Contrast Enhancement of Degraded Document Image using Partitioning based Genetic Algorithm

Manosij Ghosh
Computer Science & Engineering Department
Jadavpur University
Kolkata, India
manosij1996@gmail.com

Suman Kumar Bera
Computer Science & Engineering Department
Jadavpur University
Kolkata, India
berasuman007@gmail.com

Ritam Guha
Computer Science & Engineering Department
Jadavpur University
Kolkata, India
ritamguha16@gmail.com

Ram Sarkar
Computer Science & Engineering Department
Jadavpur University
Kolkata, India
raamsarkar@gmail.com

***Abstract*—Contrast enhancement is an integral part of document image processing that helps improving the picture quality even in poor-quality documents. The restoration of documents in digital form makes this step quite important to get the better accuracy in text recognition. We present an optimization approach named Partition based Genetic Algorithm (PGA) to enhance the contrast of low-illumining documents. In this approach, a recursive partitioning is used to divide an image until we get sub-images with lower intensity variations. On each sub-image, GA is applied to retain most of text-pixels for a better contrast enhancement. The extensive experiment on DIBCO 2013 and H-DIBCO 2016 datasets and the subsequent binarization expose that our approach gives satisfactory results for a better data retention. Though our approach is quite effective but easy to implement.**

Keywords—image enhancement, document image, dynamic partitioning, genetic algorithm

I. INTRODUCTION

Document image processing has been studied enormously since last few decades. This field covers some important research areas that include preprocessing, layout analysis, optical character recognition (OCR), keyword spotting, signature verification, and writer identification among others. Few important application areas of document image processing are office automation, forensics, and digital libraries etc. However, primeval printing and imaging techniques are generally the reasons for producing poor-quality document images. But, there are several occasion when dealing with such poor-quality images is obvious. Ancient texts or old documents generally suffer from physical degradation due to aging. Even the quality of many printed media, for example newspapers and magazines, is not very good also. The reason for this is the usage of very thin or inferior quality of papers during their production. But some of these damaged or poor-quality documents contain important information. Hence an accurate methods is required to restore them. Degradation found in document images ascends primarily from two sources: printing-imaging processes, and physical phenomena. Due to the adverse effect of degradation, sometimes document images become illegible after scanning. As a result, research on document image processing becomes a real challenge. Despite some significant advancements in this field, modelling defect and degradation in document image processing is still considered as an open and active research problem.

Lot of attempts have been made to address this problem since last few decades. It is noticed that a variety of degradations may arrived in a document page while digitizing it and a single approach is inadequate to remove all of the noises. Most of the existing algorithms [1-6] found in literature are thus designed to solve a particular problem. The degradations generally appear in this regard, can be low contrast illumination, irregular clutter noise, salt and pepper noise, punch holes, bleed through and broken characters. The readability of low-contrast images is improved by Leung et al. [7] by using the Partially Overlapped Sub-block Histogram Equalization Eeffect (POSHE) method based on the sub-block histogram equalization. The reduction of stroke-like pattern noise and clutter noise is addressed in [8, 9] by using the supervised classification algorithm Support Vector Machine (SVM) and Radial Basis Function (RBF). Hazi et al. [10] use Fuzzy logic to formulate the noise reduction and character recognition as a single optimization problem. She et al. [11] propose a combined approach to eliminate most of the noises introduced in a document page. Still their computational complexity remains high and the accuracy may degrade due to the non-uniformity of foreground and background intensity.

In this paper, we have made a sincere attempt to enhance the contrast of the poor-quality document images by applying an evolutionary algorithm, called Genetic Algorithm (GA), in an recursive way. A few methods [12-14] on GA for image enhancement by designing a fitness function and then optimizing it but they suffer from mainly two reasons: slow speed due to evaluation of fitness function requiring the comparison of two images and algorithm's inability to select automatic appropriate filters for optimization procedure. As a remedy, we introduce a dynamic partitioning to create sub-images on which GA is performed and to design a fitness function to retain the number of sharp edges. Our end results are validated by measuring the quality of the binarized version of the enhanced images. To evaluate our proposed GA based recursive image enhancement model, we have used printed and handwritten documents from DIBCO 2013 and H-DIBCO 2016 document image binarization competition dataset respectively.

The contribution of this work can be summarized as follows:

- Dynamic partitioning of images and using an evolutionary algorithm to enhance an image to have better contrast.
- Adaption of GA operations to fit it into this problem domain.
- Proposed method can retain maximum data during binarization.

II. PROPOSED WORK

In the present work, image enhancement using PGA is performed on grey scale images to improve its quality. Documents images, though important, are difficult to store in a long run as passages of time causes degradation in form of discoloration, destruction of documents. These facts necessitate the documents be stored in digital format for better preservation. Images in poor quality need to be enhanced for further processing of the same. Such enhancement makes information retrieval from the document images much easier.

