An Optimal Binarization Algorithm Based on Particle Swarm Optimization

P. Subashini, N. Sridevi

Abstract— Document binarization is an active research area for many years. Binarization algorithms play an important role in the preprocessing phase of any character recognition system. This paper compares several alternative binarization algorithms for handwritten documents, by evaluating their performance. The algorithms evaluated are, global thresholding, Otsu thresholding, Kittler-Illingworth and local thresholding, Niblack algorithm along with the proposed PSO algorithm. From the tests and results, we can wrap up with the assumption that the proposed algorithm shows improved results.

Index Terms—Evaluation, Global thresholding, Image Binarization, Local thresholding, PSO.

I. INTRODUCTION

Binarization or thresholding is the process that converts an image into black-and-white: a threshold value is defined and the colors above that value are converted into white, while the colors below it are converted into black. This is a very simple process in digital image processing when one has a document with black ink written on a white paper. Document image binarization is an important step in the document image analysis and recognition pipeline. The performance of a binarization technique directly affects the recognition analysis [7]. The quality of the images however has a significant impact on the OCR performance, since most historical archive document images are of poor quality due to aging and discolored cards and ink fading. The PSO, first introduced by Kennedy and Eberhart is a flexible, robust, population based stochastic search/optimization algorithm with inherent parallelism [3, 11]. In recent years this method has gained popularity over its competitors due to its simplicity, superior convergence characteristics and high solution quality. This paper presents Otsu thresholding based on particle swarm optimization (PSO) algorithm. The binarization methods that are used in the evaluation are described in Section 2 and Section 3 describes the tests that were run and their results. The paper concludes in Section 4.

II. BINARIZATION ALGORITHMS

In order to reduce storage requirements and to increase processing speed, it is often desirable to represent gray scale or color images as binary images by picking a threshold value.

Dr.P.Subashini, Department of Computer Science, Avinashilingam Institute of Home Science and Higher Education for Women, Coimbatorte, India, 9442271971., (e-mail: mail.p.subashini@gamil.com).

N.Sridevi, Department of Computer Science, Avinashilingam Institute of Home Science and Higher Education for Women, Coimbatorte, India, 9043126984., (e-mail: sridevi.n78@gnaul.com).

Binarization algorithms are classified into global and local methods [10]. Fig 1 shows the block diagram of the binarization method.
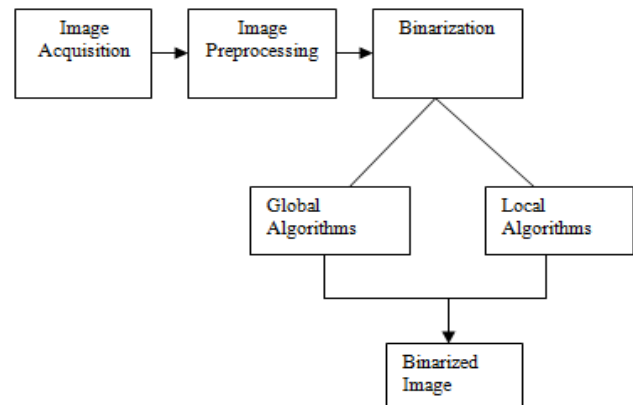

Figure 1: Block Diagram of Image Binarization Method

The global algorithms calculate one threshold for the entire image. The pixels are separated into two classes, foreground and background [1]. This can be expressed as in the equation (1).

$$I_b(x, y) = \begin{cases} black & if & I_f(x, y) \leq Thr \\ white & if & I_f(x, y) > Thr \end{cases} \quad (1)$$

where, $I_f(x, y)$ is the pixel of the input image and $I_b(x, y)$ is the pixel of the binarized image. While the local thresholding algorithms calculate different threshold values depending on the local regions of the image. A threshold value can be derived for each pixel in the image, and the image can be separated into foreground and background [1] which can be expressed as given in equation (2).

$$I_b(x, y) = \begin{cases} black & if & I_f(x, y) \leq Thr(x, y) \\ white & if & I_f(x, y) > Thr(x, y) \end{cases} \quad (2)$$

A. Global Thresholding Methods

a. Otsu Thresholding

Otsu is an often used global thresholding method. It is based on treating the gray level intensities present in the image as values to be clustered into two sets, one foreground (black) and one background (white) [9].

