International Journal of Enhanced Research in Science, Technology & Engineering
ISSN: 2319-7463, Vol. 4 Issue 12, December-2015

Document Image Binarization

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ABSTRACT

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) and Document Image Retrieval(DIR). This research area has been studied for decades; many techniques have been reported and applied on different commercial document analysis applications. However, there are still some unsolved problems need to be addressed due to the high inter/intra-variation between the text stroke and the document background across different document images. Images with text are frequently used on Internet for different purposes. The textual information embedded in web images is useful for different applications, such as web page understanding, filtering and retrieval. Automatically recognition of text from web images plays an important role on extraction and retrieval of web information. However, the texts in web images are usually of low resolution and contain different kinds of degradation including computer-generated character artifacts, and special effects on images for attractiveness purpose. It makes word recognition a challenge task even after the text has been localized. Document image deblurring is a mathematically ill-posed problem, because it tries to invert a low-pass filter, and wants to reconstruct the formerly suppressed dimensions of information. To find a unique and meaningful solution, some constrains and prior knowledge have to be incorporated in the deconvolution process. We explore some of research effort in literature, many restoration methods have been proposed and gain successful achievements in many fields. And an adaptive novel technique is proposed for document image domain. However, there still exist many unsolved problems needed to be investigated. In summary, although there have been many achievements in the research area of document image enhancement, the enhancement tasks are still difficult and need to be further explored.

I. INTRODUCTION

There is huge amount of textual information that is embedded within images. For example, more and more documents are digitalized everyday via camera, scanner and other equipment, many digital images contain texts, and a large amount of textual information is embedded in web images. It would be very useful to turn the characters from image format to textual format by using optical character recognition (OCR). This converted text information is very important for document mining, document image retrieval and so on. However, in many cases, the document images cannot be directl fed to an OCR system due to the following reasons

- The original document papers suffer from different kinds of degradation including smear, ink-bleeding through and intensity variation, especially for historical documents.
- The process of obtaining digital images from the real world is not perfect. There are many factors that may cause image distortion, such as incorrect focal length, over/under exposure, camera shaking/object movement, low resolution, etc.
- The web images in the internet are often susceptible to certain image degradation such as low resolution and small size, which is specially designed for faster network transmission rate, computer-generated-character artifacts, and special effects on images to attract visual attention.

II. BINARIZATION

The objective of image segmentation is to group image pixels according to constituent regions or objects. On document images this problem consists of two classes: foreground and background. The “binarized image should be perceptually similar". For the binarization of documents global and adaptive binarization methods exist. While the same single threshold is applied on every pixel by global algorithms, adaptive methods define local regions in which separate threshold values are calculated. Current binarization methods use gray value images as input. Color images can be converted with the standard conversion

$$I(x, y) = 0.3R(x, y) + 0.59G(x, y) + 0.11B(x, y)$$

where R, G and B are the Red, Green and Blue channel of the color image. For an m × n gray value image I(x, y) with intensity values between 0 and 1 and a threshold T(x, y) each image pixel is classified in foreground (labeled as 1) and background (labeled as 0) resulting in the thresholded image $I_{th}(x, y)$:

$$I_{th}(x, y) = \begin{cases} 1 & \text{if } I(x, y) > T(x, y) \\ 0 & \text{if } I(x, y) \leq T(x, y) \end{cases}$$

where T(x, y) = Tg = constant if a global threshold is applied. Adaptive methods have the characteristic that the value of T depends on the local gray value characteristics. Global thresholds are suitable for images with a bimodal gray value distribution, where adaptive methods can handle documents with e.g. non-uniform illumination. Recent developments (see DIBCO and H-DIBCO) show that binarization methods estimate the background or combine multiple binarization methods to achieve a better segmentation. The methods presented comprise Niblack, Sauvola and a color segmentation method. In the following, state of the art methods of image binarization are categorized in global and adaptive methods, methods based on background estimation and methods that use a combination of binarization methods.

III. OBJECTIVE

Historical degraded document shows variation in terms of stroke width, brightness, connection etc. some time the writing on back side of paper too seeps through to the front. These types of degraded document make document binarisation a big challenge. As many historical libraries and government document need to be preserved, so these challenges are tried to overcome a lot of researchers. Our work too will be in addition of work done till now. The main problem in image binarisation is adaptive thresholding. Since document image may suffers from invariant illumination which offers threat in deciding a threshold value which converts the document into binary image. Major class of researchers has used otsu's global thresholding as adaptive thresholding algorithm which is based on histogram bins of image. This performs well in case of non uniform illumination but in image binaristaion results can be improved by selecting the algorithm which is invariant to illumination changes.

