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Restoring Degraded Images and Edge Detection Using Optimal Adaptive Thresholding and Filters

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Abstract - An edge in an image is a boundary or contour at which a significant change occurs in some physical aspect of an image, such as the surface reflectance, illumination or the distances of the visible surfaces from the viewer. Changes in physical aspects manifest themselves in a variety of ways, including changes in intensity, color, and texture. Edge detecting in an image significantly reduces the amount of data and filters out useless information, while preserving the important structural properties in an image. There are many ways to perform edge detection. However, the majority of different methods may be grouped into two categories, gradient and Laplacian. The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image. The Laplacian method searches for zero crossings in the second derivative of the image to find edges. Statistical analysis of optimal adaptive thresholding is one of the methodologies used in which input parameters are of a choice. To find an edge map after denoising a corrupted gray scale image a new proposed filter which functions with an aim to find better edge map in a restored gray scale image. Subjective method has been used by visually comparing the performance of the proposed filter with other existing first and second order derivative filters. The root mean square error and root mean square of signal to noise ratio have been used for objective evaluation of the derivative filters.
Keywords: Weiner2 filter, Optimal Adaptive Thresholding, Root-mean-square error, Signal-to-noise ratio.

I. Introduction

A. Edge Detection Approaches

There are many methods for edge detection, but most of them can be grouped into two categories, search-based and zero-crossing based. The search-based methods detect edges by first computing a measure of edge strength, usually a first-order derivative expression such as the gradient magnitude, and then searching for local directional maxima of the gradient magnitude using a computed estimate of the local orientation of the edge, usually the gradient direction. The zero-crossing based methods search for zero crossings in a second-order derivative expression computed from the image in order to find edges, usually the zero-crossings of the Laplacian or the zero-crossings of a non-linear differential expression. [1] .As a pre-processing step to edge detection, in a smoothing stage, typically Gaussian smoothing, is almost always applied (see also noise reduction).

Canny considered the mathematical problem of deriving an optimal smoothing filter given the criteria of detection, localization and minimizing multiple responses to a single edge. He showed that the optimal filter given these assumptions is a sum of four exponential terms. He also showed that this filter can be well approximated by first-order derivatives of Gaussians. [2]Canny also introduced the notion of non-maximum suppression, which means that given the pre smoothing filters, edge points are defined as points where the gradient magnitude assumes a local maximum in the gradient direction. [5].

B. Mathematical Details

Detectors based on optimality criteria are often derived in continuous one dimensional domain and are extended to two dimensional domains in a subjective way that lacks firm logical justification. Also, a problem very commonly faced by detectors is the choice of threshold values, which are often chosen on heuristic basis. Prewitt's, Roberts', and Sobel's operators and zero-crossing edge detectors use thresholds which are generally selected without any precise objective guideline. In the Mat lab [6], [7] version of Canny's edge detector the most popular among all edge detectors the default value of upper threshold is suggested to be 75th percentile of the gradient strength.

In order to automatically find a threshold, standardization of gradient magnitudes is to be done relative to the surrounding pixels' gradient magnitudes, and, then, it is to be tested whether the obtained value is large or not. A natural way of doing such standardization in any procedure is to use appropriate statistical principles. A way of accomplishing the above objective is obtained by the method proposed [9] in this work. This method of standardizing the gradient strength at each pixel locally before thresholding results in the removal of the ambiguity and inap-propriateness in choosing global threshold values, and thereby produces reliable, robust, and smooth edges. Local image statistics have been used earlier by Chow and Kaneko [3] to get boundaries in images, and their algorithm was modified by Peli and Lahav [4] for the purpose of detecting bright objects in darker backgrounds.

Suppose that an image contains only two principal gray-level regions. Let z denote gray-level values. The values are considered as random quantities, and their histogram may be considered an estimate of their probability density function (PDF), P (z).This overall density function is the sum or mixture of two densities ,one for the light and the other for the dark regions in the image. The mixture parameters are proportional to the relative areas of the dark and light regions. The form of densities is known or assumed, it is possible to determine an optimal threshold (in terms of minimum error) for segmenting the image into two distinct regions. Assume that the larger of the two PDFs correspond to the background levels while the smaller one describes the gray levels of objects in the image. The mixture probability density function describing the overall gray-level variation in the image is

$$P(z) = P1p1(z) + P2p2(z) \qquad 3.3.1$$

Obtaining the analytical expression for T requires that we know the equations for the two PDFs.

