Restoration of Degraded Historical Document Image: An Adaptive Multilayer-Information Binarization Technique

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Binary image is the essential format for document image processing, and the operation of the subsequent steps depends on the quality of the binarization process. The objective of this research is to propose a new binarization method based on adaptive multilayer-information for restoration of degraded historical document images. This paper focuses on degraded Thai historical document images, which are in the form of handwritten and machine-printed documents images. The proposed method consists of five stages including noise elimination, majority pixel analysis, degradation of the background layer estimation, thresholding and vicinity analysis. The experiments are performed on 480 degraded Thai historical document images provided by National Library of Thailand. The experimental results demonstrate that the proposed method performs better than five well-known adaptive binarization methods.

Keywords: binarization technique, adaptive thresholding, document image restoration, degraded Thai historical document, ground truth

1. INTRODUCTION

Historical documents are considered a significant source of national heritage and societal development. It is an essential feature of society and a reference to their culture, tradition and civilization [1, 2]. Preserving the historical documents can be considered as preserving the culture of the heritage [3]. Unfortunately, these historical documents confront with the physical degradation [4] caused a combination of factors such as temperature levels, environmental conditions and low quality paper.

The digital image database of historical documents is growing in the field of heritage studies. The work requires those images which are restored, enhanced and stored in a reasonable manner in order to simplify access and disseminate [5, 6]. In fact, the restoration and enhancement of degraded historical document images are considered a transformation process which concentrated to restore its original representation [7]. In addition, restoration and enhancement are desired to improve the results of subsequent segmentation and recognition [8].

Since the degraded historical document images are considered a combination of multilayer-information including the foreground (object) layer, background layer and the degraded layer. The image processing techniques can be applied to restore and enhance the quality of these degraded document images [9, 10]. In general, restoration of historical document images is divided into three steps: pre-processing, binarization and post-

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processing. Pre-processing step refers to the removal of noise on the image, binarization step relates to transform of gray-level image into binary image and post-processing step dedicates to enhance the quality of binary image. However, some researchers restore and enhance the document images without binarization techniques [11-14].

According to the aforementioned image processing techniques, the binarization methods play an important role in the document image restoration [15-20]. The binarization methods can be classified as global and local (adaptive) thresholding. A global thresholding, such as Otsu's [21], Kapur's [22] and Kittler's [23] methods, provide a single threshold to classify an image into foreground and background, while a local thresholding calculate an adaptive threshold value in local block. The block size must be small sufficient to indicate local details and large sufficient to eliminate noise. The optimal block size is influenced by the character size and density [13]. Bernsen's [24], Niblack's [25] and Sauvola's [26] methods are well-known local thresholding. The Bernsen's method calculates a local threshold by using maximum and minimum value of gray-level image in a local block. Let's $g(x, y)$ be a gray-level image, $\max(g(x, y))$ and $\min(g(x, y))$ be the maximum and minimum of the gray-level value of local block. The threshold of Bernsen's method defined as $T_{Ber}g(x, y)$ can be calculated by using the following formula:

$$T_{Ber}\, g(x, y) = 0.5 \cdot (\max(g(x, y)) + \min(g(x, y))) . \tag{1}$$

Whereas, Bernsen's method computes an adaptive threshold by using the maximum and minimum gray-level value of the local block, which will lead to a discrete threshold value problems. The Niblack's method calculates a local threshold by using the mean and standard deviation value of gray-level image in a local block. Let's $g(x, y)$ be a gray-level image, and $\mu(g(x, y))$ and $\sigma(g(x, y))$ be the average and standard deviation of gray-level values of $g(x, y)$. A variable "k" is used to adjust a ratio of foreground pixels particularly for edge of character. The threshold of Niblack's method defined as $T_{Nib}g(x, y)$ is computed by the following formula:

$$T_{Nib}\, g(x, y) = \mu(g(x, y)) + (k \cdot \sigma \cdot g(x, y)) . \tag{2}$$

In uneven illumination images, the Niblack's method usually generates poor quality result. Because of this, the Sauvola's method as an improved Niblack's method is proposed to solve this problem. A variable "r" is added to Niblack's formula to change behavior from static to dynamic range standard deviation. The threshold of Sauvola's method defined as $T_{Sau}g(x, y)$ is calculated by using the following formula:

$$T_{Sau}\, g(x, y) = \mu(g(x, y)) \cdot ((1-k) \cdot (1 - \frac{\sigma \cdot g(x, y)}{r})) . \tag{3}$$

In addition, Huang's [27] and Gatos's [28] methods are interesting methods that apply local thresholding to deal with uneven illumination and degraded document images. Huang's method separates an image into some non-overlapping blocks then applies existing Otsu's methods to binarize each block. This method is based on a pyramid data structure, and the block size is adaptively selected according to the Lorentz information measure.

