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Handwritten Manuscripts Binarization Approach using Moth-Flame Optimization

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ABSTRACT

Mostly, historical documents contain a lot of information which is more useful for different kinds of generation. They had been written for 1000 years ago, but these documents suffer from a lot of various types of noise that may be based on external factors such as poor storage, atmospheric factors as moisture, and high temperatures. In order to ensure the safety of these documents, they should be saved in a digital form to keep them safe, quick access to all their information easily using different available document analysis applications. In this paper, a global binarization approach for handwritten Arabic manuscript image binarization is proposed. This approach depends on employing a nature-inspired optimization algorithm called Moth-flames for minimizing K-means objective function. The used dataset consists of 50 handwritten manuscripts images. The proposed approach is compared with some of the well-known binarization approaches like Otsu's, and Niblack's. Experimental results were made in terms of different visual inspection, F-measure, p-FM, PSNR, GA, DRD, NRM, and MPM. Moreover, the comparison with the state-of-art methods proved the success of the proposed approach.

Keywords

Bi-level. Optimization. Moth-flame optimization. Historical Manuscripts.

1. Introduction

Nowadays, all countries seek to digitize and enable all transactions (both financial and paper types) to ensure the speed and efficiency for achieving sustainability. Hence, a good example of these transformations in the scientific and cultural fields was presented. Digital libraries are the main target and they will be called soon smart libraries through smart applications on all mobile phones. The degraded manuscripts are considered real treasure because they contain fundamental information in different fields including history, geographic, religion, etc. The accuracy of different applications that process these manuscripts such as OCR, data hiding, word spotting, and indexing directly depends on the quality of the binarization process of these documents. Recently, Swarm Optimization Algorithm (SOA) is used to improve the machine learning techniques for solving different real-life problems. The main role of SOA is to adjust the parameters of these techniques to reach the optimal results [39].

In this paper, we present a global binarization approach based on Moth Flame Optimization (MFO) algorithm [1] for minimizing the *k* means objective function. The contributions of this paper could be summarized as follow:

1- Collect the degraded Arabic manuscripts with different kinds of noise, and made a ground truth for each image for the evaluation phase,
2- Different performance measures, like F-measure, p-FM, PSNR, GA, DRD, NRM, and MPM are used to evaluate the proposed approach.
3- Extensive experimental results were made to evaluate the proposed approach, as convergence curves analysis.

This paper is organized as follows: Section 3 presents the basics of the MFO. Section 4 shows the binarization approach. Section 5 presents the experimental results. Finally, Section 6 presents conclusions and future work.

2. Related Work

There are different approaches proposed and tested in relation to the binarization field on different datasets. (H)- DIBCO datasets are considered the most common available dataset with their ground truth images. The most common techniques in binarization field are three main types: local, global, and hybrid [2]. Local methods depend on the statistical values of the pixel neighborhood. The global methods depend on the single value of the whole image. Hybrid methods depend on the integration of local and global methods. In fact, the local methods provide better quality than global methods, but some noise has still existed in the background. The following methods are recently proposed in the binarization field. Chen et al. [3] presented an extended version of the non-local method named Wellner's method [4] for binarizing the broken degraded images. This approach was compared with Niblack

[5], Sauvola [6], Chou [7] Gatos [8] Kim [9] and Wagdy [10], where 150 noisy images were collected from Chou et al. [7], in addition to 28 images were downloaded from the internet. OCR, PSNR and FM are used as performance measures including (Precision, Recall, and Time(s)). The proposed approach results are better than the comparative methods, but this method suffers from the expensive computational cost and still needs a pre-and post-processing phase.
Lelore et al. [11] proposed a FAIR algorithm for document image restoration. It depends on double-threshold edge detection and able to detect the small parts of the image. (H)-DIBCO (2009-2012) datasets are used with FM, PSNR, DRD, and MPM as performance measures. FAIR is compared with different methods such as Ramirez's method [12], Otsu's [13], Chens's method [14], Fabrizio's method [15], and Sauvola [6]. Different experiments with different datasets including OCR, computational time, and visual considerations measure were used to evaluate the efficiency of FAIR. FAIR results are better than the compared methods.