IV. FIREFLY OPTIMIZATION

The sky filled with the light of fireflies is a marvelous sight in the summer in the moderately temperature regions. There are near to two thousand firefly species, and most of them produce short and rhythmic flashes. The pattern observed for these flashes is unique for most of the times for a specific species. The rhythm of the flashes, rate of flashing and the amount of time for which the flashes are observed are together forming a kind of a pattern that attracts both the males and females to each other. Females of a species respond to individual pattern of the male of the same species. We know that the intensity of light at a certain distance r from the light source conforms to the inverse square law. That is the intensity of the light I goes on decreasing as the distance r will increase in terms of I α 1/r2 Additionally, the air keeps absorbing the light which becomes weaker with the increase in the distance. These two factors when combined make most fireflies visible at a limited distance, normally to a few hundred meters at night,

Which is quite enough for fireflies to communicate with each other.In the firefly algorithm, there are two important points: the variation in the light intensity and formulation of the attractiveness. For simplicity, we can assume that the attractiveness of a firefly is determined by its brightness which in turn is connected with the encoded objective function. In the simplest case for maximum optimization problems, the brightness I of a firefly for a particular location x could be chosen as I(x) f(x). Even so, the attractiveness β is relative, it should be judged by the other fireflies. Thus, it will differ with the distance rij between firefly i and firefly j. In addition, light intensity decreases with the distance from its source, and light is also absorbed by the media, so we should allow the attractiveness to vary with the varying degree of absorption. In the simplest form, the light intensity I(r) varies according to the inverse square law.

$$I(s) = \frac{I(r)}{r^2} \quad (1)$$

Where Is is the intensity at the source. For a stated medium with a fixed light absorption coefficient γ, the light intensity I varies with the distance r. That is

$$I = I_0 e^{-\gamma r}$$

Where Io is the initial light intensity, In order to avoid the singularity at r = 0 in the expression $\frac{I(r)}{r^2}$, the combined effect of both the inverse square law and absorption can be approximated as the following Gaussian form

$$\beta = \beta_0 e^{-\gamma r^2}$$

Where β0 is the attractiveness at r = 0. Since it is often faster to calculate 1/(1 + r2) than an exponential function, the above function, if necessary, can be approximated as

$$\beta = \frac{\beta_0}{(1+\gamma r^2)}$$

In the real time implementation, the attractiveness function β(r) can be any monotonically decreasing functions such as the following generalized form

$$\beta(r) = \beta_0 e^{-\gamma r^m}$$

For a fixed, the characteristic length becomes

$$\Gamma = \gamma^{-\frac{1}{m}}$$

Conversely, for a specific length scale Γ in an optimization problem, the parameter γ can be used as a typical initial value. That is

$$\gamma = \frac{1}{\Gamma^m}$$

The distance between any two fireflies i and j at xi and xj , respectively is the Cartesian distance.

$$r_{i,j} = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2}$$

The movement of the firefly i is attracted to another more attractive (brighter) firefly j is determined by

$$x_i = x_i + \beta_0 e^{-\gamma r^2}(x_j - x_i) + \alpha€\mathrm{i}$$

Where the second term is due to the attraction and third term is randomization with α being the randomization parameter, and is a vector of random numbers being drawn from a Gaussian distribution or uniform distribution. For example, the simplest form is €i could be replaced by (rand − ½) where rand is a random number generator uniformly distributed in [0, 1]. For most of our implementation, we can take βo 1 and α Є [0, 1].

It is worth pointing out that above equation is a random- walk partial towards the brighter fireflies. If βo = 0, it becomes a simple random walk.

The parameter γ now characterizes the contrast of the attractiveness, and its value is crucially important in determining the speed of the convergence and how the FA algorithm behaves. In theory, γ Є [0, ∞), but in actual practice, γ O(1) is determined by the characteristic length Γ of the system to be optimized. Thus, for most applications, it typically varies from 0.1 to 10.