Gatos's method tries to solve the problems on non-uniform illumination by using adaptive thresholding. At the beginning, Niblack's method is applied to estimate foreground regions, then background regions are estimated sequentially. The background regions estimation is guided by the value of the initial binary image. After the binarization process by using local thresholding, post-processing is performed to reduce noise and enhance the quality of text regions.

Moreover, some works try to binarize historical document and uneven illumination images. Nikolaos and Dimitrios [29] compare some classical thresholding methods and select Bernsen's method to binarize degraded document images. Tan and Chen [30] apply classical thresholding methods to verify license plate. First, the Otsu's method is used and if the binary image result is not sharp enough to extract important features, then Bernsen's and Niblack's methods are used respectively. Zhou *et al.* [31] select Laplacian-Gauss method related to estimating the foreground regions. Gangamma *et al.* [32] propose a novel method for document images enhancing which combines bilateral filter and mathematical morphology. Chou *et al.* [33] propose the method that divide an image into several regions and binarize each region by using the decision rules which derived from a learning process. Wen *et al.* [34] combine curvelet transform and Otsu's method to binarize the non-uniform illuminated images. Feng and Weide [35] propose an adaptive background strength compensation technique. Cheng [36] applies an iterative algorithm to go through single threshold segmentation on images. Valizadeh and Kabir [37] use feature spaced partitioning and classification to calculate a threshold. Zhang *et al.* [38] propose a unify framework for document restoration by using inpainting and shape-from-shading.

As described above, various methods have been proposed for degraded document restoration. The local thresholding methods, including Bernsen's, Niblack's, Sauvola's, Huang's and Gatos's methods, are especially able to adapt to local variation on document images. This capability is very important in the case of degraded historical documents. However, these methods do not produce satisfactory, suitable and usable results in degraded Thai document image processing, since the characteristic of degraded Thai historical documents is not similar to those foreign historical documents. In degraded document images, the classification of foreground from background depends on the degradation clarification, which is not clarified and fluctuates according to the context of document images. In general, degraded Thai historical document images represent a brownish background. The degradation of the background depends on the quality of paper and document age. Variations in background color usually affect the quality of the binary image. Advanced binarization techniques are required to reduce the effect of the degradation of background.

This paper proposes a new binarization method based on an adaptive multilayer-information for the restoration of degraded Thai historical document images. The rest of this paper is organized as follows. Section 2 describes the proposed method followed by a description of the experiment in section 3. Finally, the paper is concluded in the last section.

2. THE PROPOSED METHOD

This section presents the description of the proposed method based on an adaptive multilayer-information binarization for restoration of degraded Thai historical document images. The overview of the proposed method is illustrated in Fig. 1.

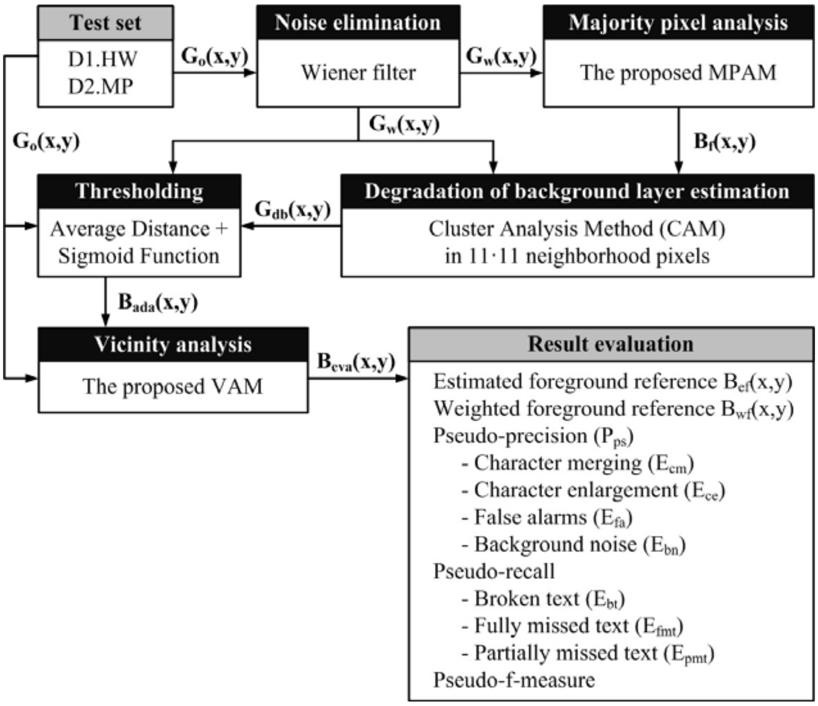


Fig. 1. The proposed method overview.