Deep supervised networks are employed for image binarization by Nhat Vo et al. [16]. This approach is learned to predict the text from the image at various feature levels. It was conducted on DIBCO (2011,2013) and H-DIBCO (2014,2016) datasets, including FM, P-FM, PSNR, and DRD as performance measures. The results proved that it gives better performance than Bernsen's [17], Gatos et al. [18], Otsu's [13], Su's [19], Sauvola's [6], Niblack's [5], Howe's [20], CNN based (CNN) [21], LSTM based [22] methods, and the top-three ranked submitted approaches to (H) -DIBCO. But, it needs training before it works and fails to predict in some cases as in weak strokes that are detailed in [16].

Three phases of image binarization are proposed in Mitianoudis et al. [23]. The first phase is utilized to remove stains and others based on the adaptive median filter. In the second phase, the Local Co-occurrence Map (LCM) is used to separate the misclassified background and character pixels. Finally, a morphological 8-connected object segmentation is used to remove the isolated misclassified pixels (artifacts). (H)-DIBCO (2009-2013) datasets were used with the FM, PSNR, Recall, Precision, MSE, and NRM as performance measures. it compared with Otsu [13], Sauvola [6], Bern [17], Badekas and Papamarkos [24], Gatos et al [8]. Howe [20], Su et al. [25], and Ramirez-Ortegon et al [26], [27], [28]. A low-complexity is considered the best advantage of this approach.

Recently, Jia et al. [29] proposed a novel local threshold to binarize the degraded manuscript images based on structural symmetric pixels (SSPs). It is compared with eight previous methods named Otsu [13], Sauvola [6], Howe [20], Lu [30], Su [19], Lelore [11], Mitianoudis [23] and his previous method Jia et al. a [31]. DIBCO/H DIBCO (2009-2016) are used to test this approach based on their numerical values obtained from FM, p-FM, PSNR, DRD, NRM, and MPM. The results of this method proved that it was better than the compared methods.

From this literature, some remarks could be concluded as follow:

- The recent methods provide higher results than the well-known methods (Otsu, Sauvola).
- The recent methods require some additional phases to improve their results (i.e. training phase, pre or post-processing phases), which require a high computational complexity.
- The binarization process is still an open challenge problem, and it's a very important process in many fields.

2.1 Problem Statement

Binarization process of the degraded manuscripts image is considered as an open challenge till now. There are different methods divided as global methods, local methods or hybrid between them [2]. The input is the handwritten image that suffers from different kinds of noise. This noise is more than one type as multicoloured, bleed-through, the ink on both sides of the document, a part of an image with broken characters, stains, weak stroke, and uneven illumination. The mentioned types of noise are a sample of these types. The output is named a binary image, where its pixels are only black and white pixels. The text (character) is presented by black pixels, while the background is white. The binarization problem is considered as an unbalanced problem in which the number of black pixels is less than the white pixels. Figure 1 summarizes this process. The problem of these images can be described as follow:

Figure 1-a illustrates that the part from the original handwritten image. As we noticed, this part is a background; it contains a hidden word which is considered a big problem for obtaining a high-quality binarized image. Figure 1-b shows the original degraded image as a complete image. Finally, Figure 1-c presents the binarized image which is considered the main target (output). Thus, a solution based on the concept of the optimization is proposed in this paper as it uses one of the recent optimization algorithms named MFO.

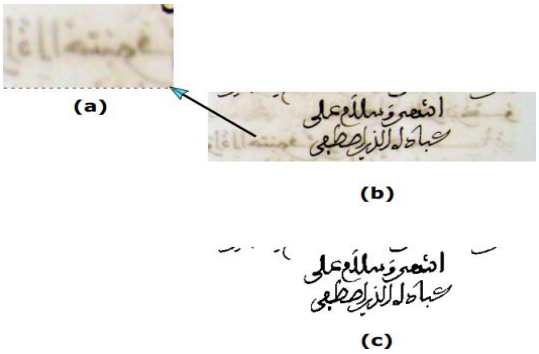

Figure 1: A graphical illustration of the problem statement

3. Nature-Inspired Moth-Flame Optimization: Basics

Mirjalili in [1] proposed a novel optimization algorithm which it's mimic the behavior of moths in nature. There are different types of moths. The moths fly uses a fixed angle regard to the moon, which is an extremely effectual approach for longer travelling distances in a conventional line. Each moth is related with a flame (flag). A transverse orientation is employed for navigation. Flame is the best solution which each moth updates their position according to it. The E function is considered the core function which moths move around the search space. Each moth updates its position according to the flame based on Equation 1.