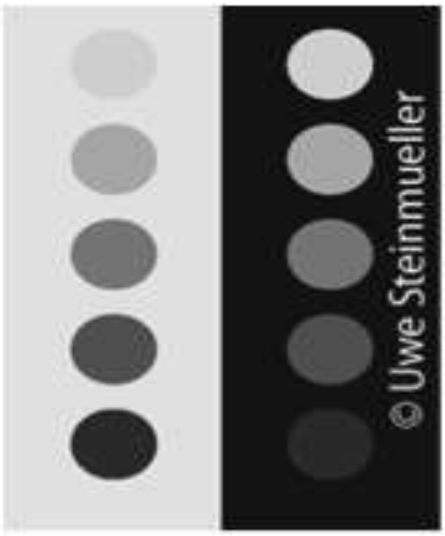
V. PROPOSED WORK

In this section proposed document binarization technique is explained. For a degraded image adaptive contrast map is constructed and then threshold is calculated from that which converts the document into binary. Here is the explanation. The human visual system is more sensitive to contrast than absolute luminance, we can perceive the world similarly regardless of the huge changes in illumination over the day or from place to place. Contrast is the difference in luminance or color that makes an object (or its representation in an image or display) distinguishable. In visual perception of the real world, contrast is determined by the difference in the color and brightness of the object and other objects within the same field of view. The contrast of image can be categorized as : global contrast and local contrast. Global contrast measures the brightness difference between the darkest and brightest element in the entire image. Tools like Curves and Levels only change global contrast as they treat all pixels with the same brightness levels identical.

The global contrast has three main regions:

- Mid-tones
- Highlights
- Shadows

The sum of the contrast amounts of these three regions defines the global contrast. This means if you spend more global contrast on the mid-tones (very commonly needed) you can spend less global contrast on highlights and shadows at any given global contrast level. The mid-tones normally show the main subject. If the mid-tones show low contrast the image lacks “snap”. Adding more global contrast to the mid-tones (“snap”) often results in compressed shadows and highlights. Adding some local contrast can help to improve the overall image presentation.
The local contrast is based on the retinex theory according to which our eyes sees the difference in respect to surroundings, a color map below can prove this point.



The circles in each row have exactly the identical brightness levels. Yet the top right circle looks a lot brighter than the one on the left. This is because our eyes see the difference to the local surrounding. The right circle looks much brighter with the dark gray background compared to a brighter background on the left. Just the opposite is true for the two circles on the bottom. For our eyes the absolute brightness is of less importance than the relative relation to other close areas. So, local contrast is very important for processing or enhancement of any image.

In our work because of this human visual system local contrast map is extracted from an image and then on the basis of that a local thresholding approach will be used to convert the image onto binary format. Previously image gradient and normalize image gradient were used to extract local contrast of image, these methods are quite good, although the variation of bright to weak contrast can be compensated by these methods yet these don’t perform well in case of document which have bright text. This is because a weak contrast will be calculated for stroke edges of the bright text. Calculation of local contrast and then global thresholding algorithm like otsu is used and then local image edge detection is used in paper published by Bolan Su (2013). We have followed the same line of action but rather than using global thresholding, we use local thresholding, it removes the need of using again local edge detection algorithm like canny edge detection. Gray level co –occurrence matrix (GLCM) also called texton co- occurrence matrix (TCM) fulfills our purpose. It is a local contrast mapping method. Here basically TCM serves two purposes: make image’s local contrast map, unaffected by the illumination variation of image and local edge detection. Further, the GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix.

A gray-level co-occurrence matrix (GLCM) is generated by calculating how often a pixel with the intensity (gray-level) value *i* occurs in a specific spatial relationship to a pixel with the value *j*. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but you can specify other spatial relationships between the two pixels. Each element (*i*,*j*) in the resultant glcm is simply the sum of the number of times that the pixel with value *i*occurred in the specified spatial relationship to a pixel with value *j* in the input image. The number of gray levels in the image determines the size of the GLCM. GLCM of an image is computed using a displacement vector d, defined by its radius δ and orientation θ. To illustrate, the following figure shows how graycomatrix calculates the first three values in a GLCM. In the output GLCM, element (1,1) contains the value 1 because there is only one instance in the input image where two horizontally adjacent pixels have the values 1 and 1, respectively. glcm(1,2) contains the value 2 because there are two instances where two horizontally adjacent pixels have the values 1 and 2. Element (1,3) in the GLCM has the value 0 because there are no instances of two horizontally adjacent pixels with the values 1 and 3. graycomatrix continues processing the input image, scanning the image for other pixel pairs (*i*,*j*) and recording the sums in the corresponding elements of the GLCM. Figure 4.1 shows this