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To carry out this, the algorithm minimizes the weighted sum of within-class variances of the foreground and background pixels to establish an optimum threshold. This is equivalent to maximizing the between-class scatter. From this a scalar number, K, is returned. This is then used to binarize the image through the following equation (3)

$$I_{bin}(x, y) = \begin{cases} 1, & if \ I_{gray}(x, y) \leq K \\ 0, & if \ I_{gray}(x, y) \leq K \end{cases} \quad (3)$$

b. Kittler and Illingworth

Kittler and Illingworth present an algorithm that is based on the fitting of the mixture of Gaussian distributions and it transforms the binarization problem to a minimum-error Gaussian density fitting problem [6]. Assume that t is a threshold value used to segment the image into background and foreground, both of which are also modeled by Gaussian distributions, $p_B(t)$ and $p_F(t)$, respectively. Define $p_{mix}(t)$ as a mixture of these two Gaussian distributions by

$$p_{mix}(t) = \alpha p_B(t) + (1 - \alpha) p_F(t) \quad (4)$$

where α is determined by the portions of background and foreground in the image.

B. Local Thresholding Methods:

a. Niblack Algorithm

Niblack's algorithm calculates a pixel-wise threshold by sliding a rectangular window over the gray level image [4]. The computation of threshold is based on the local mean m and the standard deviation s of all the pixels in the window and is given by the following equation (5)

$$T_{Niblack} = m + k * s$$

$$T_{Niblack} = m + k \sqrt{\frac{1}{NP} \sum (p_i - m)^2}$$

$$= m + k \sqrt{\frac{\sum p_i^2}{NP} - m^2} = m + k\sqrt{B} \quad (5)$$

where NP is the number of pixels in the gray image, m is the average value of the pixels p_i, and k is fixed to -0.2 by the authors. Advantage of Niblack is that it always identifies the text regions correctly as foreground but on the other hand tends to produce a large amount of binarization noise in non-text regions also.

C. Proposed Thresholding Algorithm

In many application of image processing, the gray levels of pixels belonging to the object are substantially different from the gray levels belonging to the background. Thresholding then becomes a simple but effective tool to separate objects from the background. There are many methods for thresholding. All this algorithms have their own metrics and defects at the same time. Maximum between-class square error should be a good method to select proper threshold on the condition that images must be processed on real time and the number of pixels in each class are close to each other. In nature, maximum classes square error belongs to Otsu method, which employs a criterion for maximizing the between-class variance of pixel intensity and can detect proper threshold. The antonym of Otsu is to pursue the maximum between-class variance, which can be viewed as an optimization problem [12]. Recently as it known from literature, Particle Swarm Optimization (PSO) algorithm is used to solve many of difficult problems in the field of pattern recognition [8]. Hence, we can employ PSO to deal with it.

a. PSO Algorithm

Let X and V denote the particle's position and its corresponding velocity in search space respectively. At iteration K, each particle i has its position defined by $X_i^k = (x_{i1}, x_{i2}, \ldots x_{in})$ and a velocity is defined by $V_i^k = (v_{i1}, v_{i2}, \ldots v_{in})$ in search space n. Velocity and position of each particle in next iterations can be calculated using following equation (6) and (7)

$$v_{ij}^{k+1} = w v_{ij}^k + c_1 r_1 \left(pbest_{ij}^k - x_{ij}^k \right) + c_2 r_2 \left(gbest_j^k - x_{ij}^k \right) \quad (6)$$

$$x_{ij}^{k+1} = x_g^k + v_g^k \quad (7)$$

where k is the current iteration number, w is inertia weight, v_{ij} is then updated velocity on the jth dimension of the ith particle, c_1 and c_2 are acceleration constants, c_1 and c_2 are positive constant parameters, usually $c_1 = c_2 = 2$. r_1 and r_2 are the real numbers drawn from two uniform random sequences of U (0, 1).

The quality of solution is measured by the objective function. The fitness function f (t) of each particle can be formulated as equation (8).

$$f(t) = \omega_0(t) \times \omega_1(t) \times (\mu_0(t) - \mu_1(t))^2 \quad (8)$$

Such that t is a gray level between 0 and 255 which can be obtained through the particle's position. $\omega_0(t)$ is amount of pixels whose gray value is lower than t, $\omega_1(t)$ is amount of pixels whose gray value is higher than t, $\mu_0(t)$ is the means of pixels with gray value less than t, $\mu_1(t)$ is the means of pixels with gray value more than t.

The algorithm starts by generating randomly initial population of the PSO. Every particle is initialized with locations and velocities.

These locations composed the initial solutions for the optimal threshold. Next the particle's fitness is calculated by the equation (8).

The algorithm keeps an updated version of two special variables through out its execution, *global best (gbest)* position and *local best (pbest)* position. It compares different positions of a particle with its current position, in order to determine the local best position for every particle. The procedure of the proposed PSO algorithm is described as follows:

Step 1: Initialize N particles with random positions $x_1, x_2, ...x_N$ according to Eq. (6) and velocities V_i i = 1, 2,...N.