$$M_i = E(M_i, E_j) \quad (1)$$

$$E(M_i, F_j) = D_i e^{b\,t}\ cos(2\pi\ t) + F_j \quad (2)$$

where D_i is the distance of the *i-th* moth for the *j-th* flame, *t* is a random number in [-1,1] and *b* is a constant for presenting the shape of the *P.* and *D* is computed as:

$$D_i = |\ F_j - M_i\ | \quad (3)$$

$$F_N^0 = round\left(Y - h\ \frac{Y-1}{k}\right) \quad (4)$$

where $F_N o$ denotes to the number of flames, *h* is the current iteration number, Y denotes to the maximum number of flames, and K represents the maximum number of iterations.

4. The Proposed Binarization Approach

The proposed approach is composed of the following phases: The initialized phase of MFO contains the following: determine the number of search agents (moths), the maximum number of iterations, fitness function which chosen as in [32] [33]. At each iteration in the optimization phase, the fitness value of each moth is evaluated based on the selected fitness function given in Equation 7 while the best solution is chosen (it is called Flame). Each moth updates the position according to the flame. Finally, each centroid of each cluster is updated based on the best position (solution). The binary image is therefore composed. These steps are illustrated in Figure 2.

4.1 Fitness Function and MFO setting parameters

In this paper, K means clustering [33] objective function is used. A distance measure d(x, c) between centers and vectors is computed as:

$$d(x_i, c_j) = \sqrt{\sum_{j=1}^{dw}(x_{im} - c_{jm})} \quad (5)$$

where is the number of features of the data vector is presented by *dw* and each cluster center c_j is computed based on the following Equation;

$$c_j = \frac{1}{n_j}\sum_{\forall x_i \in s_j} x_i . \quad (6)$$

The number of data vector is presented by n_j in the subset S_j. The used objective function is defined as:

$$J = \sum_{j=1}^{k}\sum_{i=1}^{n} ||\, x_i^j - c_j\, ||^2, \quad (7)$$

where $||\, x_i^j - c_j\, ||^2$ is the distance measure. Each cluster is presented within a single centroid. Each moth presents one solution and the position is updated according to the flame (best solution) based on Equation 1.

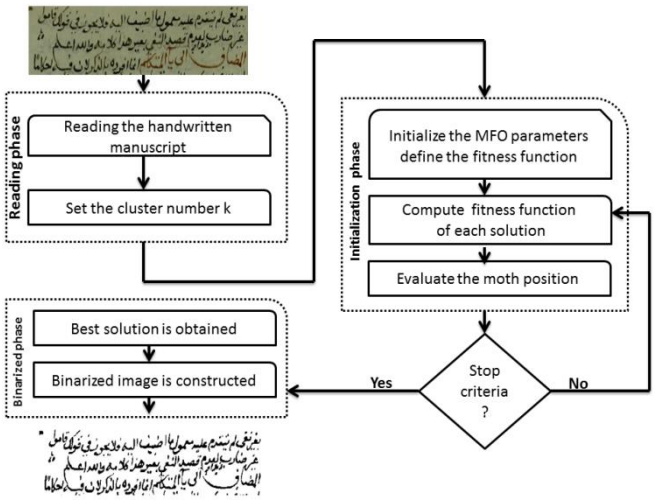

Figure 2: Flow chart of the proposed binarization approach

4.2 Parameters Tuning of MFO

For any optimization algorithm, we define some parameters that should be provided for an excellent performance of the examined approach. For the moth-flame optimization parameters setting, the parameters are chosen as follow: the number of moths is 25, the number of iterations is 15, number of runs is 10, number of clusters is 2, and the search space range is [0 255]. These values are selected based on different experimental results.

5. The Experimental Result and Discussion

5.1 Dataset characteristics

The handwritten degraded manuscripts images were selected from [i]. This site contains a huge number of historical books and manuscripts images written in Arabic language. The selected images suffer from various types of noise such as bleed-through, smudges over different parts of images, hidden text and so on. Some samples are illustrated in Figure 3.

Figure 3: Degraded manuscripts images

5.1.1 Performance measures

In order to evaluate the proposed approach, different performance measures are used and employed for this task. The high value of F-measure, p-FM, PSNR, GA and a low value on DRD, NRM, and MPM indicates that the best result.

