ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)
Vol 3, Issue 8, August 2016

# De-Noising Of Degraded Document Image Using Adaptive and OTSU Thresholding Techniques

[1] Chittari Padma, [2] Pullarevu Sreenivasulu
[1] Communication and Signal Processing
G.Pullareddy College of Engineering
Kurnool, A.P, India
[2]chittaripadma@gmail.com

***Abstract:*** **Segmentation of text from badly degraded document an image is a very challenging task due to the high inters/intra variation between the document background and the foreground text of different document images. In this project, we propose a novel document image binarization technique that addresses these issues by using adaptive image contrast. The adaptive image contrast is a combination of the local image contrast and the local image gradient that is tolerant to text and background variation caused by different types of document degradations.**

**In the proposed technique, an adaptive contrast map is first constructed for an input degraded document image. The contrast map is then binarized and combined with Canny's edge map to identify the text stroke edge pixels. The document text is further segmented by a local threshold that is estimated based on the intensities of detected text stroke edge pixels within a local window. The proposed method is simple, robust, and involves minimum parameter tuning**

## I. INTRODUCTION

## LITERATURE REVIEW

### *1.1 Degraded Document Images*

Documents can be a valuable source of information but often they suffer degradation problems, especially in the case of historical documents, such as strains, background of big variations and uneven illumination, ink seepage, etc.

Different types of degraded document images are as show below:


***FIG 1.1 different types of degraded document images***

### *1.2 Binarization Technique*

We try to develop robust and efficient document image binarization techniques which are able to produce good results for badly degraded document images. Binarization technique can be applied to both regular and historical document images.Document binarization is a useful and basic step of the image analysis systems. When applied, it converts gray-scale document images to black and white (binary) ones. In the transformed binary image the background is represented by white pixels and the text by black ones. By using binarization, the problems, mentioned before, are treated in order to provide a document form more suitable for further processing.

No matter how simple and straightforward, this procedure seems, it has been proved to be a complex task. The binary document image is essential to have good quality in order to proceed to the further stages of document analysis independent whether we are interested in performing OCR, or document segmentation, or just presentation of the document after some restoration stages. Knowledge can be extracted from the documents and suchsystems are used in many applications, from electronic libraries or museums to search engines and other intelligent systems.Any remaining noise, due to bad binarization, could reduce the performance of the forthcoming processing stages and in many cases could even cause their failure.

ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)
Vol 3, Issue 8, August 2016

Many thresholding techniques have been reported for document image binarization. As many degraded documents do not have a clear bimodal pattern, global thresholding is usually not a suitable approach for the degraded document binarization. Adaptive thresholding, which estimates a local threshold for each document image pixel, is often a better approach to deal with different variations within degraded document images. For example, the early window-based adaptive thresholding techniques estimate the local threshold by using the mean and the standard variation of image pixels within a local neighborhood window. The main drawback of these window-based thresholding techniques is that the thresholding performance depends heavily on the window size and hence the character stroke width. Other approaches have also been reported, including background subtraction texture analysis, recursive method, decompositionmethod, contour completion, Markov RandomField, matched wavelet, cross section sequencegraph analysis, self-learning, Laplacian energy user assistance, and combination of binarization techniques. These methods combine different types of image information and domain knowledge and are often complex.

The local image contrast and the local image gradient are very useful features for segmenting the text from the document background because the document text usually has certain image contrast to the neighboring document background. They are very effective and have been used in many document image binarization techniques.

The local contrast is defined as follows:

$C(i, j) = Imax(i, j) - Imin(i, j)$

where $C(i, j)$ denotes the contrast of an image pixel $(i, j)$, $Imax(i, j)$ and $Imin(i, j)$ denote the maximum and minimum intensities within a local neighborhood windows of $(i, j)$, respectively. If the local contrast $C(i, j)$ is smaller than a threshold, the pixel is set as background directly. Otherwise it will be classified into text or background by comparing with the mean of $Imax(i, j)$ and $Imin(i, j)$. Bernsen's method is simple, but cannot work properly on degraded document images with a complex document background.

