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COMPARATIVE STUDY OF IMAGE DENOISING TECHNIQUES

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ABSTRACT

This paper addresses the effect of pre-processing on binarization. Here, pre-processing and binarization operations are performed on a Lena image document. After scanning, pre-processing operations are applied on the image to remove noise. Pre-processing techniques play an important role in binarization. Newly developed pre-processing techniques are Non Local means (NLM) and Total Variation methods. Total Variation methods are motivated by the developments in compressive sensing methods like optimization. Binarization is used as a pre-processor before further steps are performed.

Keywords: Total variation methods, NL means, Pre-processing filters, Binarization, Otsu Binarization.

I. INTRODUCTION

In the scanned image, often there are a number of factors that affect the accuracy of an image. Scanned documents often contain noise that arises due to printer, scanner, print quality, age of the image. In the case of some images, the quality is usually very low, and the images suffer high degradation. The degradation on the images is mainly due to fading of ink, scanning, paper aging and bleed-through.

The reminder of this letter is organized as follows. Section II shows the steps involved in preprocessing. Section III deals with noise removal techniques. It comprises of conventional and new filtering methods. Otsu Binarization algorithm is discussed in Section IV. Section V deals with the experimental results and in Section VI we conclude the discussion.

II. STEPS INVOLVED IN PREPROCESSING

In preprocessing bellow steps involved scanning & image digitization. Before going into OCR process it is important that if quality scanning is not done then it will hard for OCR to read image & to make correct interpretation. Once quality scanning done image is stored in jpeg/bmp format. To improve quality of image we have to go for noise removel for noise removel Scanning of image itself can introduce some amount of noise. To have suitable further processing scanned image is to be free from any existing noise.

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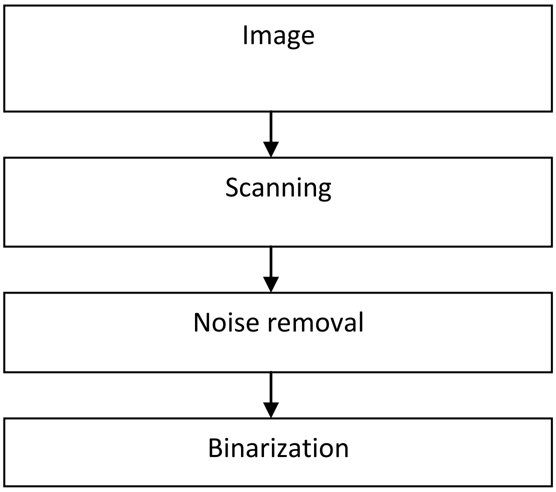

Fig. 1 Overview of basic steps in preprocessing

Filtering is a neighborhood operation, in which the value of any given pixel in the output image is determined by applying some algorithm to the values of the pixels in the neighborhood of the corresponding input pixel. Various methods are applied to reduce noise. The most important reason to reduce noise is to obtain easy way of recognition of documents.

Binarization

In image binarization Convertion of gray scale image Image into black & white image (0&1 form).Depending upon quality of image choice of binarization algorithem selected. Hence binarization algorithems that work best on one image may not be best for anather.

III. NOISE REMOVAL METHODS

3.1. Conventional methods

3.1.1. Mean filter

It is the simplest linear filter calls it as sliding window spatial filter, which replaces center pixel of window by the average of all values in the window. The size of window determines the image contrast. as we increase size of window, image becomes more & more blurred.

3.1.2. Median filter

It is non linear as well as sliding window spatial filter, which replaces the center of pixel the window by the median of all the values in window. It is widely used because it will remove the noise while preserving the edges present in the image.

3.1.3. Wiener filter

Wiener filter is an adaptive linear filter, which takes local variance of the image into account. When the variance in an image is large, the Wiener filter results in light local smoothing, while when the variance is small, it gives an improved local smoothing.

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Figure 2 shows the effect of filters on images. Mean filters smoothen the edges of the image and back ground. The median filter works better than the mean filter and preserves useful details in the image. Wiener filter produces a fair amount of edge blurring.

(a) (b)

(c) (d)

Fig. 2. Samples showing the effect of preprocessing filter (a) The original image, (b) Mean filter (c) Median filter (d) Wiener filter

3.2 Non Local Means

The conventional filtering methods remove fine details present in the image along with noise. Most denoising algorithms make two assumptions about the noisy image. One is that noise image contained white noise. The second assumption is the true image is smooth means it contains only low frequencies. But some images details and structures which have high frequencies. Filtering removes these high frequency in addition to the high frequency noise, and these methods do not remove low frequency noise present in image. These assumptions can cause blurring and loss of detail in denoised image. The Non-local means assumes that the image contains an extensive amount of redundancy and exploits these redundancies to remove the noise present in the image. In some images have adjacent pixels & similar neighborhoods, but non-adjacent pixels can also have similar neighborhoods as shown in the figure below. Pixels with similar neighborhoods can be used to determine the denoised value of a pixel.