- **F-measure [34]**

$$F\text{-measure} = \frac{2 \times Recall \times Precision}{Recall + Precession} \quad (8)$$

where $Recall = \frac{TP}{TP + FN}$ and $Precision = \frac{TP}{TP + FP}$, the FP, TP, and FN represent the false positive, the true positive, and false negative values.

- **pseudo-F-measure (p-FM) [35]**

$$pesudo - FM = \frac{2 \times pRecall \times Precision}{pRecall + Precession} \quad (9)$$

Which $pRecall$ is expressed as the percentage of the skeletonized GT image.

- **Geometric Accuracy (GA) [37]**

$$\text{Geometric Accuracy} = \sqrt{\frac{b}{B} * \frac{w}{W}} \quad (10)$$

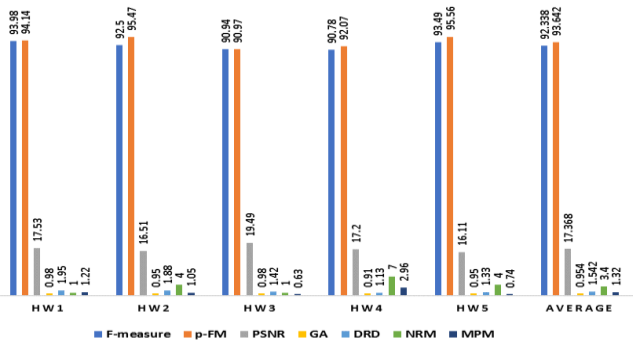

Figure 4: The result of MFO on selected handwritten images

the corrected classified pixels (black and white) represented by b, w and the total number of black and white pixels by B and W, respectively.

- **Misclassification Penalty Metric (MPM) [35] [38].**

$$MPM = \frac{MP_{FN} + MP_{FP}}{2} \quad (11)$$

where $MP_{FN} = \frac{\sum_{i=1}^{N_{FN}} d_{FN}^{i}}{D}$, $MP_{FP} = \frac{\sum_{i=1}^{N_{FN}} d_{FP}^{j}}{D}$,

the distance of the i^{th} false negative pixel and the j^{th} false positive from the contour of the text in the GT image are represented by d_{FN}^{i}, d_{FP}^{j}. The sum of whole pixel-to-contour distances of the GT object are depicted by the normalization factor D.

- **Negative Rate Metric (NRM) [35]**

$$NRM = \frac{NR_{FN} + NR_{FP}}{2} \quad (12)$$

where $NR_{FN} = \frac{N_{FN}}{N_{FN} + N_{TP}}$,

$NR_{FP} = \frac{N_{FP}}{N_{FP} + N_{TN}}$. It employed for measuring the mismatched between the GT and predicted image.

- **Distance Reciprocal Distortion (DRD) [36]**

$$DRD = \frac{\sum_{g} DRD_{g}}{\text{NUBN}} \quad (13)$$

where $NUBN$ represents the number of non-uniform 8×8 blocks in the GT and DRD_k represents the distortion of the g^{th} flipped pixel.

- **Peak Signal-to-Noise Ratio (PSNR) [34]**

$$PSNR = 10\log\left(\frac{C^2}{MSE}\right) \quad (14)$$

Where x $MSE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[P_{bin}(i,j) - P'_{bin}(i,j)\right]^2}{MN}$,

C indicates the difference between the background and text.

5.1.2 Numerical Results

In Figure 4, the statically result of the proposed binarization approach are presented. The results of five images from the handwritten Arabic data set were selected, in which each row indicates one image. These images are labeled with HW X, where X denotes the number of the image as HW1……..HW5. Each column presents the name of the performance measures used as depicted. F-measure is very high in image HW1 while the low value in image HW4. p-FM value is high in HW5. In addition, PSNR is the best regarding other images in HW3. The excellent GA result in image HW1 and HW3 is with a value of 0.98. The image HW4 has the best DRD with a value of 1.33. HW3 is the best MPM with a value of 0.63. The best NRM value appears in image HW1 and HW3 than other images. The good binarized image is HW3. It could be noticed that HW3 is the best-binarized image. Figure 5 shows the comparative analysis of the proposed approach with the compared methods named Otsu's [13], Niblack's [5], and Triangle [40]. These results show that the proposed approach performs well than other compared methods. As shown in Figure 5, the proposed approach is the best of f-measure with value 92.34, while the second ranked method is Otsu's with value 89.29, while the worst value appears in Triangle's method with value 76.53. PSNR with value of 17.37 is the best value provided by the proposed method and the lowest values of DRD, NRM, and MPM with values 1.54, 3.4, and 1.32, respectively. The Otsu's method provides the acceptable result in all performance measures, while the worst result is with the Triangle's methods. Finally, the proposed approach provides the encouraging result in all measures. From these results, the proposed approach is able to deal and processes different kinds of noise in the degraded manuscripts image.