We have earlier proposed a novel document image binarization method by using the local image contrast that is evaluated as follows:

$C(i, j) = Imax(i, j) - Imin(i, j) / Imax(i, j) + Imin(i, j) + E$

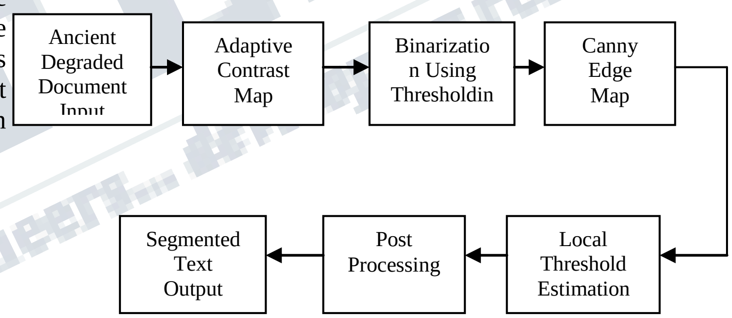
where E is a positive but infinitely small number that is added in case the local maximum is equal to 0. Compared with Bernsen's contrast in Equation, the local image contrast in Equation introduces a normalization factor to compensate the image variation within the document background. Take the text within shaded document areas such as that in the sample document image. The small image contrast around the text stroke edges in Equation resulting from the shading will be compensated by a small normalization factor due to the dark document background as defined in Equation.

**CHAPTER 2**

## II. PROPOSED METHOD

Given a degraded document image, an adaptive contrast map is first constructed and the text stroke edges are then detected through the combination of the binarized adaptive contrast map and the canny edge map. The text is then segmented based on the local threshold that is estimated from the detected text stroke edge pixels. Some post-processing is further applied to improve the document binarization quality.

### *2.1 Block Diagram of Proposed Method:*




### *2.1.1 Contrast Image Construction*

The image gradient has been widely used for edge detection and it can be used to detect the text stroke edges of the document images effectively that have a uniform document background. On the other hand, it often detects many nonstroke edges from the background of degraded document that often contains certain image variations due to noise, uneven lighting, bleed-through, etc. To extract only the stroke edges properly, the image gradient needs to be normalized to compensate the image variation within the document background.

### *2.2 Text Stroke Edge Pixel Detection*

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The purpose of the contrast image construction is to detect the stroke edge pixels of the document text properly. The constructed contrast image has a clear bi-modal pattern, where the adaptive image contrast computed at text stroke edges is obviously larger than that computed within the document background.We therefore detect the text stroke edge pixel candidate by using Otsu's global thresholding method. As the local image contrast and the local image gradient are evaluated by the difference between the maximum and minimum intensity in a local window, the pixels at both sides of the text stroke will be selected as the high contrast pixels. The binary map can be further improved through the combination with the edges by Canny's edge detector, because Canny's edge detector has a good localization property that it can mark the edges close to real edge locations in the detecting image.In addition, canny edge detector uses two adaptive thresholds and is more tolerant to different imaging artifacts such as shading. It should be noted that Canny's edge detector by itself often extracts a large amount of non-stroke edges without tuning the parameter manually. In the combined map, we keep only pixels that appear within both the high contrast image pixel map and canny edge map. The combination helps to extract the text stroke edge pixels accurately.

### *2.3 Local Threshold Estimation*

The text can then be extracted from the document background pixels once the high contrast stroke edge pixels are detected properly. Two characteristics can be observed from different kinds of document images. First, the text pixels are close to the detected text stroke edge pixels. Second, there is a distinct intensity difference between the high contrast stroke edge pixels and the surrounding background pixels.

The document image text can thus be extracted based on the detected text stroke edge pixels as follows:

$$R(x, y) = 1 \quad I(x, y) \leq Emean + Estd/2; \quad 0 \text{ otherwise}$$

Where Emean and Estd are the mean and standard deviation of the intensity of the detected text stroke edge pixels within a neighborhood window W, respectively. The neighborhood window should be at least larger than the stroke width in order to contain stroke edge pixels. So the size of the neighborhood window W can be set based on the stroke width of the document image under study, EW, which can be estimated from the detected stroke edges. Since we do not need a precise stroke width, we justcalculate the most frequently distance between two adjacent edge pixels (which denotes two sides edge of a stroke) in horizontal direction and use it as the estimated stroke width.