The non local means replaces a pixel by the weighted average of other neighborhoods in the image. This method is the best possible denoising method for natural images. First we make a list of all similar neighborhoods in the image. Neighborhood of each pixel is then linearized to form a row in a matrix and L2 norm is computed between each row. Let $N_{x,y}$ and $N_{r,s}$ and denotes over pixel (x, y) and (r, s) respectively. Let the window size be MxM, where M is the odd. Similarity between the two neighborhoods can be found using L2-norm

$$||N_{x,y} - N_{r,s}||_2$$

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This norm then defines a weight to be used in our weighted average

$$W\,(N_{x,y}, N_{x,y}) = \frac{exp(-(N_{x,y} - N_{r,s}))^2}{h^2}$$

Where h is a parameter that needs to be fine-tuned. Similar neighborhoods give w = 1. If the two neighborhoods are very different w =0.

Then each pixel in our new image g(x,y) is a weighted average of the pixels in f(x,y), weighted by how similar the neighborhoods are

$$g(x,y) = \frac{\sum_r \sum_s f(r,s).w(N_{x,y}, N_{r,s})}{\sum_r \sum_s w(N_{x,y}, N_{r,s})}$$

When Lena image with noise is subjected to NL means algorithm, we get result as shown in figure. Smaller neighborhoods remove noise better.

3.3 Total Variation

3.3.1 Tikhnov model

Total variation of the image is reduces by TV Denoising. Total Variation is used when characters in the image are highly degraded. For preserving the edges it filters out noise.

(a) **(b)**

Fig. 3. Effect of NL means algorithm is shown

(a) Original image, (b) image denoised using NL means with window size=3**.**

The resulting filtered image should have the same statistical properties as the original image, along with sharp edges and low noise.

Finding the denoised image can be mathematically described as an optimization problem:

Where p (u/f) is the posterior probability of a hypothesis u & p (u/f) is written as

$$P\left(\frac{u}{f}\right) = \frac{p\left(\frac{f}{u}\right)p(u)}{p(f)}$$

P (u) is the prior probability of u & $p\left(\frac{f}{u}\right)$ is observed data f explained by u.

$$p\left(\frac{u}{f}\right) = \prod_{(x,y)\in D} \frac{1}{4\mu\Pi v}\, e^{\frac{-(f(x,y)-u(x,y))^2}{2\mu^2} + \frac{|\nabla u(x,y)|^2}{2v^2}}$$

Maximizing this probability is equivalent to minimizing the negative term in the exponent on the set of pixels D

$$\frac{(f(x,y)-u(x,y))^2}{2\mu^2} + \frac{|\Delta u(x,y)|^2}{2v^2}$$

This leads to our image restoration problem

$$\min_u\{E(u)\} = \frac{1}{2}\int_\Omega |\nabla u(x,y)|^2\, d\Omega \; + \frac{1}{2\lambda}\int_\Omega (f-u)^2 d\Omega$$

The first term is regularization which derived from prior & second is data fidelity. The data fidelity measures how far the current solution u is from the observed image f. This is Tikhonov model.

The parameter λ is a non-negative coefficient that governs the balance between the data fidelity and the regularization. A large value for λ will produce an image with few details, removing small features, while a small value will yield an image same as u. In Tikhnov model, since we use image prior as a set of smooth images, we obtain blurred images as output.

3.3.2 ROF Model

Is similar to the Tikhonov model but the regularization has been changed to the TV norm instead of the quadratic norm. In its original formulation, the ROF model is defined as the constrained optimization problem

$$\min_u\left\{\int_\Omega |\nabla u|\, d\Omega\right\} s.t \int_\Omega (u-f)^2 d\Omega = \sigma^2$$

Where f is observed image function and u is the unknown denoised image.

The original non-convex ROF model can be turned into a convex problem by replacing the equality constraint

$$\int_\Omega (u-f)^2 d\Omega = \sigma^2$$

Fig. 4. Result of denoising using Tikhnov model

(a) The original image, (b) Tikhonov Filtered image

By the inequality constraint

$$\int_\Omega (u-f)^2 d\Omega \leq \sigma^2$$

Which in turn can further be transformed to the unconstrained (or Lagrangian) model

$$\min_u\left\{\int_\Omega |\nabla u|\, d\Omega + \frac{1}{2\lambda}\int_\Omega (u-f)^2 d\Omega\right\}$$

Where λ is a Lagrange multiplier.

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(a) **(b)** **(c)**

Figure 5. Result of denoising using ROF model (a) The original image, (b) TV using λ=3, (c) TV using λ=5.