A. *Dynamic Partitioning*

The global thresholding scheme becomes trivial when there are at most two sharp peaks in the histogram of an image because of the ease with which we can select the threshold value. Two sharp peaks indicate distribution of pixel intensities among two major groups and so we can select the average of the peaks as the threshold. If the number of peaks is less than or equal to 2, the enhancement can be done efficiently otherwise our proposed method tries to partition the image to make the number of peaks in the sub images as close to 2 as possible. The main idea behind this partitioning technique is to enhance the sub images efficiently and combine the enhanced sub images to enhance the contrast of original image.

Unsymmetrical partitioning of the document image is done using algorithm called Sharp-Peak-Count. This algorithm first creates the image's intensity histogram and counts the number of peaks. An intensity is said to be a peak if frequency of all 4 (2 previous and 2 next intensity values) are lower than its own value. Thereafter, the average of all the frequency of the peaks are taken and if any peak has a value greater than the average frequency, then it is considered as a sharp peak. The number of sharp peaks in an image is called $countSharpPeak$. The image is recursively partitioned into 4 equal rectangular images if $countSharpPeak$ is greater than ∂ and value of Partition Parameter (PP) is less than the number of rows and columns in the sub-image. The value of ∂ is taken as 2. To define PP, Partition Ration (PR) is calculated. PR is the ratio between number of pixels having grey scale values greater than the average value and the number of pixels having grey value lesser than the average. PP is n times the value of PR. We have used the value of n as 20. The detailed algorithm of the recursive partitioning process is provided in Algorithm 1 named Recursive-Partition-Evaluate. If partitioning condition is not satisfied then an optimization algorithm is applied on the image to find near optimal values for the pixel intensities to enhance the image. In this paper, we have selected GA as the optimization algorithm.

Algorithm 1: Recursive-Partition-Evaluate

Input: Gray scale image I, level.

Output: Enhanced Image I'.

Step 1: Calculate the number of sharp peaks using Sharp-Peak-Count algorithm

$$numSharpPeak \ = \ CountSharpPeak(I);$$

Step 2: Count the Sharp peaks $numSharpPeak$

Step 3: If partition criteria is not satisfied then apply GA and terminate the program

$If\ (level > 2\ or\ numSharpPeak\ <= \ 2)\ \ then$

$I' \ = \ geneticAlgorithm(I);$

$End\ If$

Step 4: Partition I into 4 rectangular partitions: I_1, I_2, I_3, I_4

Step 5: Test the 4 partitions recursively for further partitioning

$For\ each\ partition\ I_k\ where\ k\ is\ in\ [1,4]\ do$

$numSharpPeak \ = \ CountSharpPeak(I_k)$

$If\ (numSharpPeak \ > \ 2)\ then$

$Compute\ Partition\ Ratio\ (PR)\ of\ I_k$

$Compute\ Partition\ Parameter\ (PP) \ = \ n \ * \ Partition\ Ratio$

$If\ (number\ of\ rows\ and\ columns\ of\ I_k \ > \ PP)\ then$

/* recursively call the partition evaluate function for the subparts */

$I'_k = \ Recursive - Partition - Evaluate(I_k, level + 1)$

$Else$

$I'_k \ = \ geneticAlgorithm(Ik)$

$End\ If$

$End\ If$

$End\ For$

Step 6: $I' \ = \ combination\ of\ I'_k\ where\ k\ is\ in\ [1,4]$

B. *Intensity Optimization*

After partitioning is accomplished according to the proposed scheme of PGA, a number of smaller sub images are obtained. Each of these sub images then undergo optimization to find optimal intensity values for proper contrast enhancement. Since the number of sub images increases exponentially, the optimization process needs to be computationally inexpensive. To keep the computational cost as low as possible, we have used a simple yet sophisticated optimization algorithm namely GA. It is able to perform parallel search which reduces the time complexity and requires less number of input parameters. Thus, GA seemed to be the ideal choice for the contrast enhancement problem. The major operations of GA are crossover and mutation. In this work, uniform crossover and uniform mutation is used. The operations are performed on a set of chromosomes (x_i) which form a population. The chromosomes are vectors of integer values. The chromosome is built from the initial image, all the unique integer values present in an image form the chromosome. The values are placed in the chromosomes sorted in ascending order. Since this is performed on grey level images, the maximum size of the chromosome can be 256. For the image given in Figure 1 (a), the chromosome is provided in Figure 1 (b).