The proposed method consists of five stages. The noise elimination stage aims to eliminate noise areas by using a Wiener filter. The majority pixel analysis stage extracts the foreground pixels from the binary images of three well-known binarization methods. The degradation of the background layer estimation stage, based on the cluster analysis method, estimates the degradation of the background layer by replacing the foreground area with the estimated background which is the average value of cluster pixel. The thresholding stage transforms gray-level image into a binary image by calculating the threshold value in accordance with the gray value of the estimated degradation of the background layer. Finally, the vicinity analysis stage enhances the quality of the binary image by analysing and categorizing the pixels of binary image into the correct group. The proposed method is fully described following.

2.1 Noise Elimination

The noise elimination stage aims to eliminate noise areas by applying the existing well-known filtering technique. Based on the survey, Wiener filter [39-41], homomorphic filter [42-44] and mathematical morphology filter [45-47] are analyzed to find the suitable filter for this research. The Wiener filter is adopted as a proper method and is proved an efficient technique for degraded document image filtering. The original gray-level image will be separated into 5·5 local blocks around corresponding pixel (x, y). Let μ and σ be mean and variance in a local block, Avg(σ) be an average variance of the original image. The gray-level value of the original and filtered image of pixel (x, y) are defined as $G_o(x, y)$ and $G_w(x, y)$ respectively. The $G_o(x, y)$ is transformed to $G_w(x, y)$ by using the following formula:

$$G_w(x, y) = \mu + \left(\frac{\sigma}{\sigma + Avg(\sigma)}\right)(G_o(x, y) - \mu)\,. \tag{4}$$

2.2 Majority Pixel Analysis

The existing foreground extraction method commonly applies one binarization technique. Gatos *et al.* use Niblack's method to estimate the foreground areas. Zhou *et al.* use Laplacian-Gauss's method to estimate the foreground region. In order to extract the closely superset of possible foreground layer, the Majority Pixel Analysis Method (MPAM) is proposed. The idea of the MPAM is a combination of three well-known binarization methods including Bernsen's, Niblack's and Sauvola's methods to extract the foreground layer. The reason of using these three methods is that they are one step transformation without additional filter or method which deleting some possible foreground pixels. Furthermore, the methods have been successfully applied by several researchers related to foreground extraction in document image. These methods have their own advantage and disadvantage. The advantage of combined method is the combined effect between its methods where the strength of one method can compensate the weakness of another. However, the selection of binarization methods and parameters has not been previously analyzed in depth. The filtered image $G_w(x, y)$ is transformed to three binary images $B_1(x, y)$, $B_2(x, y)$ and $B_3(x, y)$ based on the Eqs. (1)-(3) respectively. The extracted foreground layer in form of binary image defined as $B_f(x, y)$ is calculated using the following formula:

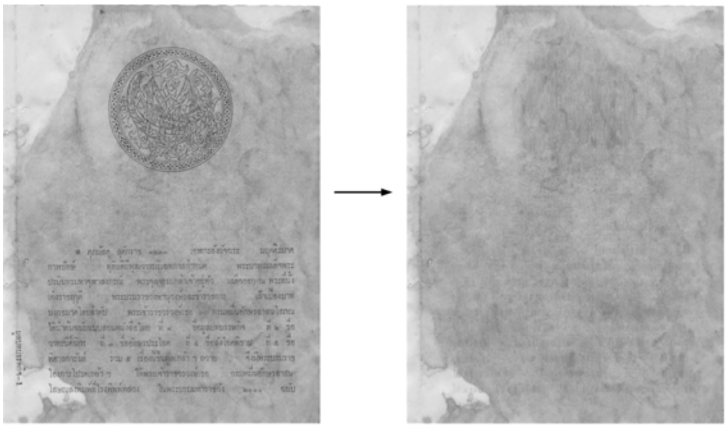
$$B_f(x, y) = \begin{cases} 1, \text{if } \sum_{i=1}^{i=3} B_i(x, y) \geq 2 \\ 0, \text{otherwise} \end{cases}. \tag{5}$$

2.3 Degradation of the Background Layer Estimation

In this stage, the degradation of the background layer is estimated. The idea to estimate the degradation of the background layer is that the gray value of the filtered gray-level image $G_w(x, y)$ appertain to the degraded and background layer if the considered pixels of foreground layer are zero. Based on cluster analysis method of Kim [48], the pixels of foreground layer are replaced by the average gray value of 11·11 neighborhood pixels. The gray value of pixel (x, y) of the degradation of the background layer defined as $G_{db}(x, y)$ is calculated by using the following formula:

$$G_{db} = \begin{cases} G_w(x, y) \ if \ B_f(x, y) = 0 \\ \dfrac{\sum_{i=x-5,\, j=y-5}^{i=x+5,\, j=y+5} G_w(i, j)}{100} \ if \ B_f(x, y) = 1 \end{cases} . \tag{6}$$

Fig. 2 shows an example of estimated degradation of the background layer $G_{db}(x, y)$.