$$p(z) = \frac{p_1}{\sqrt{2\pi\sigma_1}} e - \frac{(z-\mu_1)^2}{2\sigma^2{}_1} + \frac{p_2}{\sqrt{2\pi\sigma_2}} e - \frac{(z-\mu_2)^2}{2\sigma^2{}_2} \qquad 3.3.2$$

Where μ_1 and $\sigma^2{}_1$ are the mean and variance of the Gaussian density of one class of pixels and μ_2 and $\sigma^2{}_2$ are the mean and variance of the other class. Using the general equation results in the following solution for the threshold T:

$$AT^2 + BT + C = 0 \qquad 3.3.3$$

Where

$$A = \sigma^2{}_1 - \sigma^2{}_2$$

$$B = 2\left(\mu_1\sigma^2{}_2 - \mu_2\sigma^2{}_1\right) \qquad 3.3.4$$

$$C = \sigma^2{}_1\mu^2{}_2 - \sigma^2{}_2\mu^2{}_1 + 2\sigma^2{}_1 2\sigma^2{}_2 \ln\left(\sigma_2 p_1 / \sigma_1 p_2\right).$$

Since a Quadratic equation has two possible solutions, two threshold values may be required to obtain optimal solution.

If the variances are equal, $\sigma^2 = \sigma^2{}_1 = \sigma^2{}_2$, a single threshold is sufficient:

$$T = \frac{\mu_1 + \mu_2}{2} + \frac{\sigma^2}{\mu_1 - \mu_2} \ln\left(\frac{p_2}{p_1}\right). \qquad 3.3.5$$

If P1=P2, the optimal threshold is the average of the means. The same is true if $\sigma = 0$.

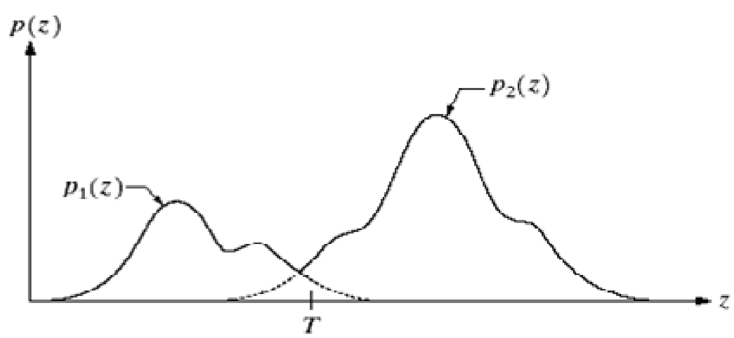


Figure 1. PDF of standard gradient Magnitude

Taking two simple Adaptive filters into consideration its behavior changes based on statistical characteristics of the image inside the filter region defined by the m x n rectangular window S_{xy}. The response of the filter at any point (x,y) on which the region is centered is to be based on four quantities a) g(x,y), the value of the noisy image at (x,y)

; b) $\sigma^2{}_\eta$, the variance of the noise corrupting f(x,y) to form g(x,y) ; c) m_L ,the local mean of the pixels in S_{xy} ; the local mean of the pixels in $S_{xy;}$ and d) $\sigma^2{}_L$,the local variance of the pixels in $S_{xy.}$

An Adaptive expression for obtaining $\hat{f}$ (x,y) based on these assumptions can be written as :

$$\hat{f}\,(x, y) = g(x,y) - \frac{\sigma_{2\eta}}{\sigma^2{}_L}\left[g(x,y) - m_L\right]. \qquad 3.3.6$$

The noise in our model is additive and position independent, so this is reasonable assumption to make because $S_{xy\ is}$ a Subset of g(x, y).S(x, y) denotes the standardized gradient magnitude at every pixel (x, y). For every pixel S(x, y) is calculated and if it is found to be sufficiently large, pixel (x, y) is taken as edge pixel.

Alternatively, a minimum mean square approach may be used to estimate a composite PDF from the image histogram

$$e_{ms} = \frac{1}{n}\sum_{i=1}^{n}\left[p(Z_i) - h(Z_i)\right]^2 \qquad 3.3.7$$

The reason for estimating the complete density is to determine the presence or absence of dominant modes in the PDF. Two dominant modes typically indicate the presence of edges in the image or sub image.

It may be noted that the output obtained after implementing the above procedure may contain thick edges. As already mentioned, an edge pixel is that pixel for which the rate of change of intensity is maximum. So, a way of detecting an edge pixel from the region extracted is to use nonmaxima suppression algorithm. In order to obtain smooth and continuous edges, it is suggested to use two threshold values S1 and S2 (S1 < S2 say) for the statistic S and implementing the idea of thresholding with hysteresis.