First the edge image is scanned horizontally row by row and the edge pixel candidates are selected as described in step 3.

If the edge pixels, which are labeled 0 (background) and the pixels next to them are labeled to 1 in the edge map, are correctly detected, they should have higher intensities than the following few pixels. So those improperly detected edge pixels are removed in step 4. In the remaining edge pixels in the same row, the two adjacent edge pixels are likely the two sides of a stroke, so these two adjacent edge pixels are matched to pairs and the distance between them are calculated in step 5. After that a histogram is constructed that records the frequency of the distance between two adjacent candidate pixels. The stroke edge width *EW* can then be approximately estimated by using the most frequently occurring distances of the adjacent edge pixels.

### *2.4 Image Contrast And Gradient*

#### *2.4.1 Image Contrast*

Contrast is the difference in luminance and/or color that makes an object 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. Because 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. The maximum contrast of an image is the contrast ratio or dynamic range.Contrast is also the difference between the color or shading of the printed material on a document and the background on which it is printed, for example in optical character recognition.

Contrast resolution is the ability to distinguish between differences in intensity in an image. The measure is used in medical imaging to quantify the quality of acquired images. It is a difficult quantity to define, because it depends on the human observer as much as the quality of the actual image. For example, the size of a feature affects how easily it is detected by the observer.

One definition of image contrast is:

$C = (S_A-S_B)/(S_A+S_B)$

where $S_A$ and $S_B$ are signal intensities for signal producing structures A and B in the region of interest. A disadvantage of this definition is that the contrast C can be negative. An alternative definition is:

$C = (S_A-S_B)/(S_{ref})$

Where $S_{ref}$ is a reference signal intensity, which is independent of the type of signal producing structure under investigation.

In MRI, determining contrast is of high importance for calibration because the operator has a high degree of control of how the signal intensities of various structures vary in the images by using different MRI methods and imaging parameters. Unlike most other imaging modalities, such as x-ray CT in which the Hounsfield units value for water is set to zero, there is no standard reference signal for MRI. Thus the contrast-to-noise ratio is often employed as an index for contrast because this metric does not require a reference signal.Contrast resolution or contrast-detail is an approach to describing the image quality in terms of both the image contrast and resolution.Contrast resolution is usually measured by generating a pattern from a test object that depicts how image contrast changes as the structures being imaged get smaller and closer together. The picture below shows one such set of images produced using the low contrast detectability inserts of the phantom employed in the MRI accreditation program of the American College of Radiology.

### *2.4.2 Image Gradient*

An image gradient is a directional change in the intensity or color in an image. Image gradients may be used to extract information from images.In graphics software for digital image editing, the term gradient or color gradient is used for a gradual blend of color which can be considered as an even gradation from low to high values, as used from white to black in the images to the right. Another name for this is color progression.Mathematically, the gradient of a two-variable function at each image point is a 2D vector with the components given by the derivatives in the horizontal and vertical directions. At each image point, the gradient vector points in the direction of largest possible intensity increase, and the length of the gradient vector corresponds to the rate of change in that direction.

Since the intensity function of a digital image is only known at discrete points, derivatives of this function cannot be defined unless we assume that there is an underlying continuous intensity function which has been sampled at the image points. With some additional assumptions, the derivative of the continuous intensity function can be computed as a function on the sampled intensity function, i.e., the digital image. It turns out that the derivatives at any particular point are functions of the intensity values at virtually all image points. However, approximations of these derivative functions can be defined at lesser or larger degrees of accuracy.The Sobel operator represents a rather inaccurate approximation of the image gradient, but is still of sufficient quality to be of practical use in many applications. More precisely, it uses intensity values only in a 3×3 region around each image point to approximate the corresponding image gradient, and it uses only integer values for the coefficients which weight the image intensities to produce the gradient approximation.