Filtered image $G_w(x, y)$ Estimated degradation of the background layer image $G_{db}(x, y)$

Fig. 2. Example of estimated degradation of the background layer.

2.4 Thresholding

In this stage, the average distance from foreground to background defined as Avg_{dt} which is derived from Otsu's method is combined with the logistic sigmoid function [49]. This stage aims to adapt the adaptive threshold value in accordance with the gray value of the degraded and background layer. The efficiently adaptive thresholding should be preserved the text pixel even if the gray value of the degraded and background layer get close to black color value. Then the adaptive threshold value must be smaller than the gray value of the degraded and background layer. Let v_1 be a variable used to adjust the threshold weight of Avg_{dt}. The logistic sigmoid function is defined as $S_{curve}(x, y)$. The adaptive threshold defined as $T_{ada}(x, y)$ can be calculated by using the following formula:

$$T_{ada}(x, y) = (v_1 \cdot Avg_{dt}) \cdot S_{curve}(x, y) . \tag{7}$$

In general, the histogram of degraded document image has two peaks, one peak refers to foreground region and the other peak refers to background region. The benefit of using distance from two peaks (or from foreground to background) is firstly described in Otsu's method. The average distance from foreground to background $\mathrm{Avg}_{\mathrm{dt}}$ can be calculated by using the following formula:

$$Avg_{dt} = \frac{\sum_{x=1,\,y=1}^{x=width\; y=height} (G_{db}(x,y) - G_w(x,y))}{\sum_{x=1,\,y=1}^{x=width\; y=height} B_f(x,y)}. \tag{8}$$

Let v_2 and v_3 be the variables used to adjust weight of adaptive behavior of sigmoid function and Avg_{db} is the average gray value of filtered image $G_{db}(x, y)$. The $S_{curve}(x, y)$ of Eq. (7) can be calculated by using the following formula:

$$S_{curve}(x,y) = \frac{1-v_2}{1+\exp\left(\frac{-4G_{db}(x,y)}{Avg_{db}(1-v_3)} + \frac{2(1+v_3)}{1-v_3}\right)} + v_2. \tag{9}$$

Based on the experiment performed on degraded Thai document images, the optimal value of v_1, v_2 and v_3 are 0.70, 0.65 and 0.55 respectively. Fig. 3 illustrates an adaptive behavior of the adaptive threshold $T_{ada}(x, y)$ according to Eq. (7).

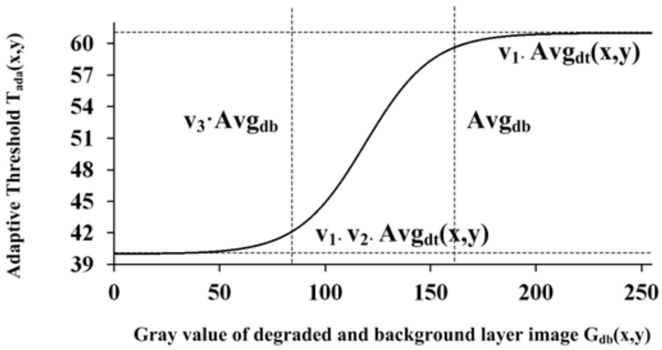


Fig. 3. A simulation of the adaptive threshold $T_{ada}(x, y)$.

Based on the adaptive threshold $T_{ada}(x, y)$, the binary image defined as $B_{ada}(x, y)$ is created by using the following formula:

$$B_{ada}(x,y) = \begin{cases} 1, G_{db}(x,y) - G_o(x,y) > T_{ada}(x,y) \\ 0, \text{otherwise} \end{cases}. \tag{10}$$

2.5 Vicinity Analysis

The existing post-processing method commonly used the information of binary image to enhance the quality of binary image. Gatos applies shrink and swell filter to remove noise and fill gaps and holes in the foreground. Dokladal and Dokladalova [47] apply a mathematical morphology to enhance the quality of binary image. Yang and Yan [50] propose a local run length feature to detect the false information in binary image. In this stage, the Vicinity Analysis Method (VAM) is proposed. The idea of VAM is using both the information in binary and gray value of the original image. The binarization method can be considered as categorization the image's pixels into two groups. The binary image is a trustworthy categorization result of its gray-level image then the most pixels with similar gray values of considered pixel can be categorized into the same group [51]. If the group of considered pixel is not equal to the major group of the similar vicinity pixels, the group of considered pixel is corrected by reversing. In order to improve the quality of the binary image $B_{ada}(x, y)$, two different VAM are applied sequentially. The first VAM defined as VAM_1 investigates 8 vicinity pixels around the considered pixel. Then, the second VAM defined as VAM_2 investigates all the pixels in a vicinity block. Let $G_{con}(x, y)$ be the gray value of considered pixel, $G_{vic}(x, y)$ be the gray value of vicinity pixels and the threshold is the value to decide whether the two pixels are in the same group or not. Based on the experiment performed on degraded Thai document images, the optimal value of threshold is 10%. VAM_1 continuously investigates the 8 vicinity pixels around the considered pixel and counts the number of hits and misses by using the following formula:

$$VAM = \begin{cases} hit \ \ , \left|G_{con}(x,y) - G_{vic}(x,y)\right| < threshold \\ miss, \text{ otherwise} \end{cases}. \tag{11}$$

