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Document image binarization by PSO-GSA optimization

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Abstract

In this work we will deal with the problems of document image binarization and an adaptive thresholding algorithm will be developed which can dealt with these kind of artifacts and illumination variation problem in text images. a combination of particle swarm optimization and recently introduced gravitational search algorithm is introduced in this work. This hybrid algorithm will tune the threshold value for adaptive block size and gain values.

Keywords: Image binarization; PSO; GSA; optimization

1. Introduction

Document Image Binarization is performed in the preprocessing stage for document analysis and it aims to segment the foreground text from the document background. A fast and accurate document image binarization technique is important for the ensuing document image processing tasks such as optical character recognition (OCR). Though document image binarization has been studied for many years, the thresholding of degraded document images is still an unsolved problem due to the high inter/intra-variation between the text stroke and the document ackground across different document images. As illustrated in Fig. 1, the handwritten text within the egraded documents often shows a certain amount of variation in terms of the stroke width, stroke brightness, stroke connection, and document.

This paper presents a document thresholding technique that is able to binarize degraded historical document images efficiently. One distinctive characteristic of the proposed technique is that it makes use of the image contrast that is evaluated by using the local maximum and minimum. Compared with the image gradient, such image contrast is more capable of detecting the high contrast image pixels (lying around the text stroke boundary) from historical documents that often suffer from different types of document degradation. And compared with the previous methods, the proposed method is better while handling document images with complex background variation. Given a historical document image, the proposed technique first determines a contrast image based on the local contrast.

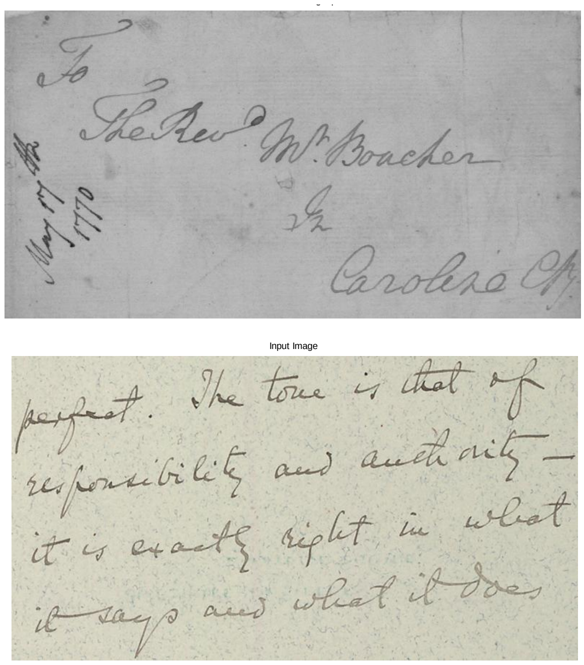

Figure 1: Handwritten historical document

The high contrast image pixels around the text stroke boundary are then detected through the global thresholding of the determined contrast image. Lastly, the historical document image is binarized based on the local thresholds that are estimated from the detected high contrast image pixels. The method adopted in this work is an example of adaptive thresholding algorithm as an hybrid optimisation algorithm named PSO-GSA is used in it.

2. Proposed work

In or work of historical document binarisation, local threshold value is calculated on the basis of contrast of image and the formula developed for local thresholding is further enhanced to make it adaptive for any kind of contrast of image. Sample contrast images of historical document are shown in figure 1.1. For calculating the contrast, we used texton co-occurrence matrix (TCM) in which same pixel values is looked for in a pair at an angle of 0^o. MATLAB as a tool has been used to develop the script for the algorithm, and it provides a function to use for calculating TCM contrast. The local threshold value is calculated for each pixel in the image and the threshold matrix size will be equal to test image. The formula is given in equation 1.

$$Threshold(i,j) = k(I_{mean}\ (i,j) + \sqrt{contrast}) \ ..... \ (1)$$

Where 'k' is the gain factor, I_{mean} is the local threshold mean and 'contrast' is contrast value calculated for complete image by TCM. Here gain factor and block size, used for calculation of local mean are measure deciding factor for threshold value in equation 2.1. these values should be set on an optimal value so that image can be converted into binary without any noise and omit of edges of letters in document image.

For this purpose an optimisation algorithm, based on combination of two algorithms which are Particle swarm optimisation (PSO) and Gravitational Search Algorithm (GSA) is used. This combination performs well as both these algorithms are different in their behaviour as PSO is a local optimisation algorithm while GSA is global optimisation algorithm. Both optimization are based on the position updates of agents in GSA and particles in PSO.

The counterpart of agents and particles in GSA and PSO respectively in our work is the tuning variables. The position of a single agent or single particle is defined by the number of tuning variables. Co ordinates used to define the position in a searching space are equal to the variables to be tuned. For example in our case we have considered block size and gain factor which has to be optimally defined. So there will be two tuning variables and hence 2 co ordinates to define the location of a single agnet/particle in a searching space. A table indicating significance of variables used in bio inspired algorithm with our technical terms is shown in table 1.