The gradient of the image is one of the fundamental building blocks in image processing. For example the Canny edge detector uses image gradient for edge detection.Image gradients are often utilized in maps and other visual representations of data in order to convey additional information. GIS tools use color progressions to indicate elevation and population density, among others.Image gradients can be used to extract information from images. Gradient images are created from the original image generally by convolving with a filter, one of the simplest being the Sobel filter for this purpose. Each pixel of a gradient image measures the change in intensity of that same point in the original image, in a given direction. To get the full range of direction, gradient images in the x and y directions are computed.

## *2.5 Local Thresholding*

### *2.5.1 Adaptive Thresholding*

Thresholding is the simplest way to segment objects from a background. If that background is relatively uniform, then you can use a global threshold value to binarize the image by pixel-intensity. If there’s large variation in the background intensity, however, adaptive thresholding may produce better results.Here, we binarize

IFERP
ISSN (Online) 2394-6849
International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)
Vol 3, Issue 8, August 2016

an image using the threshold_adaptive function, which calculates thresholds in regions of size block_size surrounding each pixel. Each threshold value is the weighted mean of the local neighborhood minus an offset value.Adaptive thresholding typically takes a grayscale or color image as input and, in the simplest implementation, outputs a binary image representing the segmentation. For each pixel in the image, a threshold has to be calculated. If the pixel value is below the threshold it is set to the background value, otherwise it assumes the foreground value.

There are two main approaches to finding the threshold: (i) the Chow and Kaneko approach and (ii) local thresholding. The assumption behind both methods is that smaller image regions are more likely to have approximately uniform illumination, thus being more suitable for thresholding. Chow and Kaneko divide an image into an array of overlapping subimages and then find the optimum threshold for each subimage by investigating its histogram. The threshold for each single pixel is found by interpolating the results of the subimages. The drawback of this method is that it is computational expensive and, therefore, is not appropriate for real-time applications.An alternative approach to finding the local threshold is to statistically examine the intensity values of the local neighborhood of each pixel. The statistic which is most appropriate depends largely on the input image.

Simple and fast functions include the mean of the local intensity distribution,

T=mean

the *median* value,

T=median

or the mean of the minimum and maximum values,

T=(max+min)/2

The size of the neighborhood has to be large enough to cover sufficient foreground and background pixels, otherwise a poor threshold is chosen. On the other hand, choosing regions which are too large can violate the assumption of approximately uniform illumination. This method is less computationally intensive than the Chow and Kaneko approach and produces good results for some applications.

### *2.5.2 OTSU Thresholding*

Otsu's method is an image processing technique that can be used to convert a greyscale image into a purely binary image by calculating a threshold to split pixels into two classes. More generally, Otsu's method can be used to split a histogram into two classes which minimizes the intra-class variance of the data contained within the class. The technique is named after Nobuyuki Otsu.

#### *How it Works*

Otsu's method works by first computing a set of histogram data, usually from pixel based image data of a greyscale image. Then for each possible threshold value. we calculate the variance of all the bins before and the bins after that point to evaluate the spread within each of the classes. As each potential threshold is evaluated, we keep track of the threshold that produced the minimum intra-class variance so far.

Mathematically speaking, this can be defined by:
σ2=W1σ21+W2σ22
Where Wx is the weighting of the class given by:
Wx=ΣbaP(i)
Where P(i) is the class probability; the total number of pixels in the image divided by the number of pixels in the class.

For practical purposes, calculating the intra-class variance can become very time consuming. Alternatively, variance between classes can be calculated instead. The between class variance is the opposite of the intra-class variance in that we take the threshold that produces the maximum amount of variance, rather than the minimum and can be calculated using the following formula
σ2=W1W2(μ1−μ2)2

### *2.6 Edge Detection*

### *2.6.1 Fundamentals Of Edge Detection*

Edge detection refers to the process of identifying and locating sharp discontinuities in an image. The discontinuities are abrupt changes in pixel intensity which characterize boundaries of objects in a scene. Classical methods of edge detection involve convolving the image

 

ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)
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with an operator, which is constructed to be sensitive to large gradients in the image while returning values of zero in uniform regions. There is an extremely large number of edge detection operators available, each designed to be sensitive to certain types of edges. Variables involved in the selection of an edge detection operator include:

***Edge orientation****:* The geometry of the operator determines a characteristic direction in which it is most sensitive to edges. Operators can be optimized to look for horizontal, vertical, or diagonal edgesNoise environment: Edge detection is difficult in noisy images, since both the noise and the edges contain high-frequency content. Attempts to reduce the noise result in blurred and distorted edges. Operators used on noisy images are typically larger in scope, so they can average enough data to discount localized noisy pixels. This results in less accurate localization of the detected edges.