A hit means that vicinity and considered pixel are in the same group and a miss means that they are in two different groups. In case of the number of misses is higher than the number of hits, the considered pixel is corrected by reversing. In another way, the considered pixel is not changed. After the VAM_1 is applied completely, then VAM_2 will be applied by using the same method as VAM_1. VAM_2 counts the number of hits and misses in the same way. However it has two differences, the first difference is VAM_2 examines all pixels in the vicinity block that defines as investigating area. The second difference is VAM_2 toughens the criteria which are used to correct the considered pixel. When the hit number is lower than a half of miss number, the considered pixel is reversed. In this research, the suitable vicinity block size to correct a considered pixel is 11·11. The description of the experiment on the proposed method with 480 degraded Thai historical document images and results evaluation and discussion will be described in the next section.

3. THE EXPERIMENT

In order to investigate and demonstrate the advantage of the proposed method, the experiments on degraded Thai historical document images are carried out with 480 degraded Thai historical document images. The experimental results are evaluated by using Ntirogiannis's method [52] which comprise of state-of-the-art indices including pseudo-precision, pseudo-precision supplement, pseudo-recall, pseudo-recall supplement and pseudo-f-measure. The description of the experiment is fully described in this section.

3.1 Test Set

The proposed method is tested on real degraded Thai historical document images which are divided into two categories: handwritten and machine-printed document images. The test set is provided and supported by the National Library of Thailand consisting of 480 degraded Thai historical document images. The characteristics of all images are various contrast, resolution and background complexity. There are many causes of degradation in the test set including smudge, spot, unsuitable storage method, temperature, poor quality paper and etc. Test set 1 defined as D1.HW consists of 240 degraded Thai handwritten document images. Test set 2 defined as D2.MP has 240 degraded Thai machine-printed document images. The examples of test set of both types are shown in Fig. 4.

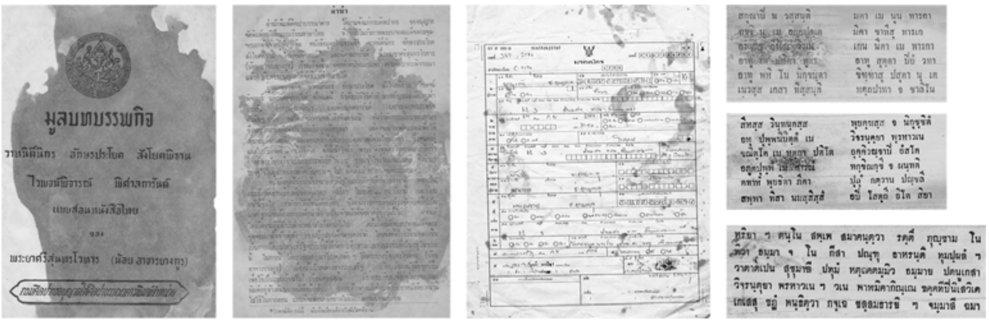


Fig. 4. Examples of images in the test set.

3.2 Evaluation

To evaluate the quantitative efficiency of the proposed method, three state-of-the-art indices including pseudo-precision, pseudo-recall and pseudo-f-measure are adopted. Furthermore, pseudo-precision supplement and pseudo-recall supplement are also adopted. To calculate those indices, the foreground reference (ground truth) images are the essential element. In this research, two types of the foreground reference images derived from Ntirogiannis's method [52], namely the estimated foreground reference images defined as $B_{ef}(x, y)$, and weighted foreground reference image defined as $B_{wf}(x, y)$, are established.

To construct the estimated foreground reference $B_{ef}(x, y)$, the original gray-level image $G_o(x, y)$ is transformed to binary image $B_{Nik}(x, y)$ by using Nikolaos and Dimitrios method [53]. Then the Nikolaos and Dimitrios method is not included in experimental results comparisons to abstain from bias. Suddenly, a skeletonization method of Lee and Chen [54] is applied to create skeletonized binary image $B_{sf}(x, y)$ which refers to characters are drawn a one pixel wide approximately in the middle of a character. Whereas artifacts in the character, skeletonization method does not always create the perfect skeleton character. Then the intuition of human is required to draw the disappearance or remove spurious parts. In next step, all pixels of $B_{sf}(x, y)$ are dilated until half of edge pixels of binary image $B_{Nik}(x, y)$ are covered by the dilated $B_{sf}(x, y)$ under the condition that the dilated image cannot be larger than the binary image $B_{Nik}(x, y)$. Finally, the last step dilated image is the estimated foreground reference $B_{ef}(x, y)$. Fig. 5 shows the construction of estimated foreground reference.