Table 1: Technical counterpart of bio inspired variables

Sr. No	**Variable in Bio Inspired Algorithm**	**Terms in our technical concept**
1	Position of agents/swarms	Block size and gain factor of in threshold formula
2	Number of dimension of searching space	Number of variables to be tuned for stability
3	Update in positions	Change in the block size and gin value

The hybrid GSAPSO algorithms work in the manner that GSA becomes alive to update the velocity of particles in the PSO algorithm. The combination of two different optimization algorithms is done in a way that local optimization algorithm is controlled by global optimization GSA algorithm. The update in position of particles in PSO required update in which is updated by GSA by the formula

$$v_i^d(t+1) = rand_i x v_i^d(t) + a_i^d(t)$$

This make the convergence faster with each minima point checked. A step by step algorithm for the proposed work is given as:

STEP1. Initialize the random positions and velocities of particles.

STEP2. Consider the searching space dimension as two since two variables to be tuned.

STEP3. Initialize the weighting parameters of PSO as 0.5 and 1.5.

STEP4. Generate the random positions of particles initially within limit of block size values which is 1-50 and gain value 0.8-1 and calculate the fitness function for each particle.

STEP5. Compare the fitness value of each particle with the previous best position of bacteria. If fitness function value is less for this new position than previous position then it will be assigned as new.

STEP6. The present bets position is termed as current position of particle for PSO and output of fitness function is Jlocal for the PSO.

GSA Starts here:

STEP7. The current position selected in previous step is used to get the mass for each agent as per GSA algorithm. The minimum value of fitness function is selected as best and maximum as worst position and using the formulas, mass of each agent can be calculated as:

$$m_i(t) = \frac{fit(t) - worst(t)}{best(t) - worst(t)}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)}$$

STEP8. Gravitational force is calculated as:

$$F_{ij}^d(t) = G(t).\left(M_{pi}(t) \times \frac{M_{ai}(t)}{R_{ij}(t)} + \varepsilon\right).\left(x_j^d(t) - x_i^d(t)\right)$$

STEP9. This new velocity is the direction of particle in PSO is updated as

$$velocity = velocity + c1 * acceleration + c2(gbest - current\ position)$$

Here gbest is the global best position of particles in PSO and acceleration is calculated in GSA as $a_i^d(t) = F_i^d(t)/M_{ii}(t)$.

GSA ends here

STEP10. Add the new velocity to old position of particles and get the new updated positions which are conserved towards the minimization of objective function.

STEP11. Above all steps repeats till iterations last.

STEP12. Result will be positions of particles with minimum fitness function output. These positions are block size and gain factor.

Following these steps in optimization of GSA and PSO an optimal value of variables is achieved in our work.

Since the above method discussed calculates the local threshold, the operations are done in image blocks like if outcome of the algorithm is block size =55, then image matrix will be segmented into 55 by 55 blocks and thresholded. The fitness function value thus calculated will be the inverse of sum of peak signal to noise ratio (PSNR) and F-measure. Mathematically it can be shown as:

$$min\ \ Objf = 1/(\mathrm{F - measure + PSNR} + 0.001)$$

Here 0.001 is used to avoid the fall of fitness function into infinity.

Volume 1, Issue 6, 2016, pp. 11-18

3. Results and discussion

In our work we have used DIBCO 2010 data sets of images. This data set consists of a set of 10 degraded document images of various contrast level. Before processing the image pre processing of image is done by the use of wiener filter. The Wiener filter minimizes the mean square error between the estimated random process and the desired process. Further PSO-GSA is used and run for 140 iterations. In each iteration a new value of gain factor and window size is calculated and PSNR and F-measure output is observed at each iteration. The optimization targets to minimize the objective function. If with the number of iterations, cost value or objective function value id decreasing and almost fixed at a minimum value, then optimization results can be considered as good results. In our case cost function graph is shown in figure 2, for the test image shown in figure 3. We have compared the results with GSA algorithm too. The objective function is also compared in figure 2. It is set to a minimum value with increase in iterations. Because of these much iterations, our algorithm takes time to binaries the image.