5.1.3 Visual Inspection

The visual inspection is very important process in the document analysis field. In this study, two images were selected for presentation. Figures 6 and 7 illustrate the binarized image as the output of proposed approach with the compared methods. Figure (6-a) shows the original degraded image which suffers from noise such as: multicolored noise and suffering of ink to both sides of the image. Figure (6-d) shows the ground truth image. The worst result appears in Figure (6-d) as each character is bolder than it appears in the original image. The result in Figure (6-b) - which is provided by Otsu's - is acceptable, but some of the text characters are incomplete structure. In Figure (6-c), apart from an image is hidden (non-appeared text). The cleared binarized image appears in Figure (6-f) is provided by the proposed approach. . Figure (7-a) shows the original degraded image which suffers from noise such as different smudges overall image and background noise. Figure (7-d) shows the ground truth image. The unacceptable result with Triangle's method in Figure (7-e) in which each character appears larger than the original image and some small black pixels are around each character. Although the Otsu's and Niblack's methods provide an acceptable result with some small black pixels around characters, it's less than the Triangle's method (7-e,c). The good binarized image appears in Figure (7-f). The similarity between the proposed approach and the ground truth is very high except for some small issues which could be treated in the future work by adding the post processing phase.

5.2 Analysis of the MFO Convergence Curves

The analysis of the convergence curve is considered the main measure to evaluate any optimization algorithm. As a result, in this section, the convergence curves of MFO are plotted and analyzed. The fitness value of each best flame is saved at each iteration. Four convergence curves of different images are figured out in Figure 8. In our paper, the optimization problem is minimizing the objective function. It is noticeable from these Sub figures the following:

• a) the convergence curve is directed down quickly.

• b) The accelerated degrade of each convergence curve.

• c) The last convergence curve is reached faster than others.

From the above analysis, we conclude the success of the proposed method. Another good evidence about the success of the proposed approach appears in Figure 9. The number of the flames appears in Figure (9-a, b), with the values 40, and 25 with numbers of iterations 25, and 15, respectively. The moths revise their position only according to the best flames in the final step of iterations. As reported in [1], the regular decrement in the number of flames balances the exploration and exploitation of the search space. When the E function in Equation 1 is terminated, the best moth is obtained as the best-gained estimate of the optimal. As shown in Figure (9-a,b), the two values of flames are gradually decreased till the number of iteration is completed, and it achieves the great balance between the exploration and the exploitation phase, which has a direct influence on the MFO performance.