Fig. 5. The estimated foreground reference construction.

Regarding to the construction of the weighted foreground reference images $B_{wf}(x, y)$, the Ntirogiannis's method [51] is derived. Let $D_{Chebyshev}(x, y)$ be the Chebyshev distance metric of the foreground reference image which the contour points are used as starting points, $G_{sw}(x, y)$ be the stroke width image of the foreground reference characters and N_R be the pixel-wise normalization factor of the $D_{Chebyshev}(x, y)$ can be calculated by using the following formula:

$$N_R(x,y) = \begin{cases} \left(\dfrac{G_{sw}(x,y)}{2}\right)^2 & ,G_{sw}(x,y)\bmod(2)=1 \\ \left(\dfrac{G_{sw}(x,y)}{2}\right)\left(\dfrac{G_{sw}(x,y)}{2}-1\right) & ,\text{otherwise} \end{cases}. \tag{12}$$

Thus, the weighted foreground reference images $B_{wf}(x, y)$ can be constructed by using the following formula:

$$B_{wf}(x,y) = \begin{cases} \dfrac{D(x,y)}{N_R(x,y)} & ,G_{sw}(x,y) > 2 \\ \dfrac{1}{G_{sw}(x,y)} & ,\text{otherwise} \end{cases}. \tag{13}$$

Fig. 6 shows the construction of weighted foreground reference in form of numeric representation.

0	0	0	1	0	0	0
0	0	0	1	0	0	0
0	0	0	1	0	0	0
0	0	0	1	0	0	0

Skeletonized foreground reference B_{sf}(x,y)

0	1	0	0	0	1	0
0	1	0	0	0	1	0
0	1	0	0	0	1	0
0	1	0	0	0	1	0

Contour point of foreground reference

1	0	1	2	1	0	1
1	0	1	2	1	0	1
1	0	1	2	1	0	1
1	0	1	2	1	0	1

Chebyshev distance map D(x,y)

0	0	0	5	0	0	0
0	0	0	5	0	0	0
0	0	0	5	0	0	0
0	0	0	5	0	0	0

Local thickness

0	5	5	5	5	5	0
0	5	5	5	5	5	0
0	5	5	5	5	5	0
0	5	5	5	5	5	0

Stroke width G_{sw}(x,y)

0	0	1/6	2/6	1/6	0	0
0	0	1/6	2/6	1/6	0	0
0	0	1/6	2/6	1/6	0	0
0	0	1/6	2/6	1/6	0	0

Weighted foreground reference B_{wf}(x,y)

Fig. 6. The weighted foreground reference construction.

After the end of the estimated and weighted foreground reference image construction, the quantitative efficiency of the proposed method is evaluated in terms of pseudo-precision, pseudo-precision supplement (character merging, character enlargement, false alarms and background noise), pseudo-recall, pseudo-recall supplement (broken text, partially missed text and fully missed text) and pseudo-f-measure. The complete details and formula of each index can be founded in [52].

The pseudo-precision index defined as P_{ps} is the percentage of the estimated foreground reference images $B_{ef}(x, y)$ that are detected in the evaluated binary image defined as $B_{eva}(x, y)$ after weighted map defined as $P_w(x, y)$ is applied. The complete details and formula of $P_w(x, y)$ can be founded in [51] and the pseudo-precision index value can be calculated by using the following formula:

$$P_{ps} = \frac{\sum_{x=1,y=1}^{x=width,y=height}((B_{ef}(x,y)\cdot(P_w(x,y)\cdot B_{eva}(x,y))}{\sum_{x=1,y=1}^{x=width,y=height}(P_w(x,y)\cdot B_{eva}(x,y))}\cdot 100\cdot \qquad (14)$$

Furthermore, the pseudo-precision supplement including character merging, character enlargement, false alarms and background noise are adopted to interpret the characteristic of pseudo-precision index (pseudo-precision + character merging + character enlargement + false alarms + background noise = 100). The character merging index defined as E_{cm} is the false positive pixel within the area around the estimated foreground reference image which is responded for merging adjacent estimated foreground reference components. The character enlargement index defined as E_{ce} is the false positive pixel within the area around the estimated foreground reference image which is responded for enlarging estimated foreground reference components without merging point. The false alarm index defined as E_{fa} is the connected component of the evaluated binary image which is not detected in estimated foreground reference image. The background noise index defined as E_{bn} is the false positive pixel in the background which the value of weighted map $P_w(x, y)$ equal to 1. The complete details and formula of pseudo-precision supplement can be founded in [51].