150	48	48	91
123	32	45	12
123	32	21	91
102	12	21	0

(a)

0	12	21	32	45	48	91	102	123	150

(b)

Figure 1: (a) Structure of chromosome (b) Derived from grey-level image

Application of crossover and mutation on the parent (old) chromosomes (x_i) creates new chromosomes (x_k). The image represented by the chromosome x_k is derived from the original image by substituting in the original image all occurrences of the value x_{ij} (the j^{th} term in the chromosome x_i) with the value x_{kj} . This function for transformation of image is given in equation 1.

$$transformed\ image = T(image, x_k) \tag{1}$$

Here uniform crossover allows for exchange of information in the parallel search by the different chromosomes. The probability of crossover is taken as 0.5. In mutation each value in the chromosome (x_{ij}) is mutated with a probability of 0.4. Value of chromosome (x_i) at the j^{th} position (x_{ij}) is changed by m which is determined by equation 2. A perturbation factor (p) is taken to ensure that the chromosome does not get stuck in a local optimum.

$$m = \left(rand * x_{i(j-1)} - x_{i(j+1)}\right) + \mathrm{p} * (2 * rand - 1) \tag{2}$$

The application of GA helps to transform the image to an enhanced version of itself. The fitness evaluation in GA is done using equation 3. The fitter the chromosome lower is the fitness.

$$fitness(x_i) = \log(\log(D(T(image, x_k)))) * Edges(T(image, x_k)) \tag{3}$$

Thus, the ultimate objective becomes to improve the value of the fitness function.

III. Experimental Results

To validate the outcomes of the proposed image enhancement method, the enhanced images are binarized using Ostu's method [15] and are compared with the ground truth. The datasets used are DIBCO 2013 and H-DIBCO 2016. H-DIBCO 2016 consists of 10 handwritten document images. The images contain all possible types of degradation. The average results are shown in Table 1 and image-wise results are provided in Table 2 and 3. The comparison of the generated image with the ground truth is measured in terms of 6 metrics namely Precision, Recall, F-measure, Accuracy, Peak Signal to Noise Ratio (PSNR) and Distance Reciprocal Distortion (DRD). From the mean results it can be seen that PGA is able to improve the quality of the images gained from Ostu's binarization by enhancing the images. Though improve ion precision is minimal or none, the improvement in terms of Recall and F-measure is quite remarkable. There is also a decent improvement in terms of Accuracy, PSNR and DRD.

For DIBCO 2013 dataset, the results of image 8 are much better for enhanced than normal. The enhancement can be seen in from Figure 2(a) to 2(b). There has been significant removal of noise which can be visually perceived also. A limitation of this work is that in case where a sub-image does not include any text, the algorithm in order to increment the edges magnifies the noise so as to turn them into prominent components in the image. This leads to a drop in precision which can be seen in Image 1. In case of uniform presence of text in the image, our method performs well as seen in Image 7-10 of H-DIBCO 2016. In this dataset, in terms of precision in 6 images enhancement brings about an increase precision. Improvement is seen in 3 images in case of Recall. In 5 images PGA increases accuracy, F-measure, PSNR and DRD. For the DIBCO 2013 dataset though precision is not improved much, accuracy and DRD is improved in 6 images. Both F-measure and PSNR undergoes improvement in all 8 images, while recall is improved in 7 images. In both the datasets, PGA has a higher recall which shows that the contrast enhancement is able to enhance the data pixels and prevent data loss through binarization.

TABLE I. RESULTS AFTER BINARIZATION ON BOTH ENHANCED AND NORMAL IMAGES

Dataset	Type	Precision	Recall	F-measure	Accuracy	PSNR	DRD
H-DIBCO 2016	Enhanced	**0.93384**	**0.773243**	**82.94477**	**0.975271**	**17.23964**	**5.843301**
	Normal	0.933505	0.712647	76.14092	0.96375	16.88016	7.229465
DIBCO 2013	Enhanced	0.843158	**0.870762**	**84.68515**	**0.961215**	**15.38142**	**8.056414**
	Normal	**0.861058**	0.776976	80.60863	0.954542	14.3096	8.78502

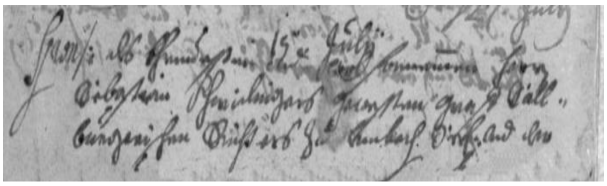
TABLE II. IMAGE WISE RESULTS FOR H-DIBCO 2016 USING PGA.

