A Fuzzy C-Means Based Approach Towards Efficient Document Image Binarization

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*Abstract*— Many traditional binarization techniques fail to overcome the challenging impediments fostered by degraded historical handwritten document images. In this paper, we present a fast and competent, yet simple binarization technique that uses a Fuzzy C-Means based global thresholding approach, aided by background separation. The proposed method uses a superset of foreground regions to correctly assess background of the document image. Background is estimated based on a sliding interpolation window of variable dimension, judged by appraising the nature of text stroke. Ultimately a global approach is undertaken to binarize the background-separated normalized and enhanced image by clustering the pixels using Fuzzy C-Means. This helps considering indeterministic nature of each pixel and the bland nature of the normalized image. The proposed technique is applied on the most recent (2016) benchmarking dataset of Handwritten counterpart of Document Image Binarization Contest (H-DIBCO). In order to substantiate its competence and accuracy, the experimental results are compared with the top-three winning techniques in the contest and other well-known techniques, in terms of an ensemble of parameters. It is observed that the proposed technique outperforms the best competing techniques in almost all the measuring parameters.

Keywords— Document image binarization, background estimation, fuzzy c-means, image normalization, H-DIBCO.

# Introduction

*Document image binarization* (DIB) facilitates transforming a grayscale document image into a binary image with dual values of pixel intensities, high intensity (255) representing *background* and low intensity (0) representing *foreground*. DIB serves as a paramount preprocessing phase for assessment of document images specifically in the fields of pattern recognition, feature extraction, optical character recognition (OCR) and information retrieval. It also finds application in the domain of signature matching, storage of stained maps in digital format, preservation of historically significant degraded documents in machine-encoded text format. But, such kinds of document images predominantly possess disconnected or imperceptible text strokes, low contrast, perspective and geometric distortions, uneven background, non-uniform illumination, ink seepage, smudges, smear, strain, bleed-through, background ink-stains. Degradations could also get caused by various other imaging artifacts like aging medium, poor acquisition, bad scanning. These pose as hindrance to the process of binarization and thus limit its further downstream applications making it difficult and erroneous for computers to automatically recognize optical characters, shapes and features. The urge to minimize the limitations and maximize the efficiency has appealed binarization techniques to be explored colossally. As a result, a large number of binarization algorithms have been published in the literature till date. Worldwide participation in annual DIB competitions, latest held in DIBCO 2017, the ICDAR 2017 competition accord a good indication overall to establish the fact that there are still some unexplored scope of improvement in the branch of document image binarization. This provides an impetus to our present work.

This paper is organized in five sections. In following part, we present allied work done by several researchers. In section three, we present the proposed approach through five distinctive stages. This is followed by section four comprising the experimental results and associated observations. Finally, in section five, the epilogue with way forward is presented.

# Background and Related Work

Till date, many binarization techniques have been tried and tested to handle the aforementioned challenges. Some researchers prefer a simple and fast *global* approach, while some favor an adaptive *local* approach, albeit time-consuming and performance-heavy. The *global thresholding* technique computes a single threshold value applicable across the whole image, but is at times unable to deal with several complex challenges. *Local thresholding* is an adaptive thresholding process to compute a threshold for each sub-image or each pixel of the image.

Otsu’s [1] technique is one of the most renowned and classic method. It uses a clustering based *global thresholding* algorithm which minimizes the intra-class variance and maximizes the inter-class variance, but has the drawback of proffering best results only in case of a bimodal histogram. Brink [2] computes threshold value by maximizing the information theoretic entropy from resultant background and probability distributions of objects by appraising two-dimensional (2D) entropies by using the underlying 2D scatterplot.

Niblack’s method [3] remains a classic and widely incorporated technique, which calculates a pixel-wise threshold with the help of standard deviation and localized mean computed on all pixels in a sliding window. But this usually gives different results with changing window size and often provides a superset of actual foreground regions. Sauvola and Pietikäinen [4] modify this by introducing the variance standardization value. Local thresholding involves a lot of manually tuned parameters and tends to provide better results in stained or poorly illuminated documents at the cost of time and performance. Huang et al. [5] use a mathematical morphological technique in combination with Bradley’s algorithm [6] and adaptive K-means clustering. Jacobs and Momoniat [7] use linear diffusion text binarization.