The pseudo-recall index defined as R_{ps} is the percentage of the weighted foreground reference images $B_{wf}(x, y)$ that is detected in the evaluated binary image $B_{eva}(x, y)$ which can be calculated by using the following formula:

$$R_{ps} = \frac{\sum_{x=1,y=1}^{x=width,y=height}(B_{wf}(x,y)\cdot B_{eva}(x,y))}{\sum_{x=1,y=1}^{x=width,y=height}B_{wf}(x,y)}\cdot 100\cdot \qquad (15)$$

In addition, the pseudo-recall supplement including broken text, fully missed text and partially missed text are adopted to interpret the characteristic of pseudo-recall index (pseudo-recall + broken text + fully missed text + partially missed text = 100). The broken text index defined as E_{bt} is the false negative pixel which is the result of local breaking of the weighted foreground reference component into two or more components. The fully missed text index defined as E_{fmt} is the connected component of the weighted foreground reference image which completely missed in the evaluated binary image. The partially missed text index defined as E_{pmt} is the false negative pixel which is not the result of local breaking of the weighted foreground reference component into two or more components. The complete details and formula of pseudo-recall supplement can be founded in [52].

Finally, the average value of the pseudo-precision and pseudo-recall indices namely pseudo-f-measure defined as F_{ps} can be specified by using the following formula:

$$F_{ps} = \frac{2 \cdot P_{ps} \cdot R_{ps}}{P_{ps} + R_{ps}}. \tag{16}$$

The values of these indices vary from 0 to 100, 0 for a completely incorrect and 100 for a perfectly binary image.

3.3 Experimental Results

Based on visual criteria which observe for qualitative efficiency evaluation, the proposed method outperforms five well-known binarization methods related to image quality and meaningful of the document. Fig. 7 shows the example images and their binary results.

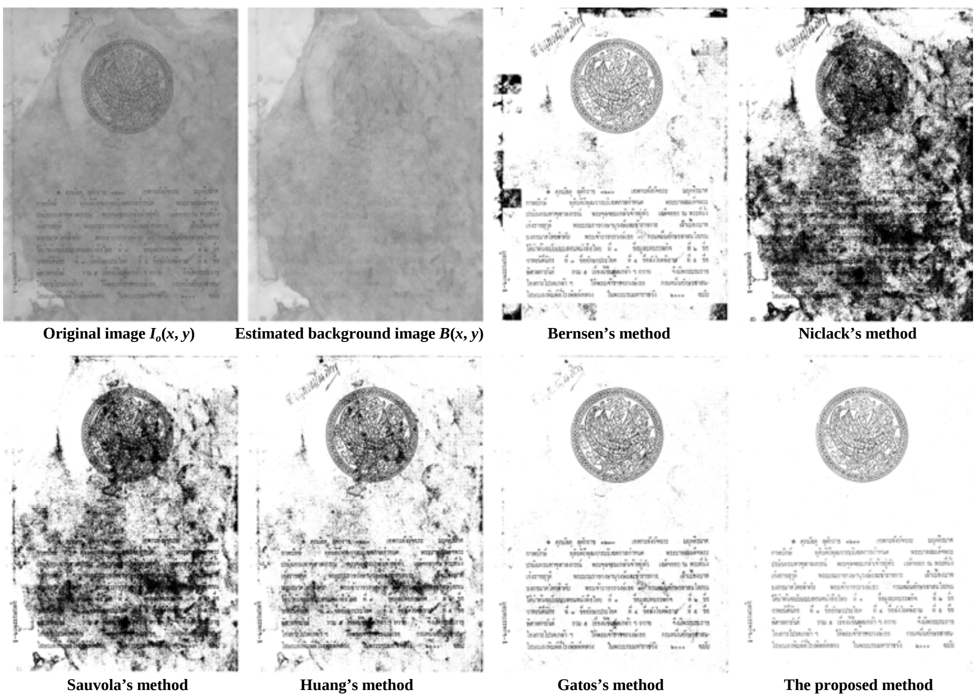


Fig. 7. The visual benchmark results.

Since the quality of binary image cannot be compared and ranked in a particular format. Then, the quantitative efficiency indices including pseudo-precision (P_{ps}), character merging (E_{cm}), character enlargement (E_{ce}), false alarms (E_{fa}), background noise (E_{bn}), pseudo-recall (R_{ps}), broken text (E_{bt}), fully missed text (E_{fmt}), partially missed text (E_{pmt}) and pseudo-f-index (F_{ps}), are compared to illustrate the performance of the proposed method. The quantitative efficiency of the proposed method (PRO) is compared with five well-known adaptive binarization methods including Bernsen's (BER), Niblack's (NIB), Sauvola's (SAU), Huang's (HUA) and Gatos's (GAT) methods. After tuning the constants and variables of the binarization formula to optimal values, the quantitative efficiency of binary images is benchmarked. To provide the overall of the evaluation indices, Table 1 illustrates the details of each index.