Image Type	Image#	Precision	Recall	F-measure	Accuracy	PSNR	DRD
Enhanced	1	0.813053	0.944548	87.38815	0.980973	17.2064	9.844363
Normal	1	**0.878161**	**0.947287**	**91.14153**	**0.987149**	**18.91066**	**5.982205**
Enhanced	2	**0.997555**	0.55305	71.15908	0.990553	20.24698	8.058038
Normal	2	0.988751	**0.64796**	**78.28762**	**0.992426**	**21.20679**	**6.211039**
Enhanced	3	**0.931294**	0.963373	**94.70618**	**0.994756**	**22.80367**	**2.246362**
Normal	3	0.924276	**0.969866**	94.65225	0.994664	22.72801	2.343065
Enhanced	4	**0.971053**	0.630714	76.47263	0.978098	16.59516	8.627232
Normal	4	0.952681	**0.709931**	**81.35847**	**0.98164**	**17.36121**	**7.104505**
Enhanced	5	**0.981444**	0.934355	95.73204	0.994296	22.43801	1.36803
Normal	5	0.962226	**0.982488**	**97.22514**	**0.99616**	**24.15686**	**1.068738**
Enhanced	6	**0.946169**	0.751689	83.77906	0.981598	17.35136	6.376716
Normal	6	0.930403	**0.810157**	**86.61265**	**0.984167**	**18.00432**	**5.572257**
Enhanced	7	0.999618	**0.434258**	**60.54805**	**0.940631**	**12.26441**	**9.271817**
Normal	7	**0.99979**	0.360021	52.94046	0.932852	11.7297	10.70113
Enhanced	8	0.830711	**0.873427**	**85.15335**	**0.956204**	**13.58563**	**7.108793**
Normal	8	**0.970552**	0.109362	19.65746	0.871451	8.909303	23.32213
Enhanced	9	0.984357	**0.777721**	**86.89231**	**0.971643**	**15.47338**	**2.634963**
Normal	9	**0.99637**	0.612244	75.84441	0.952868	13.26687	4.641319
Enhanced	10	**0.88315**	0.869296	**87.61685**	**0.963954**	**14.43143**	**2.896697**
Normal	10	0.731841	**0.977157**	83.68923	0.944125	12.52785	5.348262

TABLE III. IMAGE WISE RESULTS FOR DIBCO 2013 USING PGA.

Image Type	Image#	Precision	Recall	F-measure	Accuracy	PSNR	DRD
Enhanced	1	0.972531	**0.768733**	**85.8706**	**0.987143**	**18.90854**	**3.454047**
Normal	1	**0.978951**	0.749142	84.87663	0.986432	18.67484	3.617715
Enhanced	2	0.962704	**0.936527**	**94.94354**	**0.991092**	**20.50237**	**1.686769**
Normal	2	**0.996116**	0.819732	89.93573	0.983617	17.85616	2.906379
Enhanced	3	0.995165	**0.846813**	**91.50148**	**0.988491**	**19.38966**	**3.16812**
Normal	3	**0.999948**	0.696984	82.14208	0.977827	16.54181	6.397846
Enhanced	4	0.566051	**0.902944**	**69.58667**	0.902018	**10.08853**	25.1964
Normal	4	**0.590874**	0.724865	65.1047	**0.903537**	10.1564	**23.25952**
Enhanced	5	**0.81029**	**0.92347**	**86.31858**	**0.946177**	**12.6903**	**8.637905**
Normal	5	0.804374	0.811282	80.78132	0.929025	11.48895	10.67888
Enhanced	6	0.769838	**0.893271**	**82.69742**	0.95757	**13.72323**	9.163363
Normal	6	**0.897656**	0.763897	82.53929	**0.963313**	14.35489	**6.675288**
Enhanced	7	0.989285	**0.840963**	**90.9114**	**0.96439**	**14.48429**	**2.546359**
Normal	7	**0.996962**	0.757001	86.05667	0.948049	12.84406	3.796954
Enhanced	8	**0.679403**	0.853374	**75.65154**	**0.952842**	**13.26442**	**10.59834**
Normal	8	0.62358	**0.892904**	73.43263	0.944534	12.55971	12.94757

(a)



(b)

Figure 2: (a) The grey scale image given as input, (b) the enhanced image produced as output.

Ogled po Gorenskem.

Poljanska dolina in pot skoz njo proti Idrii.

(Konec.)

Polagoma se okrenemo okoli grička sv. Antona, in razgerne se našim očém v desni dolinici prijazno mesto Idrija. Na koncu gori ponosno stojí grajščina, iz ktere srede mali stolpiček v zrak molí; pod gradom pa se po celi dolinici razprostira mesto, v kterega sredi stojí farna

(a)

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(b)

Figure 3: (a) The degraded input image, (b) the enhanced image produced as output.

IV. CONCLUSION

The proposed algorithm called Partitioning based Genetic Algorithm or PGA partitions a document image until we get a sub-image with acceptable intensity variation. After application of dynamic partitioning, on each sub-image GA is applied to enhance the contrast PGA is able to handle the noise optimally. Evaluation of PGA using both printed and handwritten documents show that our algorithm has great data retention capacity. This can be proved from the large gain in recall seen on use of PGA pre-binarization. In the future, the fitness function can be improved to include more image-based features to evaluate the contrast enhancement. A different meta-heuristic can be tried in place of GA.

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