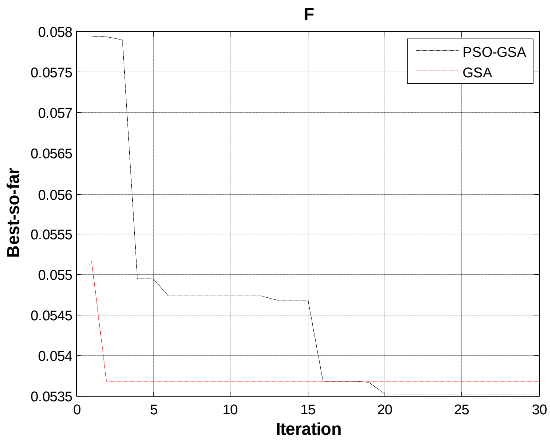

Figure 2: Cost function value after optimization of test image 1

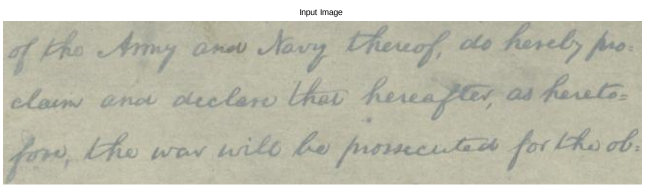

Figure 3: Input test image

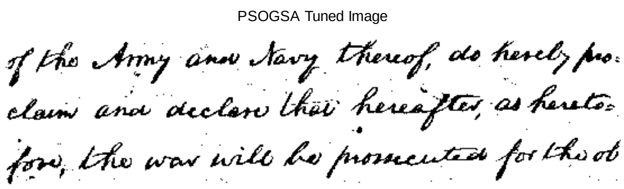

Figure 4: Final binarised image of input in figure 3

The bianrised image obtained from the optimized value of gain and block size as given in table 2 is shown in figure 4. This is the output without any post processing operation. The output efficiency is analyzed on the criteria of PSNR and F-measure value. We have compared the results for PSO-GSA with GSA and results for both are tabulated in table 2 and 3 respectively.

Table 2: Output parameters for DIBCO 2010 data sets by PSOGSA algorithm

Image	Block Size	Gain	PSNR	F-Measure
H01	49.62	0.9431	17.751	91.97
H02	44.7722	0.9173	20.848	90.76
H03	42.50	0.9070	18.04	88.27
H04	19.58	0.9339	17.5838	88.82
H05	28.4677	0.8009	19.083	88.58
H06	26.8533	0.9323	17.824	86.36
H07	24.7562	0.8819	19.092	91.23
H08	28.3754	0.9326	17.465	88.45
H09	31.9173	0.9422	20.063	89.36

Table 3: Output parameters for DIBCO 2010 data sets by GSA algorithm

Image	Block Size	Gain	PSNR	F-Measure
H01	48.41	0.9111	17.695	90.78
H02	80	0.9026	20.803	90.56
H03	49.76	0.9134	17.915	87.78
H04	37.4919	0.9029	17.332	88.29
H05	11.1502	0.8	16.511	83.15
H06	26.8533	0.9362	17.6120	85.26
H07	26.7564	0.8798	18.98	90.21
H08	13.7760	0.9595	17.106	87.41
H09	30.445	0.9480	20.022	89.18

We have compared our results with Otsu’s method (OTSU), Sauvola’s method (SAUV), Niblack’s method (NIBL), Bernsen’s method (BERN), Gatos et al.’s method (GATO), and (LMM, BE). The datasets are composed of the same series of document images that suffer from several common document degradations such as smear, smudge, bleed-through and low contrast. Our method achieves the highest score in PSNR and F-measure. The corresponding bar chart is shown in figure 5. This chart shows our algorithm’s superiority clearly. Our F-measure scores the 7-8% more degree than most efficient LMM and BE methods.

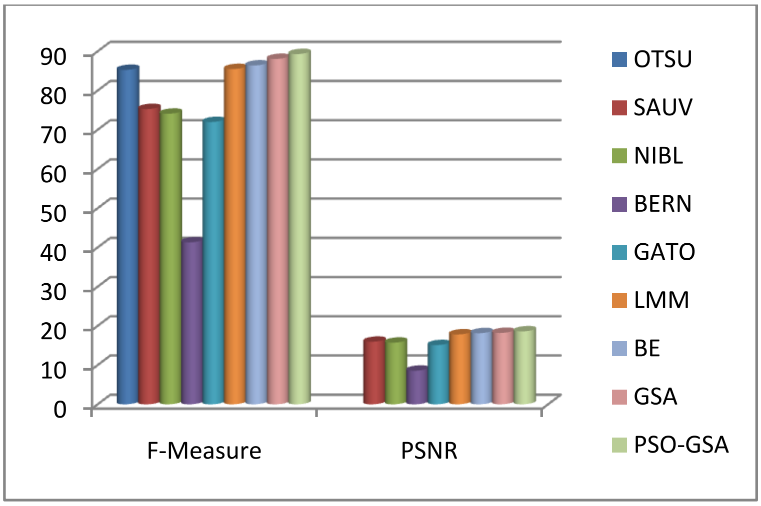

Figure 5: Comparison of PSNR and F-measure with other algorithms

4. Conclusions

In this thesis, we have proposed a novel document enhancement technique that has been tested on some public datasets and shown superior performance. We have considered the 9 test images of DIBCO 2010 data sets which are different in contrast and luminance. None of the image is similar to other. In such type of cases a single thresholding algorithm can't perform well for each image, it may give very good results for one or poor for other. So an adaptive thresholding algorithm is suggested in our work, which self tune to every image. This is a tuning method which is based on hybrid optimization algorithm named PSO-GSA.

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