 3, 5, 7, 9, and 15. From Table 1 appears that the most optimal value of b is 3. Furthermore, it appears that the smaller value of b, the segmentation performance result on low contrast images are also getting better.

The method used to measure the performance of the segmentation result is misclassification error (ME), which calculates the percentage of the number of pixels those are misclassified, and foreground area relative error (RAE), which shows the ratio between the area of the object on the segmented image with the ground truth image. The smaller the value of ME and RAE, the better the performance of the system. The example of input images with its ground truth images are shown in Figure 4 and Figure 5, while the example of the segmented images with b=3 are shown in Figure 6.

Table 1.
The comparison result of experiment on neighborhood size paremeter

Value of b	ME	RAE
3	**17.0 %**	**9.7 %**
5	17.8 %	10.1 %
7	18.4 %	10.7 %
9	18.8 %	11.1 %
15	19.4 %	12.2 %

Table 2.
The comparison result of experiment on convolution operator

Operator	ME	RAE
Sobel	19.2 %	9.7 %
Robert	17.5 %	10.4 %
Laplacian	**17.0 %**	**9.7 %**
Prewitt	18.3 %	11.0 %

Table 3.
The comparison result of segmentation methods

Method	ME	RAE
DDFBT and MAT - Sauvola	**17.0 %**	**9.7 %**
Otsu Thresholding	18.8 %	14.2 %
Sauvola Local Thresholding (b=40)	29.5 %	14.6 %
MAT - Niblack (b=3)	24.7 %	21.6 %

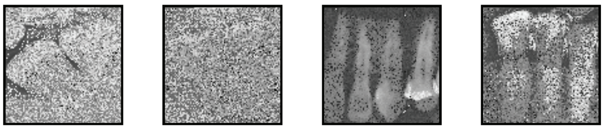
C. Experiment on Convolution Operator

In enhancement of directional images process, we do edge reinforcement to the vertical directional image by doing convolution using certain operator. We do an experiment to determine which operator will give the optimal segmentation performance result. From Table 2 appears that Laplacian operator give the optimal performance because convolution process using this operator does not provide edge thickening effect as Sobel and Prewitt operator. The example of the segmented images using Laplacian operator are shown in Figure 6.

D. Comparison With Another Segmentation Method

We do a comparison of performance result between this system (DDFBT and MAT – Sauvola) and another segmentation methods such as Otsu Thresholding, Sauvola Local Thresholding, and MAT with Niblack Local Thresholding (MAT – Niblack). Table 3 shows the comparison of performance results between those four methods, which the best result is given by this system (DDFBT and MAT – Sauvola) with the values of ME and RAE are 17.0% and 9.7%.

The example of segmented images using DDFBT and MAT – Sauvola method are shown in Figure 6, Figure 7, Figure 8, and Figure 9 respectively show the results of image segmentation using Otsu Thresholding method, Sauvola Local Thresholding method with the value of b=40, and MAT – Niblack method with the value of b=3.



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

Figure 4. The example of input images.

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

Figure 5. The example of ground truth images.

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

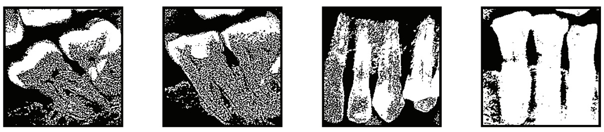
Figure 6. The example of segmentation results of the system using DDFBT and MAT – Sauvola with the value of b=3 and the operator used is Laplacian.

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

Figure 7. The example of segmentation results using Otsu Thresholding.

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

Figure 8. The example of segmentation results using Sauvola Local Thresholding method with the value of b=40.



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

Figure 9. The example of segmentation results using MAT with Niblack Local Thresholding (MAT – Niblack) method with the value of b=3.

V. CONCLUSION

Based on the results of experiment that had been conducted, Laplacian operator is used because it is not only gives the optimal performance result, but also convolution process using this operator does not provide edge thickening effect as Sobel and Prewitt operator. The optimal parameter of neighborhood size b to be used in this system is 3. Furthermore, result of experiment that had been conducted prove that the method of teeth segmentation on dental panoramic radiograph image using Decimation-Free Directional Filter Bank Thresholding (DDFBT) and Multistage Adaptive Thresholding (MAT) with Sauvola Local Thresholding gives a better performance result than Otsu Thresholding, Sauvola Local Thresholding, and MAT with Niblack Local Thresholding because it gives the lowest misclassification error (ME) value and relative foreground area error (RAE) value, which are 17.0% and 9.7%.

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VII. REFERENCES

[1] H. Shafer and Levy, Textbook of Oral Pathology (5thedn), 2006.

[2] S. I. Kvaal, K. M. Kolltveit, O. Thomsen and T. Solheim, "Age estimation of adults from dental radiographs," *Forensic Sci Int 74,* pp. 175-185, 1995.

[3] F. Yan, H. Zhang and R. Kube, "A Multistage Adaptive Thresholding," *Science Direct,* 2005.

[4] S. S. Al-amri, N. V. Kalyankar and Khamitkar, "Image Segmentation By Using Edge Detection," *Internal Journal on Computer Science and Engineering,* vol. 2, no. 3, pp. 804-807, 2010.

[5] N. Jawas, A. Z. Arifin, A. Y. Wijaya, A. Yuniarti and W. N. Khotimah, "Non-Uniform Decimation-Free Directional Filter Bank Using Histogram Analysis for Image Enhancement," in *International Conference on Information Communication Technology and Systems*, 2014.

[6] J. Sauvola and M. Pietikainen, "Adaptive Document Image Binarization," *The Journal of the Pattern Recognition Society,* vol. 33, no. Pattern Recognition, pp. 225-236, 2000.

[7] R. H. Bamberger and M. J. T. Smith, "A filter bank for the directional decomposition of images: theory and design," *IEEE,* vol. 40, no. Transactions on Signal Processing, pp. 882-893, April, 1992.

[8] N. Otsu, "A Threshold Selection Method from Gray-Level Histogram," *IEEE Transactions on Systems, Man, and Cybernetics,* pp. 62-66, 1979.

[9] P.-S. Liao, T.-S. Chen and P.-C. Chung, "A Fast Algorithm for Multilevel Thresholding," *Journal of Information Science and Engineering,* vol. 17, pp. 713-727, 2001.