Step 2: Evaluate each particle according to Eq. (8).

Step 3: Update individual and global best positions. If $f (pbest_i) < f (x_i)$, then $pbest_i = x_i$, and search for the maximum value f_{max} among $f (pbest_i)$, If max $f (gbest) < f_{max}$, then gbest $= x_{max}$, x_{max} is the particle associated with f_{max}.

Step 4. Update velocity: update the *i*th particle velocity using the Eq. (7) restricted by maximum and minimum threshold v_{max} and v_{min} .

Step 5. Update Position: update the ith particle position using Eq. (6) and (7).

Step 6. Repeat step 2 to 5 until a given maximum number of iterations is achieved or the optimal solution so far has not been improved for a given number of iteration.

III.   TEST AND RESULTS

The images are binarized by each of the binarization algorithm described in the above section. In order to measure the performance of these algorithms various evaluation metrics such as Precision, Recall, F-measure [7] and traditional measures of image quality description are used. Specifically, we used the square error (MSE), the signal to noise ratio (SNR) and the peak signal to noise ratio (PSNR) [5].

The true positives are those pixels that were black in the ground truth image and are still black in the binarized image. The false positives were white in the ground truth image and black in the binarized image. The false negatives are black in the ground truth image, but white in the binarized image. From these counts the statistics of the following are calculated [2].

$$Re\,call = \frac{TruePositive}{FalseNegatives + TruePositives} \quad (9)$$

$$Percision = \frac{TruePositive}{FalsePositives + TruePositives} \quad (10)$$

These are combined into F-measure using the following equation

$$F - measure = \frac{2.Re\,call.Percision}{Re\,call + Percision} \quad (11)$$

Let x (i, j) represent the value of the ith row and j^{th} column pixel in the original image x and let y (i, j) represent the value of the corresponding pixel in the output image y. The local error is $e(i, j) = x(i, j) - y(i, j)$ and the total square error rate will be as in equation (12).

$$MSE = \frac{\sum_i \sum_j e(i, j)^2}{MxN} \quad (12)$$

SNR is defined as the ration of average signal power to average noise power and for an MxN image is

$$SNR(db) = 10\log_{10}\left(\frac{\sum_{i,j} x(i, j)^2}{\sum_{i,j}(x(i, j) - y(i, j))^2}\right) \quad (13)$$

for $0 \le i \le M - 1$ and $0 \le j \le N - 1$. PSNR is defined as the ratio of peak signal power to average noise power

$$PSNR(db) = 10\log_{10}\left(\frac{D^2 MN}{\sum_{i,j}(x(i, j) - y(i, j))^2}\right) \quad (14)$$

for $0 \le i \le M - 1$ and $0 \le j \le N - 1$, where D is the maximum peak-to-peak swing of the signal (255 for 8-bit images). We assume that the noise $x(i, j) - y(i, j)$ is uncorrelated with the signal.