Based on approximation of the histogram of an image using a weighted sum of two or more probability densities with normal distributions. The threshold is set as the closest gray level corresponding to the minimum probability between the maxima of two or more normal distributions, which results in minimum error.

II Proposed Methodology

The shape of edges in an image depends on different attributes like, lighting conditions, the noise level, type of material and the geometrical and optical properties of the object [3].Generally, noise occurs in the image due to the result of errors in the image acquisition process, by which the intensities acquired by the pixels are not same as the pixels value in the original image [4]. The degradation models like Gaussian and Salt & Pepper are used to contaminate noise in the original image [5, 6]. For denoising a corrupted image for Gaussian noise, the Wiener2 filtering and for Salt & Pepper noise the Median filtering are used as reported by Tukey [7, 8]. The functionalities of Wiener2 filtering have been made . Fast median filtering algorithms are proposed by Huang et al. [14] and Astola and Campbell [15]. Different derivative filters of first and second order like Sobel, Prewitt, Laplacian, and Robert are used to find edge map in the image.Further it describes the Gaussian and Salt & Pepper noise models to contaminate the image. It also describes the Wiener2 and Median filtering schemes for image restoration and the methods for evaluating the performances of edge detection operators. Then classifies the first and second derivative gradient operator along with the proposed operator. Illustrates the different algorithms for corrupting an image, filtering of corrupted image, convolving an image with a spatial mask, edge detection filter, normalizing and thresholding an image.

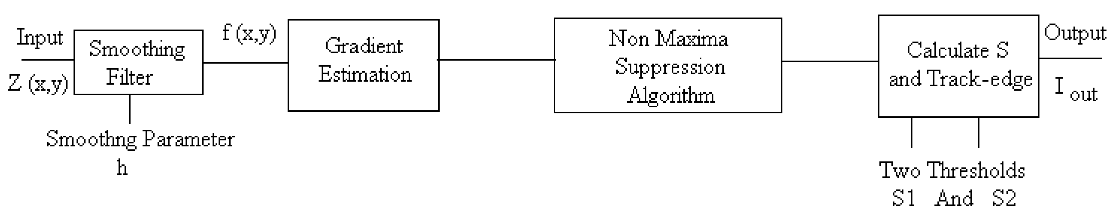


Figure 2 .Representation of Block diagram of proposed method

Brief algorithmic steps implemented for the proposed technique are follows:

1. Convolve image f(r, c) with a Gaussian function to get smooth image $\hat{f}(r,c)$.

   $\hat{f}(r,c) =$ f(r,c) * G(r,c,6) .
2. Apply first difference gradient operator to compute edge strength then edge magnitude and directions are obtained as before.
3. Apply non-maximal or critical suppression to the gradient magnitude.
4. Apply optimal adaptive threshold to the non-maximal suppression image.

In images when there is more than one homogenous region (e.g. an image has many objects with different gray levels) or where there is a change on illumination between the objects and its background. In this case, portion of the objects may be merged with the background or portions of the background may appear as an object. From the above fact, any of the automatic threshold selection techniques performance becomes much better in images with large homogenous separated regions. These conditions are fully satisfied for edge-enhanced image where most of the areas are homogenous (including the areas inside the objects plus the areas inside the background), and also having a well separated with areas that fall between the objects and the background (edges).This improved technique make use of the previous idea and works on edge-enhanced image.

The wiener2 function applies a Wiener filter (a type of linear filter) to an image adaptively, tailoring itself to the local image variance. Where the variance is large, wiener2 performs little smoothing. Where the variance is small, wiener2 performs more smoothing. This approach often produces better results than linear filtering. The adaptive filter is more selective than a comparable linear filter, preserving edges and other high-frequency parts of an image. In addition, there are no design tasks; the wiener2 function handles all preliminary computations and implements the filter for an input image. wiener2, however, does require more computation time than linear filtering. Wiener2 works best when the noise is constant-power ("white") additive noise, such as Gaussian noise. [1].

Wiener2 estimates the local mean and variance around each pixel

$$\mu = \frac{1}{NM}\sum_{n_1, n_2 \in \eta} a(n_1, n_2)$$

$$\sigma^2 = \frac{1}{NM}\sum_{n_1, n_2 \in \eta} a^2(n_1, n_2) - \mu^2 \qquad (2)$$

where η the N-by-M local neighborhood of each pixel is in the image A. wiener2 then creates a pixel-wise Wiener filter using these estimates of equation (2).

$$b(n_1, n_2) = \mu + \frac{\sigma^2 - \nu^2}{\sigma^2}(a(n_1, n_2) - \mu) \qquad (3)$$

where ν^2 is the noise variance. If the noise variance is not given, wiener2 uses the average of all the local estimated variances. In the proposed procedure, the gradient vector at each pixel of the fitted surface is calculated. The variation in the gradient vector at each pixel position is estimated using its variance covariance matrix based on standard statistical formulae. This variance covariance matrix is used to standardize the gradient vector at each pixel. [6].This leads to a statistic, which is used to extract regions in the image where the gradient magnitudes are significantly large. Edge pixels are extracted from this region using algorithms similar to nonmaxima suppression and thresholding with hysteresis.