***Edge structure****:* Not all edges involve a step change in intensity. Effects such as refraction or poor focus can result in objects with boundaries defined by a gradual change in intensity. The operator needs to be chosen to be responsive to such a gradual change in those cases. Newer wavelet-based techniques actually characterize the nature of the transition for each edge in order to distinguish, for example, edges associated with hair from edges associated with a face.There are many ways to perform edge detection. However, the majority of different methods may be grouped into two categories:

***Gradient****:*

The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image.

***Laplacian****:*

The Laplacian method searches for zero crossings in the second derivative of the image to find edges. An edge has the one-dimensional shape of a ramp and calculating the derivative of the image can highlight its location. Suppose we have the following signal, with an edge shown by the jump in intensity below:

Suppose we have the following signal, with an edge shown by the jump in intensity below:

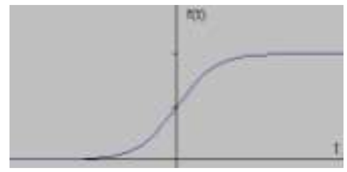

***FIG 2.2 Signal with intensity jump***

If we take the gradient of this signal (which, in one dimension, is just the first derivative with respect to t) we get the following:

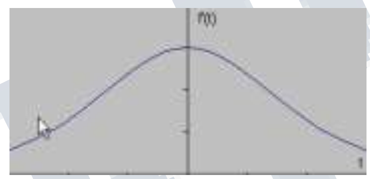

***FIG 2.3 Gradient of signal***

Clearly, the derivative shows a maximum located at the center of the edge in the original signal. This method of locating an edge is characteristic of the “gradient filter” family of edge detection filters and includes the Sobel method. A pixel location is declared an edge location if the value of the gradient exceeds some threshold. As mentioned before, edges will have higher pixel intensity values than those surrounding it.

So once a threshold is set, you can compare the gradient value to the threshold value and detect an edge whenever the threshold is exceeded. Furthermore, when the first derivative is at a maximum, the second derivative is zero. As a result, another alternative to finding the location of an edge is to locate the zeros in the second derivative. This method is known as the Laplacian and the second derivative of the signal is shown below:

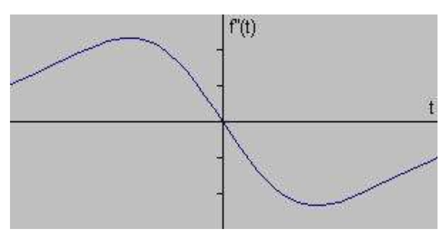


***FIG 2.4 Second derivative of signal***

***2.6.2 Edge Detection Techniques***

ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)
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## III. SOBEL OPERATOR

The operator consists of a pair of 3×3 convolution kernels as shown in Figure. One kernel is simply the other rotated by 90°.

| | | |
|---|---|---|
| -1 | 0 | +1 |
| -2 | 0 | +2 |
| -1 | 0 | +1 |

Gx

| | | |
|---|---|---|
| +1 | +2 | +1 |
| 0 | 0 | 0 |
| -1 | -2 | -1 |

Gy

*Fig 3.5 Sobel Operator*

]

These kernels are designed to respond maximally to edges running vertically and horizontally relative to the pixel grid, one kernel for each of the two perpendicular orientations. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (call these Gx and Gy). These can then be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient. The gradient magnitude is given by:

$$|G| = (G_X^2+G_Y^2)^{1/2}$$

Typically, an approximate magnitude is computed using:

$$|G| = |G_X| + |G_Y|$$

which is much faster to compute. The angle of orientation of the edge (relative to the pixel grid) giving rise to the spatial gradient is given by:
$\theta=\arctan(G_Y/ G_X)$

## IV ROBERT'S CROSS OPERATOR

The Roberts Cross operator performs a simple, quick to compute, 2-D spatial gradient measurement on an image. Pixel values at each point in the output represent the estimated absolute magnitude of the spatial gradient of the input image at that point. The operator consists of a pair of 2×2 convolution kernels as shown in Figure. One kernel is simply the other rotated by 90°. This is very similar to the Sobel operator.

| | |
|---|---|
| +1 | 0 |
| 0 | -1 |

Gx

| | |
|---|---|
| 0 | +1 |
| -1 | 0 |

Gy

*Fig 2.6 Robert's cross operator*

These kernels are designed to respond maximally to edges running at 45° to the pixel grid, one kernel for each of the two perpendicular orientations. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (call these Gx and Gy). These can then be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient.