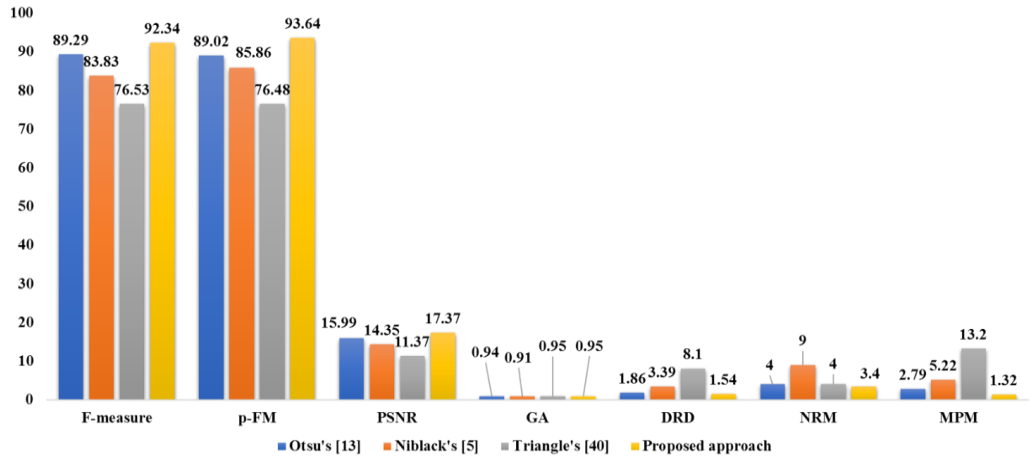

Figure 5: Comparative analysis with the previous methods

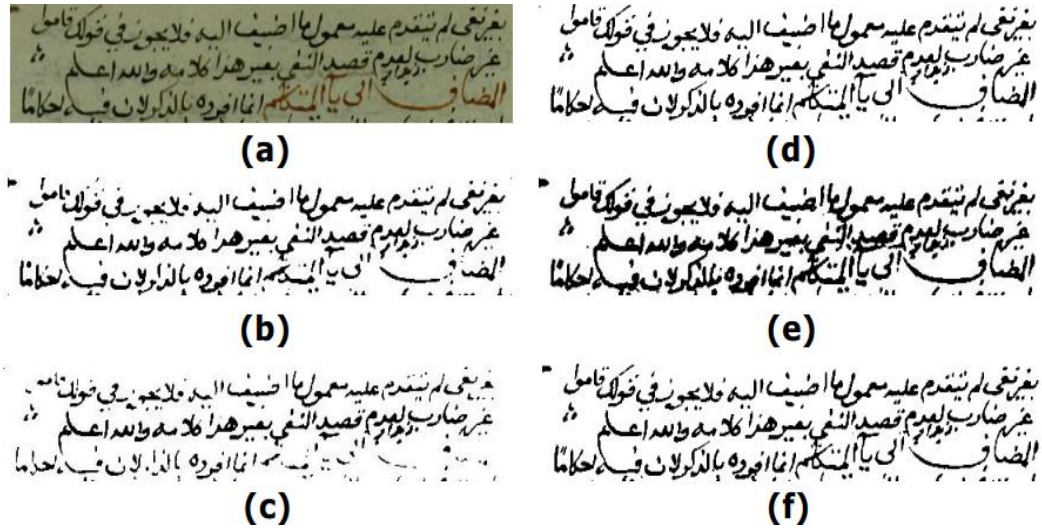

Figure 6 a): Original image, b): Otsu's result, c): Niblack's result, d): GT image, e): Triangle's result, f): proposed approach

Figure 7 a): Original image, b): Otsu's result, c): Niblack's result, d): GT image, e): Triangle's result, f): proposed approach