III Experimentation and Results

The main steps that were followed in implementing the proposed method are as follows:

1) Wiener2 filter can intensify image that has been degraded by constant power additive noise.

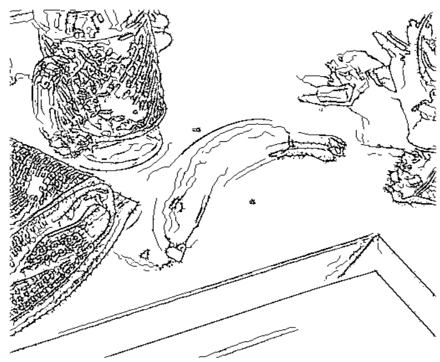
Wiener2 uses a pixel-wise adaptive Wiener method based on statistics estimated from a local neighborhood of each pixel. Wiener2 estimates the local mean and variance around each pixel. [1].

$$b(n_1, n_2) = \mu + \frac{\sigma^2 - v^2}{\sigma^2}(a(n_1, n_2) - \mu), \quad (5)$$

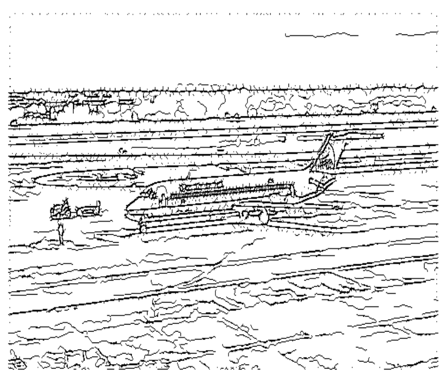
2) These the local mean and variance around each pixel is then used to compute the gradient at every pixel.
3) Then the nonmaxima suppression algorithm is applied and all the pixels that were below the threshold are suppressed and only the pixels that are expected to be an edge pixel are obtained in the output I_{temp}.
4) Based on the Statistic calculated every pixel is compared with the two thresholds and if it exceeds the threshold the S1 threshold then an edge passing through that pixel is assumed and if it exceeds S2 threshold then it is taken as an edge pixel and stored.
5) Those pixels that exceeded the S2 threshold were further applied to Track edge algorithm where it is determined to be an edge pixel or not based on its connectivity with the surrounding pixels.
6) The default values that were used to detect edges in an image are as follows: h = 1; S1 = 2; S2 = 20.

A. Edge Detection Results for Images without Noise

For all the Images the default values taken are h = 1; S1=2; S2 = 20. Results for Banana Image:



Results for Aero plane Image:



B .Edge Detection Results for Images with Noise
Results for Cameraman Image:

IV. CONCLUSION

In order to judge the performance of the proposed algorithm, comparisons are made on the same set of images with different choices of input parameters. For this purpose, two images, namely banana and aero plane image are obtained from an internet website at the University of South Florida [8]. On the same website, the best results obtained using different standard algorithms, namely Canny, Nalwa Binford, Iverson, Bergholm, and Roth well edge detectors, by changing the parameter values are available for these images. These are described as best adaptive results. The results obtained using the best fixed set of parameters for the same five methods are available for the same images. Obviously, the best adaptive results are at least as good as, if not better than, the best fixed results. The performance of proposed algorithm is discussed for each image for a default set of input parameters h = 1; S1 = 2; S2 = 20. These values are obtained after extensive research of work on real life images.

The statistical nature of the analysis conducted makes the choice of input parameters robust for noisy images, too. The methodology provides a way to estimate the variability in the image data locally at each pixel. Then, it is used to get locally standardized gradient magnitudes. This yields our statistic, which can efficiently handle random noise present in an image. It is evident from our extensive numerical investigations involving a variety of real life images that the values S1=2 and S2 =20 are generally producing results containing almost all important edges at the right locations of the images.

Since the selection of fixed set parameters plays a major role, it is important to experiment and compare different real life images. Further if the proposed algorithm is slightly modified by using any spatial masking technique which is quick and less complex in nature so that the noise present in the image is further reduced. A further research can be done on different noises and their effects on edge detection.

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