The gradient magnitude is given by: $|G|=(G_X^2+G_Y^2)^{1/2}$ although typically, an approximate magnitude is computed using: $|G| = |G_X| + |G_Y|$

which is much faster to compute. The angle of orientation of the edge giving rise to the spatial gradient (relative to the pixel grid orientation) is given by: $\theta=\arctan(G_Y/ G_X)-3\pi/4$

## V PREWITT'S OPERATOR

Prewitt operator is similar to the Sobel operator and is used for detecting vertical and horizontal edges in images.

$$h_1 = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} \quad h_3 = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

***Laplacian of Gaussian***

The Laplacian is a 2-D isotropic measure of the 2nd spatial derivative of an image. The Laplacian of an image highlights regions of rapid intensity change and is therefore often used for edge detection. The Laplacian is often applied to an image that has first been smoothed with something approximating a Gaussian Smoothing filter in

 

IFERP
ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)
Vol 3, Issue 8, August 2016

order to reduce its sensitivity to noise. The operator normally takes a single graylevel image as input and produces another graylevel image as output. Since the input image is represented as a set of discrete pixels, we have to find a discrete convolution kernel that can approximate the second derivatives in the definition of the Laplacian. Three commonly used small kernels are shown in Figure 1.

| | | |
|---|---|---|
| 0 | 1 | 0 |
| 1 | −4 | 1 |
| 0 | 1 | 0 |

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 1 | −8 | 1 |
| 1 | 1 | 1 |

| | | |
|---|---|---|
| −1 | 2 | −1 |
| 2 | −4 | 2 |
| −1 | 2 | −1 |

***Fig 2.7 Three commonly used discrete approximations to the laplacian filter.***

Because these kernels are approximating a second derivative measurement on the image, they are very sensitive to noise. To counter this, the image is often Gaussian Smoothed before applying the Laplacian filter. This pre-processing step reduces the high frequency noise components prior to the differentiation step. In fact, since the convolution operation is associative, we can convolve the Gaussian smoothing filter with the Laplacian filter first of all, and then convolve this hybrid filter with the image to achieve the required result. Doing things this way has two advantages: Since both the Gaussian and the Laplacian kernels are usually much smaller than the image, this method usually requires far fewer arithmetic operations. The LoG (`Laplacian of Gaussian') kernel can be precalculated in advance so only one convolution needs to be performed at run-time on the image.

Note that as the Gaussian is made increasingly narrow, the LoG kernel becomes the same as the simple Laplacian kernels. This is because smoothing with a very narrow Gaussian on a discrete grid has no effect. Hence on a discrete grid, the simple Laplacian can be seen as a limiting case of the LoG for narrow Gaussians.

## VI CANNY'S EDGE DETECTION ALGORITHM

The Canny edge detection algorithm is known to many as the optimal edge detector. Canny's intentions were to enhance the many edge detectors already out at the time he started his work. He was very successful in achieving his goal and his ideas and methods can be found in his paper, "A Computational Approach to Edge Detection". In his paper, he followed a list of criteria to improve current methods of edge detection. The first and most obvious is low error rate. It is important that edges occurring in images should not be missed and that there be NO responses to non-edges. The second criterion is that the edge points be well localized. In other words, the distance between the edge pixels as found by the detector and the actual edge is to be at a minimum. A third criterion is to have only one response to a single edge. This was implemented because the first 2 were not substantial enough to completely eliminate the possibility of multiple responses to an edge.