Although local approach are expected to proffer better result than global approach, but they may become quite unsuccessful in those areas of the image where variance is less. Moreover, its high computational complexity along with the former impediment has influenced us to propose a method that deploys a global approach, yet performing supremely compared to other techniques. Ahmadi et al. [8] use supervised binarization algorithm using marginal based learning for parameter estimation. Ntirogiannis et al. [9] use inpainting for background estimation, which works well with a correct window-size, but for large images, runs slow. Gatos et al [10] employ a low-pass type Wiener filter as pre-processing before utilization of Sauvola’s [4] binarization output. But it is unable to deal efficiently with faint foreground situation, and sometimes produce a blurred and spatially invariant result. Moreover, it inherits some drawbacks of Sauvola’s technique being reactive to choice of parameters and size of window and computationally slow. Chena and Wanga [11] use an extended non-local means method to reduce noises from the input document image in pre-processing step followed by adaptive thresholding based binarization done. Thereby, they finally apply post-proceesing involving de-speckling, preserving stroke connectivity and eventual improving quality of text regions.

# The Proposed Methodology

The proposed image binarization process involves five stages in chronological order as depicted as a Unified Modeling Language (UML) [12] activity diagram given in Fig. 1. The diagram shows synchronization points where two or more activities may diverge to fork or meet to join, indicating concurrent processing possibility. First, we need to perform a meaningful assessment of the text-strokes. Next, superset of foreground regions is estimated. Next two stages comprise background estimation and image normalization. Eventually, binarization is performed on the background separated normalized image using Fuzzy C-means based clustering.

## Assessment for Width of Text Strokes

In the present context, Sobel’s Edge Detection Algorithm [13] has been used to detect edges in the document image. Sobel’s method facilitates a smoothening effect through an average filter. This algorithmically simple technique eliminates randomly-spread high intensity point-noises from edge-detected image. In comparison to other edge detection algorithms, Sobel’s method provides enhanced, bright and thick edges [14]. It is evident that text stroke width assessment helps categorizing the nature of the majority of text strokes as thin or thick. The value of average character-stroke-width, aids to automate the choice of size of structuring element in morphological operations for background estimation.

Subsequent step is to detect all the connected components of the edge-detected image, referred henceforth as . The small-sized connected components are eradicated [15] as these components are likely to have been originated from isolated noise pixels in the original image. By small-sized components, we refer to the ones comprising less than β edge-pixels. Based on several test images, optimally we have found that accurate results for the value of is obtained when the value of β is taken as dimension of a small area, covering 10% of mean pixel-area of all the detected components in .



1. UML activity diagram showing the steps of the proposed method

So, to compute the stroke-width with minimal error, it is judicious not to count these in further stroke-width calculations. For the larger connected components (, the height () and width () of the smallest rectangle bounding them is computed. Each row, r, is scanned from left to right. Here, , is the number count of the connected components after smaller ones getting eliminated. In case, a pixel, is encountered, which itself is an edge-pixel and is a non-edge pixel, it is termed as a *start-pixel*.

1. Histogram showing width versus frequency of that particular width. The three dotted lines represent the stroke-widths corresponding to the three highest frequencies, specifically: f=754 for d=5, f=672 for d=6, f=510 for d=7

On the contrary, if a pixel, , is an edge-pixel and is a non-edge pixel, it is termed as an *end-pixel*. The distance between consecutive *start-pixel*s and *end-pixel*s (including the *boundary pixel*s) is termed as *stroke-width*, , computed as in Eqn. 1. (1)

Eventually a histogram (H) of the various stroke-widths () versus their frequency () of occurrence is formed (Fig. 2), for. Average of the stroke-widths corresponding to three highest frequencies of H is considered as the average stroke-width ().

## Estimation of superset of foreground region

Background image construction generally requires a preliminary identification and seclusion of the pixels belonging to the foreground region. As a yardstick, for foreground estimation, we make the presumption that all the candidate textual regions have a lower intensity than intensity of the background pixels encompassing it.

For the purpose of an initial segmentation of the foreground and background regions Gatos et al. in [10] use Sauvola’s approach for adaptive thresholding. On a counter note, in our proposed method, we prefer using Niblack Binarization algorithm [3] as a prelude of our background separation due the following advantage. It achieves a very high Recall Rate [16] by accurately detecting all text regions as foreground [17] albeit presence of a great amount of noise in non-text regions. As a result of this, it always estimates a superset of the actual foreground regions.

Niblack’s algorithm uses a rectangular window of dimension, , sliding over the grayscale image to determine pixel-wise threshold. The threshold value, assigned to each pixel, takes into account the localized mean, , and localized standard deviation, , of the pixels present in the entire window, as it is evident from the formula given in Eqn. 2,

(2)

The window size, , should conform to [18]:

1. it manifests the local lighting condition of the image precisely, and
2. it does not include foreground pixels exclusively, i.e. at least few background pixels must be within the window.