IV. BINARIZATION

Image binarization converts a gray-scale image into a black and white (0s&1s) format. For this we choose a threshold value to classify the pixels as black and white. If the pixel value is greater than the threshold value, then it is classified as white and if the pixel value is less than the whole document image, but these techniques are not suitable for degraded images. In local binarization technique, the local threshold can be calculated by using different information of the images, such as the mean and standard variation of pixel values within a local window. Binarization techniques can be either global or local. The threshold value, then it is classified as black. In global binarization we choose a single threshold for Otsu Binarization Algorithm.

4.1 Otsu Binarization Algorithm

Otsu is a global thresholding binarization algorithm .It assumes that the image contains two classes of pixels one foreground (black) and one background (white). Then it calculates the optimum threshold separating those two classes so that their intra-class variance is minimal. This is equivalent to maximizing the between-class scatter. This establishes an optimum threshold K

$$I(x, y) = \begin{cases} 1, if\ Igray(x,y) <= K \\ 0, if\ Igray(x,y) > K \end{cases}$$

V. RESULTS

The image is first filtered by each of the noise removal algorithms described in Section 3. Then each filter output along with the unfiltered original was then binarized by using Otsu binarization algorithm. Two methods are used to do the evaluation measures – MSE and PSNR.

Mean Square Error (MSE) for two m×n images *I* and *K* is given by,

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j)-K(i,j)]^2$$

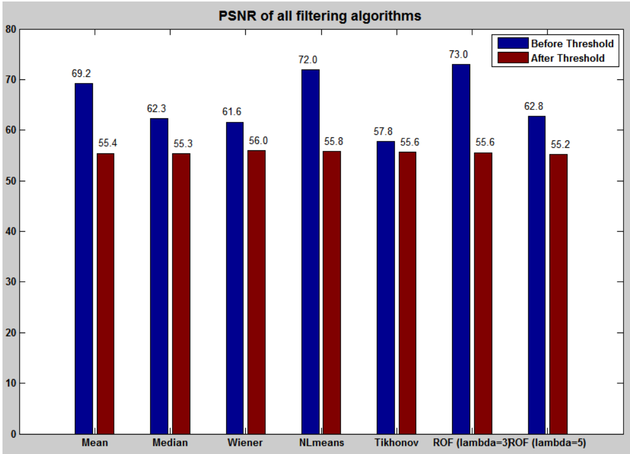
Where, one of the images is considered a noisy approximation of the other. Peak Signal-To-Noise Ratio (PSNR) is generally used to analyze quality of image in dB. PSNR calculation of two images one original and an altered image, describes how far two images are equal.

$$PSNR = 10\log_{10}\left(\frac{M_I^2}{MSE}\right)$$

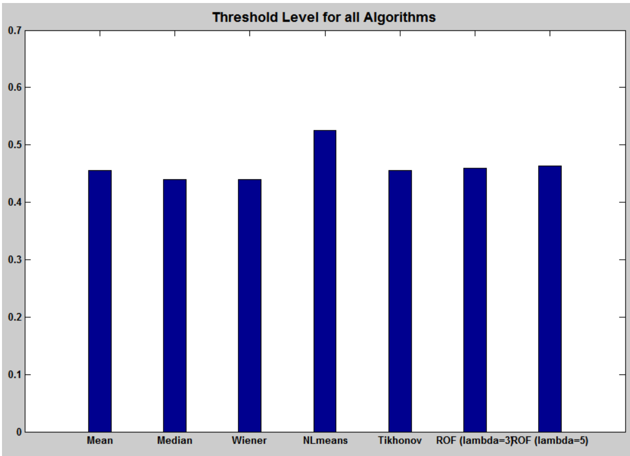
$$= 20\log_{10}\left(\frac{M_I}{\sqrt{MSE}}\right)$$

M_I Is the maximum possible pixel value of the image. These measures were calculated for every image filter combination the score obtained using preprocessing algorithms are shown in Tables 1.

In most cases the best pre-processing filter was NL means. Next best results are shown by Total Variation filter with λ=3. For the conventional filters mean, median and Wiener filter, Wiener gives best results.



(a)



(b)

Figure.6 a) PSNR of all filtering algorithms

b) Threshold level for all algorithms

VI. CONCLUSION

This paper presents a system that enhances the readability of Lena image, through effective preprocessing methods for binarization. The pre-processing techniques have been successfully tested on a degraded document. Experiments show best results for the NL means algorithm, thereby showing good binarization performance. So the proposed methods can be used for preprocessing of image.

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Table1.Performance measure of various algorithms

	Mean	Median	Wiener	NL means	Tikhonov	ROF(Lambada=3)	ROF(Lambada=5)
Before Threshold	69.2	62.3	61.6	72.0	57.8	72.0	62.8
After Threshold	55.4	55.3	56.0	55.8	55.6	56.6	55.2

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