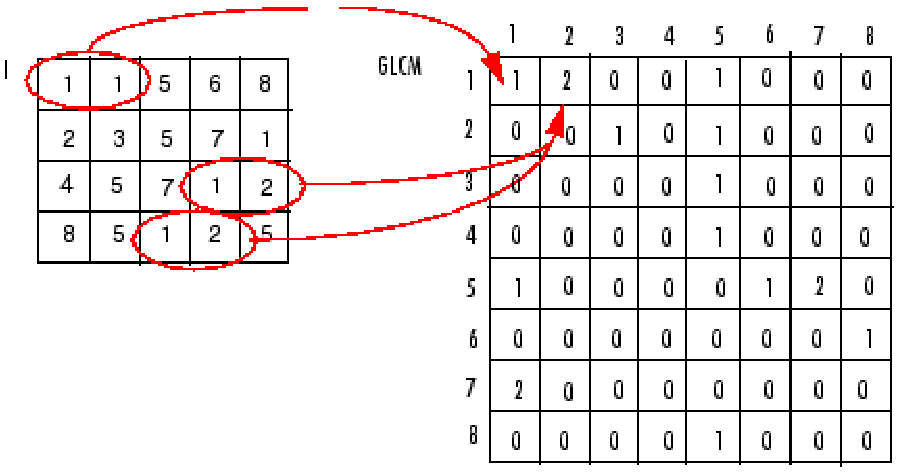


Figure 1: GLCM output of a test matrix

A single GLCM matrix might not able to define all texture features of image, so multiple GLCM at different orientations are calculated. Above given example was with 0^{o} orientation i.e. horizontally matching pairs are checked. Further it can be done at angle 45^{o}, 90^{o}, 135^{o} as shown in figure 2.

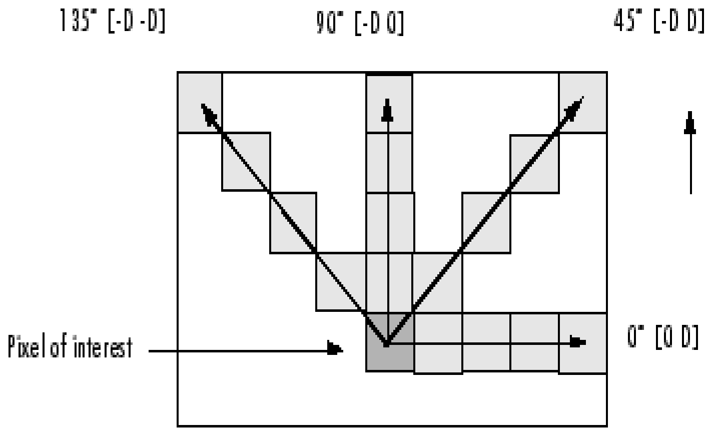


Figure 2: Multiple orientations to calculate GLCM

In actual every pixel has eight neighboring pixels allowing eight choices for θ, which are 0°, 45°, 90°, 135°, 180°, 225°, 270° or 315°. However, taking into consideration the definition of GLCM, the co-occurring pairs obtained by choosing θ equal to 0° would be similar to those obtained by choosing θ equal to 180°. This concept extends to 45°, 90° and 135° as well. Hence, one has four choices to select the value of θ.

Above we have mentioned a term radius about GLCM. In the last example matching pairs have been taken upto one distance, this constitutes the radius of GLCM. Various research studies show δ values ranging from 1, 2 to 10. Applying large displacement value to a fine texture would yield a GLCM that does not capture detailed textural information. From the previous studies, it has been concluded that overall classification accuracies with $\delta = 1, 2, 4, 8$ are acceptable with the best results for $\delta = 1$ and 2. This conclusion is justified, as a pixel is more likely to be correlated to other closely located pixel than the one located far away. Also, displacement value equal to the size of the texture element improves classification.

The dimension of a GLCM is determined by the maximum gray value of the pixel. Number of gray levels is an important factor in GLCM computation. More levels would mean more accurate extracted textural information, with increased computational costs. The computational complexity of GLCM method is highly sensitive to the number of gray levels. As in above example in figure 1, the size of GLCM is 8 by 8 matrix as 8 gray levels have been considered. Thus for a predetermined value of G, a GLCM is required for each unique pair of δ and θ. GLCM is a second-order texture measure. The GLCM's lower left triangular matrix is always a reflection of the upper right triangular matrix and the diagonal always contains even numbers. Another test matrix and its GLCM at all four rotations for radius 1 are shown in figure 3.