Thus should be assigned a value which should be more than the average stroke-width of the textual regions (to satisfy condition (ii)) and also less than the size of noise stains in the image (so that local illumination levels does not change, and condition (i) is satisfied).

|  |  |
| --- | --- |
|  |  |
| (a) | (b) |

1. Original versus corresponding superset of foreground region with (a) as original image and (b) corresponding superset of foreground region

We optimally choose a fixed parameter setting, i.e. for Niblack Binarization that efficiently handles most of the cases. This estimate of window-size is larger than the average stroke-width of most of the images, and smaller than the average noise stain dimension, and thus tends to proffer superior result in majority of the cases, hence validating it to be a credibly robust choice. The window size, , is chosen as an odd number because it facilitates the definition of a unique center pixel for the sliding window. The value of parameter is kept fixed at -0.2 as this takes care of most cases quite efficiently, as suggested by Trier and Jain [19]. This extracted foreground region is henceforth termed as Fig. 3 shows superset of foreground region corresponding to original counterpart.

## Document Image Background estimation

Most of the standard binarization algorithms provide best outcome for images having histogram plot of frequency of intensities containing at most two sharp peaks. For example, Otsu’s [1] technique, but may fail in various scale of distortions. In such unsuccessful scenarios, background estimation followed by image normalization accord a near bimodal histogram to the image, and thus makes the subsequent binarization procedure much streamlined.

The proposed method uses a simple, fast and competent process to estimate an approximate background surface, , from the original grayscale image, with the aid of the foreground regions, For the background estimation we have modified the approach adopted by Gatos et al. [10] by customizing the size of the interpolation window and making it dependent on the stroke-width of the document image. The pixels belonging to background (i.e. possess pixel intensity 1) in the binary image can be assuredly adjudged to be a part of the background region of . So, for the pixels in which has an intensity value of 1, the corresponding intensity value at is maintained same as that of . On the contrary, for the remaining pixels (the candidate foreground pixels), the intensity of the corresponding pixel in is calculated by interpolation from the neighboring background pixels in the window, by taking mean of their intensities. We consider, as the size of the interpolation window. Thus the intensity of a pixel in can be defined as in Eqn. 3, where,

(3)

|  |  |
| --- | --- |
|  |  |
| (a) | (d) |
|  |  |
| (b) | (e) |
|  |  |
| (c) | (f) |

1. Original versus corresponding background images with (a)-(c) as original images and (d)-(f) their corresponding background images

We set as this ensures that this window, in most likelihood, produces accurate estimation with at least some background pixels within it. This is true because, for a document with thick text-strokes, when the center of the window is at the core of a textual stroke, then a sufficiently large window size is required to ensure inclusion of at least some background pixels in the window. Furthermore, for a document image with relatively thinner strokes, a large window may induce error in the accuracy of the interpolation as pixels far-off from the center of the window, start affecting the corresponding intensity of the latter in . Fig. 4 shows background images corresponding to original counterparts.

## Normalization of image

Fluctuations in illumination levels across the image have been a challenging problem for binarization, and so, to procure esteemed results, it is a latent prerequisite to reduce these variations. Previous background estimation stage assesses an approximate background of a document image possessing non-uniform illumination and hence, uneven background. This stage focuses to approximately deduct the background image, from the original grayscale image, [15], so that the potential foreground remains unaltered while a nearly uniform intensity for all the background pixels is brought about. This effort balances the lighting condition of the image and thus effectuates a near bi-modal histogram to the image. After this stage, the image becomes easier to binarize with substantial success.

The original grayscale image is subtracted from the estimated document image background image, and thus the variations of illumination in are literally done away within image, , acquired as in Eqn. 4.

(4)

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| --- | --- | --- |
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| (a) | (b) | (c) |

1. Original images of Fig. 4 (a-c) in their corresponding normalized embodiment

Pixels (having lower intensity) in potential foreground regions in are interpolated from the neighboring background pixels (having higher intensity) in stage 3. On the other hand, background pixels in are brought forward as it is in . Thus intensity of all pixels in is greater than or equal to those in . Subsequently, Eqn. 4 results in a normalized image, with the 0-side representing background and 255-side representing foreground. So, the final background-separated image, is acquired by complementing each pixel, as in Eqn. 5.

(5)

where R,C represent the height and width of , respectively. Fig. 5 shows normalized images corresponding to original counterparts.