Table 1 shows the value of the evaluation metrics obtained for the proposed method and the other existing methods. From the table, we can observe that the performance of the proposed PSO method is better than the other methods. Fig 2. Shows the original images and the resultant binarized image obtained by various methods.
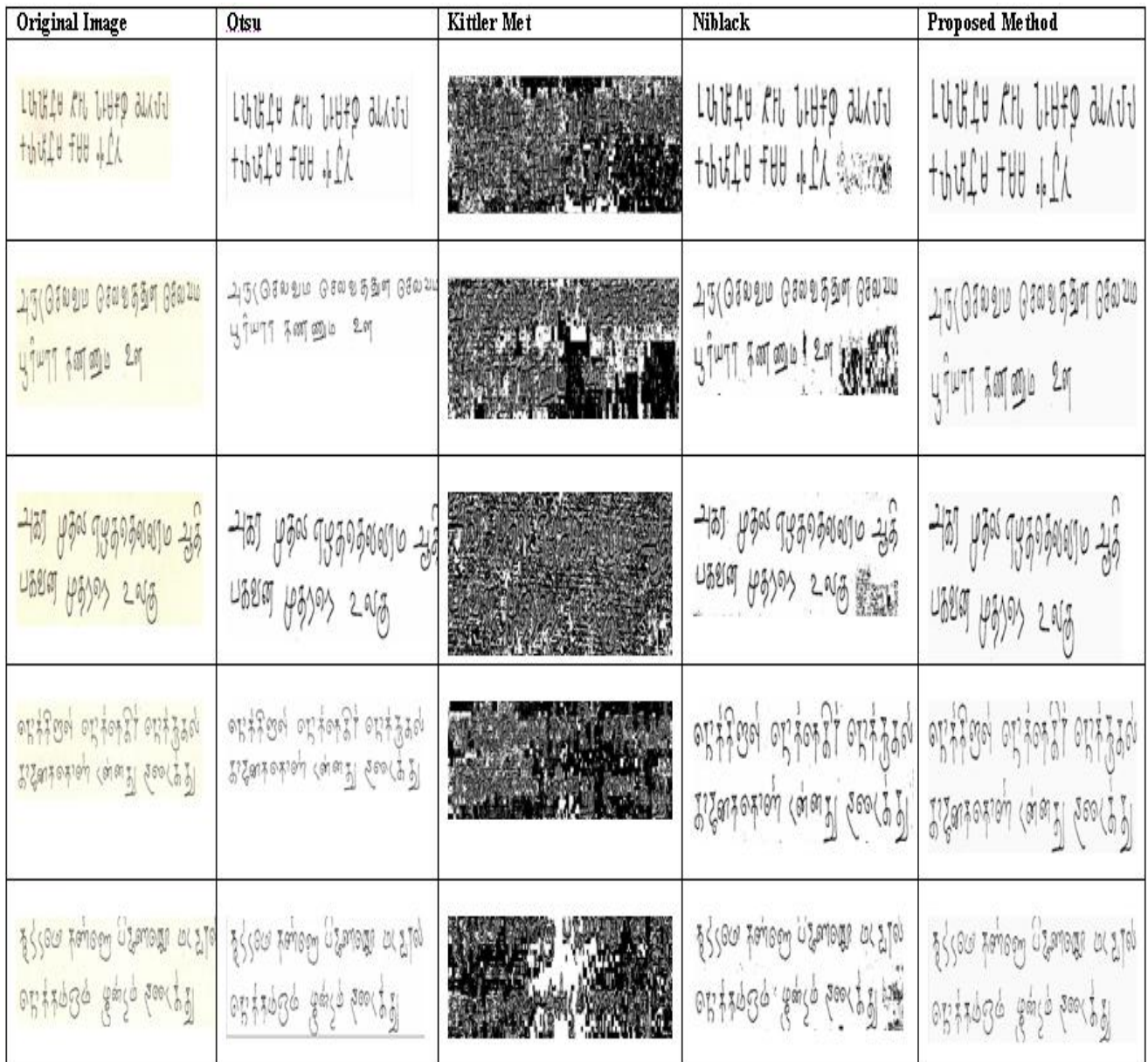
Figure 2: Original Image and Binarized Images using various algorithms

Table 1: The value of evaluation metrics for every binarization technique concerning the image of Figure 1

Performance Metrics	Otsu Algorithm	Niblack Algorithm	Kittler Met Algorithm	Proposed Method
PSNR	18.878	16.616	7.61	**19.322**
SNR	30.688	30.86	33.668	30.72
MSE	28.988	37.86	107.02	**27.94**
Precision	0.4726	0.5816	0.7845	0.5120
Recall	0.4513	0.3170	0.0633	0.4818
F-Measure	46.1731	40.4879	11.7063	**49.6418**
Sensitivity	0.4513	0.3170	0.0633	0.4818
Specificity	0.9721	0.9764	0.9684	0.9731

IV. CONCLUSION

This paper has presented comparison of various binarization algorithms by measuring their performance by evaluation metrics. In this paper, a new binarization method based on Particle Swarm Optimization (PSO) is proposed. A total of four different binarization methods such as Otsu, Niblack and Kittler Met along with proposed PSO method are considered and evaluated by evaluation metrics. From the experimental result, we can infer that proposed PSO method shows good result when compared with other methods, since their PSNR, SNR measures are higher and the MSE is lower. The higher value of PSNR means that the quality of the binarized image is better. According to the results, Proposed PSO method had the best overall performance with F-measures of 49.6418 which is higher when compared to other methods.

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AUTHORS PROFILE

Dr. P. Subashini, Associate Professor, Dept. of Computer Science, Avinashilingam Deemed University has 18 years of teaching and research experience. Her research has spanned a large number of disciplines like Image analysis, Pattern recognition, neural networks, and applications to Digital Image processing. Under her supervision she has seven research project of worth one crore from various funding agencies like DRDO, DST and UGC.

N. Sridevi M.C.A, Ph.D Research Scholar, Dept. of Computer Science, Avinashilingam University has 3 years of teaching experience and 1 year of Industrial experience. Doing her research work in Pattern recognition. Area of Specialization: Image Processing, Pattern recognition.