Based on these criteria, the canny edge detector first smoothes the image to eliminate and noise. It then finds the image gradient to highlight regions with high spatial derivatives. The algorithm then tracks along these regions and suppresses any pixel that is not at the maximum. The gradient array is now further reduced by hysteresis. Hysteresis is used to track along the remaining pixels that have not been suppressed. Hysteresis uses two thresholds and if the magnitude is below the first threshold, it is set to zero. If the magnitude is above the high threshold, it is made an edge. And if the magnitude is between the 2 thresholds, then it is set to zero unless there is a path from this pixel to a pixel with a gradient above T2.

***Step 1***

In order to implement the canny edge detector algorithm, a series of steps must be followed. The first step is to filter out any noise in the original image before trying to locate and detect any edges. And because the Gaussian filter can be computed using a simple mask, it is used exclusively in the Canny algorithm. Once a suitable mask has been calculated, the Gaussian smoothing can be performed using standard convolution methods. A convolution mask is usually much smaller than the actual image. As a result, the mask is slid over the image, manipulating a square of pixels at a time. The larger the width of the Gaussian mask, the lower is the detector's sensitivity to noise. The localization error in the detected edges also increases slightly as the Gaussian width is increased.

ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)
Vol 3, Issue 8, August 2016

***Step 2***

After smoothing the image and eliminating the noise, the next step is to find the edge strength by taking the gradient of the image. The Sobel operator performs a 2-D spatial gradient measurement on an image. Then, the approximate absolute gradient magnitude (edge strength) at each point can be found. The Sobel operator uses a pair of 3x3 convolution masks, one estimating the gradient in the x-direction (columns) and the other estimating the gradient in the y-direction (rows).The magnitude, or edge strength, of the gradient is then approximated using the formula:

$$|G| = |Gx| + |Gy|$$

***Step 3***

The direction of the edge is computed using the gradient in the x and y directions. However, an error will be generated when sumX is equal to zero. So in the code there has to be a restriction set whenever this takes place. Whenever the gradient in the x direction is equal to zero, the edge direction has to be equal to 90 degrees or 0 degrees, depending on what the value of the gradient in the y-direction is equal to. If GY has a value of zero, the edge direction will equal 0 degrees. Otherwise the edge direction will equal 90 degrees. The formula for finding the edge direction is just:

$$\text{Theta} = \text{invtan}(Gy / Gx)$$

## VII ADVANTAGES & APPLICATIONS

***Advantages***

- The image gradient has been widely used for edge detection and it can be used to detect the text stroke edges of the document images effectively that have a uniform document background.
- It often detects many non-stroke edges from the background of degraded document that often contains certain image variations due to noise, uneven lighting, bleed-through, etc.
- Canny edge detector uses two adaptive thresholds and is more tolerant to different imaging artifacts such as shading.

***Applications***

- In the study of Historical documents.
- To restore imperfectly scanned documents.
- To enhance badly degraded text images.

## VIII EXPERIMENTAL RESULTS

In this project we have used local thresholding and edge detection methods for binarization technique. The input and results of various combinations we used are shown in below screenshots.

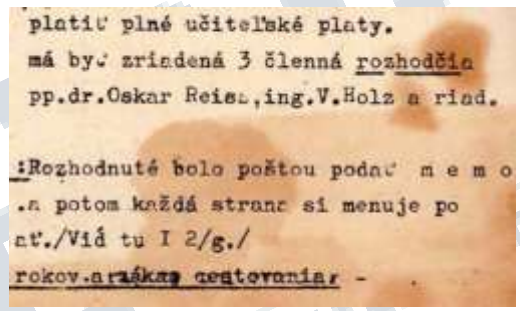
platiť plné učiteľské platy.
má byť zriadená 3 členná rozhodčia
pp.dr.Oskar Reis.,ing.V.Holz a riad.
:Rozhodnuté bolo poštou podať m e m o
.a potom každá strana si menuje po
at./Vid tu I 2/g./
rokov.a rizikám cestovania, -

Fig 4.1.1 Degraded Input Image

**4.1 RESULTS:**

Gray Scale Version of Input Image

Adaptive Contrast Image

Gradient Image

Otsu Threshold Image

ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)
Vol 3, Issue 8, August 2016