## Binarization by clustering

Background separation and image normalization relieve the image from both global and local illumination variations, like shadows and highlights. This assists in rectifying and enhancing the original image before a thresholding algorithm is finally applied. The process of binarization aims to segregate image pixels into foreground and background subdivisions based upon the relationship between the gray-level intensity of a pixel. The proposed method employs a multivariate Fuzzy C-means clustering algorithm [20] for performing segmentation in . We use the following variables within a sliding 3×3 window, for the multivariate fuzzy C-Means clustering:

* Intensity of each center pixel
* Mean of intensities of the 8-connected neighboring pixels of each center pixel.
* Standard deviation of intensities of the 8-connected neighboring pixels of each center pixel.

Values outside the bounds of are computed by mirror-reflecting the intensities across the image boundary. Clustering algorithm aims to delineate regions in an image into a number of clusters, which is carried out by identifying regions that are homogeneous in some set of local image attributes. The segregation is such that there exists high similarity of the samples inside the clusters (minimization of intra-cluster difference) and high dissimilarity between samples belonging to distinct clusters (maximization of the inter-cluster difference). Total number of the clusters is taken as 2 for the present scenario, since the proposed method aims to segregate into two subdivisions, viz. foreground (represented as black) and background (represented as white). Unlike hard clustering where each data point can belong exclusively to a single cluster, Fuzzy C-means (FCM) [20] is a technique of clustering which allows a data point to belong to two or more clusters at the same time, with varying degree of membership. A data point is constrained to each cluster by means of a membership function, which epitomizes the fuzzy behavior of the algorithm. This can be considered as a perfect analogy for the case of binarization, where excepting some indisputable foreground and background pixels, there exists pixels that cannot be unfalteringly segregated in any of these two subgroups.

Fuzzy C-means relies on the minimization goal of the objective function [20] given in Eqn. 6.

(6)

Where, the symbols are defined in Table I.

1. Symbols used in Eqn.6

|  |  |  |
| --- | --- | --- |
|  | : | Total number of data points = |
|  | : | Total number of clusters |
|  | : | ith data pixel and center of jth cluster respectively |
|  | : | Degree of membership of data pixel, in the jth cluster |
|  | : | ;controls degree of fuzzy overlap between clusters |
|  | : | Any norm metric signifying the similarity between and |

The values of the degree of membership of all data pixels in both clusters are randomly initialized. In each iteration (, the centers of the clusters are updated following the Eqn. 7 [20].

(7)

The degree of membership of each data pixel, in the jth cluster is also revised as in Eqn. 8 and the objective function is again calculated.

(8)

The process is reiterated until ceases to vary rapidly with each iteration, and centers of the two clusters converge to two solidary points, as shown in the condition given in Eqn. 9.

(9)

where , , characterizes the objective function after iteration (itr), objective function after iteration (itr-1) and a small threshold value, respectively. The value of is opted as a very small positive real number, specifically 0.00001 for the present instance.

Although each data pixel, has a degree of membership, and in each of the two clusters (, but its involvement in one cluster is dominant than the other as evident from Eqn. 10, since if is larger, must be smaller to keep the sum constant.

(10)

The proposed method exploits this characteristic in segregating each pixel into either of the clusters, as evident from the following function as in Eqn. 11.

(11)

In the aforementioned case, refers to the background cluster whose center is at a higher intensity region, that the other cluster, . The proposed method takes into account the bland nature of , caused by separation of background from Accordingly, it prioritizes the foreground pixels by maintaining the allowed range of for more than that of . We found that gives best results when it belongs to the range . Ultimately, the final binarized image is obtained as in Eqn. 12.

(12)

where corresponds to that particular pixel in from which it is extracted.

# Experimental results and Discussion

For the experiments, we have used the H-DIBCO’16 dataset, the handwritten images of the DIBCO or Document Image Binarization Contest event series, that are publicly available. All the images and their corresponding ground truths are taken from the competition’s site [22]. H-DIBCO is an established and popular forum in the field of document image binarization. Since 2009, DIBCO and H-DIBCO provide benchmarking dataset not only to the participants in the contest, but also to the research community for the purpose of research data with public domain availability. These datasets provide handwritten as well as printed character set providing challenging assignment with noises and distortions to be barely readable in its as-is form. In addition, DIBCO datasets for the contest provide a common platform of comparison yardsticks with ground truth, as created by a forum of human referees after applying different binarization techniques on the image dataset.