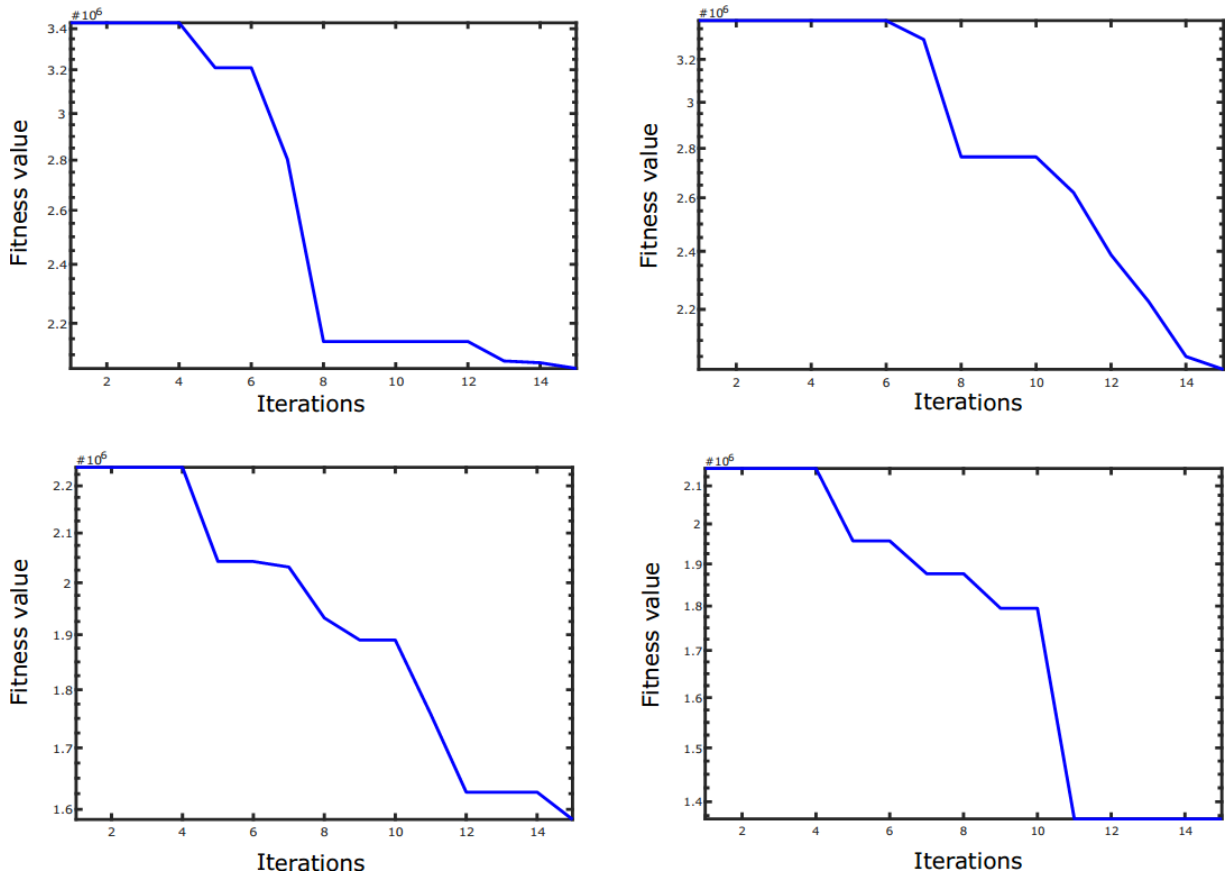

Figure 8: Convergence curves of MFO.

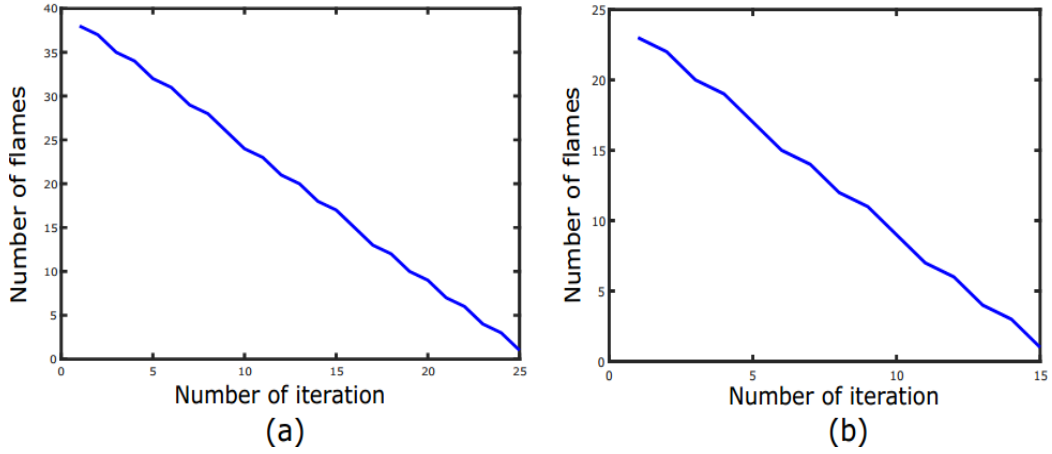

Figure 9: Number of flames against iteration number

6. Conclusions and Future Work

This paper introduces a global binarization approach based on the moth-flame optimization algorithm. It is used for minimizing the K-means objective function. Arabic manuscripts images are collected, and their ground truth images were built. These images are suffering from various types of noise. The proposed approach is compared with the well-known binarization methods, in terms of different performance measures. Technically, based on the analysis of the results, this approach can deal with several types of noise as well as producing high quality-binarized images.

Furthermore, the convergence curves rate demonstrates the fast speed of the MFO algorithm towards reaching a minimizing value of the selected objective function. However, some problems still prevented it from getting equal success on all kinds of noise. In future work, it is planned to use some pre-processing phases for excellent achievement in this field. It's also scheduled to propose a fusion version with an optimization algorithm to increase the quality of the binarized results. In addition, MFO with deep learning techniques will be considered to propose a new solution.

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