0	0	1	1
0	0	1	1
0	2	2	2
2	2	3	3

Figure 3(a) test matrix

4	2	1	0
2	4	0	0
1	0	6	1
0	0	1	2

Figure 3(b) test matrix with angle 0

6	0	2	0
0	4	2	0
2	2	2	2
0	0	2	0

Figure 3(c) test matrix with angle 45

4	1	0	0
1	2	2	0
0	2	4	1
0	0	1	0

Figure 3(d) test matrix with angle 90

2	1	3	0
1	2	1	0
3	1	0	2
0	0	2	0

Figure 3(e) test matrix with angle 135

Various GLCM parameters are related to specific first-order statistical concepts. For instance, contrast would mean pixel pair repetition rate, variance would mean spatial frequency detection etc. Association of a textural meaning to each of these parameters is very critical. Traditionally, GLCM is dimensioned to the number of gray levels G and stores the co-occurrence probabilities g_{ij}. To determine the texture features, selected statistics are applied to each GLCM by iterating through the entire matrix. The textural features are based on statistics which summarize the relative frequency distribution which describes how often one gray tone will appear in a specified spatial relationship to another gray tone on the image.

Following notations are used to explain the various textural features:
g_{ij} = $(i, j)^{th}$ entry in GLCM

$g_x(i)$ = i^{th} entry in marginal probability matrix obtained by summing rows of $gij =$
N_g = Number of distinct gray levels in the image
$\Sigma i = \sum_{i=1}^{N_g}$
$\Sigma j = \sum_{j=1}^{N_g}$
$g_y(i) = \sum_{i=1}^{N_g} g(i,j)$
Contrast (con) = $\sum_i \sum_j (i-j)^2 g_{i,j}$

This statistic measures the spatial frequency of an image and is difference moment of GLCM. It is the difference between the highest and the lowest values of a contiguous set of pixels. It measures the amount of local variations present in the image. A low contrast image presents GLCM concentration term around the principal diagonal and features low spatial frequencies. From this GLCM process local contrast of image is obtained. From this we have developed the equation to calculate the threshold value. Since it will be a local threshold value so, the size of threshold matrix will be same as test image. For this formula we were inspired by Abdenour Sehad's work in 2013. We have done changes in that and final thresholding formula includes local mean of image and a gain factor which will act as a bias factor. This factor has the range (0-1) always. Its value will be determined experimentally. This formula is used in a window size of image and later on combined. Mathematical expression is shown below.

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

Images in the database are of different kinds and different contrast with noise too. If same bias constant (k) and window size is used for all types of images then results are erroneous. For every image we have to test the 'k' for different block sizes. To avoid this work load firefly optimization (FA) is used, which will tune the gain value along with block size for every image it's a kind of unsupervised learning which will automatically set the optimal value of gain and window size to fit for every image.

Image binarisation technique requires the calculation of adaptive threshold value which can be tuned to image type and its contrast. No single method can work for all type of images. For that purpose we used self tuning optimization which will extract the threshold value depending upon image as described in previous chapter. 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. The extraction of binary image from a document image with less contrast is very easy and gives high values of out parameters. By optimization gain value and block size for every image is set. Before processing the image pre processing of image is done by using wiener filter. The Wiener filter minimizes the mean square error between the estimated random process and the desired process. The goal of the Wiener filter is to compute a statistical estimate of an unknown signal using a related signal as an input and filtering that known signal to produce the estimate as an output. For example, the known signal might consist of an unknown signal of interest that has been corrupted by additive noise. The Wiener filter can be used to filter out the noise from the corrupted signal to provide an estimate of the underlying signal of interest. Thus wiener filter removes the noise in the image and make it more approachable to desired results. Further bacterial foraging optimization 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.

CONCLUSION

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 10 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. Tuning parameters in our case are gain factor which have been taken from Niblak's method and block size of image, as we have considered the local thresholding scheme. It is shown, on the basis of a historical dataset with a defined ruling, that the layout information can be used as foreground estimation. The foreground is estimated to suppress background noise. Our results have been compared with some recent effective methods and performance is checked on the basis of peak signal to noise ration and F-measure which are the strong parameters and true evaluator for the image processing.

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