Table 1. Benchmark values of the proposed and comparison methods.

Indices \ Methods		BER	NIB	SAU	HUA	GAT	PRO
D1.HW	P_{ps}	73.89	61.87	87.43	85.31	89.72	92.63
	E_{cm}	3.35	1.55	0.45	0.93	0.28	0.61
	E_{ce}	4.86	6.53	3.15	7.11	5.07	3.72
	E_{fa}	7.63	21.38	3.56	6.47	4.65	2.85
	E_{bn}	10.27	8.67	5.41	0.18	0.28	0.19
	R_{ps}	95.61	97.37	94.42	96.06	94.26	94.41
	E_{bt}	3.18	0.71	2.16	2.17	3.06	4.25
	E_{fmt}	0.07	0.26	0.14	0.00	0.00	0.00
	E_{pmt}	1.14	1.66	3.28	1.77	2.68	1.34
	F_{ps}	83.36	75.66	90.79	90.37	91.93	93.51
D2.MP	P_{ps}	72.33	59.71	86.64	83.24	88.51	90.35
	E_{cm}	4.22	2.81	0.23	1.63	0.17	1.50
	E_{ce}	4.91	8.24	2.25	7.38	5.63	4.18
	E_{fa}	8.56	18.38	3.42	5.43	5.12	3.56
	E_{bn}	9.98	10.86	7.46	2.32	0.57	0.41
	R_{ps}	94.17	95.93	93.24	95.31	92.21	92.48
	E_{bt}	2.36	1.83	4.58	2.97	3.44	4.49
	E_{fmt}	0.19	0.37	0.27	0.16	0.00	0.00
	E_{pmt}	3.28	1.87	1.91	1.56	4.35	3.03
	F_{ps}	81.82	73.61	89.82	88.87	90.32	91.40

The capability of Gatos's method is similar to the proposed method with the degraded document image in the test set. The proposed method and Gatos's method show a relatively high quantitative efficiency in the experimental results. It means that Gatos's and proposed methods durable to the degradation in historical document images. However, the proposed method has the best overall efficiency with average pseudo-f-index equal to 92.46% as shown in Fig. 8.

According to the aforementioned formula of the three indices, the pseudo-precision index is used to indicate the direct correctness of document image restoration. The pseudo-recall and pseudo-*f*-index indices do not directly indicate document images restoration performance. However, they are useful for an indirect corrective measure of

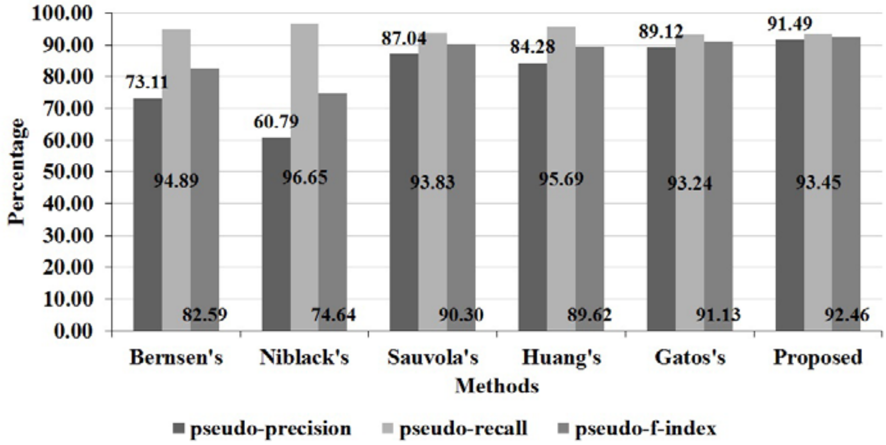


Fig. 8. Benchmark graph of the proposed and comparison methods.

document restoration. Absolutely, the pseudo-*f*-index illustrates the accommodation between the pseudo-precision and pseudo-recall indices.

4. CONCLUSION

In this research, the new binarization method based on an adaptive multilayer-information for the restoration of degraded Thai historical document images is proposed. The experiments are implemented by using MATLAB. The experimental results of the proposed method with 480 document images perform the level of pseudo-precision, pseudo-recall and pseudo-f-index at 91.49%, 93.45% and 92.46% respectively. Moreover, the proposed method demonstrates superior performance against five well-known adaptive binarization methods on various degraded Thai historical handwritten and machine-printed document images. Furthermore, the proposed method can be applied with any degraded document images which have the same characteristics as the test set. But the parameters and techniques used in this method must be adjusted to be suitable for those document images.

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