Fig. 6 shows the final outcome after applying proposed binarization technique on the original images. The H-DIBCO’16 dataset contains twelve different competing techniques from nine distinct research groups respectively. For the evaluation purpose, an ensemble of measures has been used. In the contest of H-DIBCO’16, the evaluation measures of F-Measure (FM), pseudo-FMeasure (), Peak Signal to Noise Ratio (PSNR), Distance Reciprocal Distortion (DRD) Metric are used [21].

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|  |  |
|  |  |
| (a) | (b) |

1. (a) Few selected dataset images from H-DIBCO and (b) Binarization results obtained using proposed method

Two major goals for any performance evaluation are undoubtedly its effectiveness for practice and efficiency when compared with other algorithms. In Table II the detailed results of the three (3) best competing techniques in the H-DIBCO contest of 2016, along with the well-known techniques of Otsu [1], Sauvola [4] are presented. The results of the proposed method are accorded along with them, and compared with the former. We have also compared our results in Table II, with a process () that employs the same method of background elimination but uses a different clustering algoritm, specifically K-Means. Values in bold represent the first position among all the participants, as well as, Otsu’s, Sauvola’s and in each respective column. It is evident from Table II that the proposed method outperforms all the participants in H-DIBCO’16 in the measuring parameters of F-Measure, and PSNR, while it secures the third position in the field of DRD. In Table III, the individual measures and detailed results acquired by applying the proposed technique on each of images of H-DIBCO’16 are presented.

It can be adjudicated that even without any post-processing step after binarization by the proposed systematized order of steps, the method outperforms the best competing techniques in the H-DIBCO contest of 2016 in three fields, and stands shoulder to shoulder with the top two in the other measure.

1. Comparative Study of Methods on the Basis of Performance Measures

| Measures\*\* | | | | |
| --- | --- | --- | --- | --- |
| Method | F-Measure |  | PSNR | DRD |
| 3rd | 88.47 ± 4.45 | 91.71 ± 4.38 | 18.29 ± 3.35 | 3.93 ± 1.37 |
| 2nd | 88.72 ± 4.68 | 91.84 ± 4.24 | 18.45 ± 3.41 | **3.86 ± 1.57** |
| 1st | 87.61 ± 6.99 | 91.28 ± 8.36 | 18.11 ± 4.27 | 5.21 ± 5.28 |
| Otsu | 86.61 ± 7.26 | 88.67 ± 7.99 | 17.80 ± 4.51 | 5.56 ± 4.44 |
| Sauvola | 82.52 ± 9.65 | 86.85 ± 8.56 | 16.42 ± 2.87 | 7.49 ± 3.97 |
|  | 86.59 ± 6.75 | 91.17 ± 5.36 | 17.85 ± 3.52 | 4.90 ± 2.97 |
| Proposed | **89.40 ± 4.24** | **92.72 ± 5.13** | **18.51 ± 3.49** | 4.14 ± 2.42 (3rd ) |

\*\* Based on H-DIBCO’16 dataset

1. Results of the proposed method on individual H-DIBCO’16 Images in terms of different performance metrics

| Measures | #1 | #2 | #3 | #4 | #5 | #6 | #7 | #8 | #9 | #10 |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| F-Measure | 91.86 | 84.37 | 93.74 | 89.99 | 96.06 | 87.74 | 90.92 | 81.80 | 90.12 | 87.44 |
|  | 95.87 | 91.71 | 96.55 | 95.49 | 98.57 | 93.05 | 97.91 | 83.77 | 87.41 | 86.86 |
| PSNR | 19.72 | 22.16 | 22.18 | 19.73 | 22.76 | 18.20 | 17.56 | 12.54 | 16.03 | 14.18 |
| DRD | 4.37 | 5.19 | 2.56 | 3.87 | 1.37 | 5.59 | 2.30 | 9.91 | 2.65 | 3.59 |

Moreover, it is evident that clustering by applying Fuzzy C-means after background separation gives better result than that performed by K-means.

# Conclusion and Future scope

In this paper, we proposed an enriched technique with the intention of handwritten document image binarization that uses a Fuzzy C-Means based global thresholding, abetted by background separation and can handle diverse situations in an image. Our proposed methodology is directed at generic handwritten document images and it can cope up with severe instances of various types of degradation. The resultant images are validated with other classic techniques in literature, top competing techniques in the competition and also the ground truth of the images. The proposed technique is well-adapted and robust to nearly all types of degradations and it outperforms other competing techniques in terms of an ensemble of measures. However, this approach has some limitations and it secures a relatively low score in images possessing a very meager intensity-wise difference between foreground and background. This may however be improved if a tradeoff between global and adaptive approach is undertaken and this leaves a scope for our future endeavor.

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