Contrast Image


Canny Image


Otsu Combined With Canny


Restored Image


Restored Image


Otsu Combined With Tv


Otsu Combined With Sobel


Restored Image


Adaptive Threshold


Adaptive Combined With Sobel


Adaptive Combined With Canny


Restored Image


Restored Image


Adaptive Combined With

Tv

 

Restored Image

***Fig 4.1: Figures showing different types of binary results of badly degraded document image***

***Table 4.2 Evaluation of PSNR & MSE Values***

| | PSNR | MSE |
|---|---|---|
| Otsu_canny | 58.6323 | 0.0891 |
| Otsu_sobel | 58.6306 | 0.0891 |
| Otsu_tv | 58.5757 | 0.0903 |
| Adapt_canny | 60.8628 | 0.0533 |
| Adapt_sobel | 60.8622 | 0.0533 |
| Adapt_tv | 60.8621 | 0.0533 |

## IX CONCLUSION & FUTURE SCOPE

***Conclusion:***

This project presents an adaptive image contrast based document image binarization technique that is tolerant to different types of document degradation such as uneven illumination and document smear.

The proposed technique is simple and robust, only few parameters are involved. Moreover, it works for different kinds of degraded document images. The proposed technique makes use of the local image contrast that is evaluated based on the local maximum and minimum. The proposed method has been tested on the various datasets. Experiments show that the proposed method outperforms most reported document binarization methods in terms of the PSNR and MSE.

***Future scope:***

To develop an efficient image processing technique for de-noising degraded images, blur effects and other noisy images.

## REFERENCES

[1] Bolan, Shijanlu, and Chew Lim Tan."Robust document image binarization technique for degraded document images."Image processing, IEEE Transactions on 22.4(2013):1408-1417

[2] B. Gatos, K. Ntirogiannis, and I. Pratikakis, "ICDAR 2009 document image binarization contest (DIBCO 2009)," in Proc. Int. Conf. Document Anal. Recognit.,Jul.2009, pp.1375–1382.

[3] I.Pratikakis,B. Gatos, and K Ntirogiannis,"ICDAR 2011 document image binarization contest (DIBCO 2011)," in Proc. Int. Conf. Document Anal. Recognit., Sep. 2011, pp. 1506–1510.

[4] I.Pratikakis ,B.Gatos, and K. Ntirogiannis, "H-DIBC2010 hand- writtendocument image binarization competition," in Proc. Int. Conf. Frontiers Handwrit. Recognit., Nov. 2010, pp.727–732.

[5] B.Su,S. Lu, and C.L.Tan,"Binarizationof historical handwritten images using local maximum and minimum filter,"in Proc.Int.Workshop Anal.Syst.,Jun.2010,pp.159–166.

[6] Leedham, C. Yan, K. Takru, J. Hadi, N. Tan, and L. Mian, "Compar-ison of some thresholding algorithms for text/background segmentation in difficult document images," in Proc. Int. Conf. Document Anal. Recognit., vol. 13. 2003, pp. 859–864.

[7] M. Sezgin and B. Sankur,"Survey over image thresholding techniques and quantitative performance evaluation," vol. 13, no. 1, pp. 146–165, Jan. 2004.

[8] O.D.Trier and A. K. Jain,"Goal-directed evaluation of binarization methods," IEEE Trans. Pattern Anal. Mach. Intell., vol. 17, no. 12, pp. 1191–1201, Dec. 1995.

[9] O.D. Trier and T. Taxt, "Evaluation of binarization methods for document images," IEEE Trans. Pattern Anal. Mach. Intell., vol. 17, no. 3, pp. 312–315, Mar. 1995.

[10] A.Brink," Thresholding of digital images using two-dimensional entropies,"Pattern Recognit.,vol.25, no. 8,

 

pp.803–808,1992.

[11] J. Kittler and J. Illingworth, “On threshold selection using clustering criteria,” IEEE Trans. Syst., Man, Cybern., vol. 15, no. 5, pp. 652–655, Sep–Oct.1985.

[12] N. Otsu, “A threshold selection method from gray level histogram,” IEEE Trans.Syst.,Man,Cybern.,vol.19, no. 1, pp.62–66, Jan.1979.