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REGRESSION ANALYSIS BASED NOISE ESTIMATION AND AN ITERATIVE HIGH DENSITY COLOR NOISE REMOVAL

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ABSTRACT

Noise corruption is the main role played in pulling back the image processing technology useless. So analysis and how to mitigate the noise in 2D images would be very worth in medical image processing, satellite image processing and various other domains. The main disadvantage in Switching median filters are known to outperform standard median filters in the removal of impulse noise due to their capability of filtering candidate noisy pixels and leaving other pixels intact. The boundary discriminative noise detection (BDND) is one powerful example in this class of filters. Certain issues in BDND algorithms are evaluated and enhanced by increasing the window size of the filter. In this project, we propose modifications to the filtering step of the BDND algorithm by increasing the window size one step higher to existing size to address these issues. Experimental evaluation shows the effectiveness of the proposed modifications in producing sharper images than the BDND algorithm. The noise elimination with around 90% of noise has been proposed and implemented using MATLAB 7.12 using image processing tool box.

INTRODUCTION

Image noise is undesired variation in pixel intensity values in a captured or transmitted image. Images captured with digital cameras or conventional film cameras or any other image sensor will pick up noise from variety of sources. Imperfect instruments, problems with the data acquisition process, interfering natural phenomena, transmission errors and compression can all introduce image noise and degrade the image quality. Image noise is an unavoidable side-effect during image capture. It is a phenemenon that no photographer can ignore. Even if noise is not clearly visible in a picture, some kind of image noise is bound to exist.

In digital images, noise corrupts the smooth surface with non-uniform specks, thereby degrading the image quality to greater extent. Various factors like lighting conditions, sensitivity setting in the camera, exposure time and temperature produce random variation of brightness or color information in images. The following is a noisy image with excessive random noise.

Image denoising is the process of removing noise from images. It has remained a fundamental problem in the field of image processing. Digital images play an important role in daily life applications like satellite television, magnetic resonance imaging, computer tomography, geographical information systems, astronomy and many other research fields. While we cannot completely avoid image noise, we can certainly reduce them. The image noise is removed usually by image smoothing operation.

There are two basic approaches to image denoising, namely spatial filtering and transform domain filtering. Spatial filters operate on a set of pixels related to a given pixel, usually by a sliding window. The window (or kernel) is usually square but can be any shape. Transform domain filters, in general, change the basis of signal space to aid some processing on the image data. Examples of transform domain filtering are fourier transform and wavelet transform.

Median Filter

The median-filter is also a sliding-window spatial filter, but the center value in the window is replaced by median (middle) of all the pixel values in the window. It is a more robust method than mean filter, because it is particularly effective in preserving the sharp edges in the image. Many variations to median filter are proposed such as weighted median filter, relaxed median filter, etc. The following image shows the median-filtered version of above noisy image (5 iterations).

An ideal denoising procedure requires a prior knowledge of noise, whereas a practical procedure may not have the required information about the noise model. More advanced image-denoising methods have been developed and it remains a continous field of research in signal processing. Many latest digital cameras have employed some noise removal techniques based on the light sensitivity during image and video capture.

EXISTING SYSTEM

- Boundary discriminative noise detection is done with a window size of 13x13 size.
- 80%noise is added and tested for both monochrome and color images.

A quite interesting switching median filter is the boundary discriminative noise detection (BDND) filter that is proposed in [26]. The BDND filter is proven to operate efficiently when compared to other filters, even under high noise densities (up to 90%). Being a switching-based median filter, the BDND algorithm filters the noisy image in two steps. The first step is essentially a noise detection step which is based on clustering the pixels in the image in a localized window into three groups, namely; lower intensity impulse noise, uncorrupted pixels, and higher intensity impulse noise. The clustering is based on defining two boundaries using the intensity differences in the ordered set of the pixels in the window. The pixel is classified as uncorrupted if it belongs to the middle cluster. Otherwise it is a noisy pixel. This noise detection mechanism showed impressive detection accuracy under different impulse noise models.

Once the noise map is determined, the second step is the filtering step, which is supposed to replace the noisy pixel with an estimate of its original value. This step is applied on the identified noisy pixels only. The filtering is essentially a median filtering operation that is applied on the uncorrupted pixels found in the filtering window. The critical parameter that is required to be defined in the filtering step of the BDND algorithm is the size of the filtering window. The size of this window is determined as follows. A window of size 3 × 3 is used as initial size for the filtering window. If the number of uncorrupted pixels in the window is less than half the window size, then the window is expanded outward by one pixel in all directions. This is repeated until the number of uncorrupted pixels in the window is greater than or equal half the number of pixels in the window or the current window size is less than or equal a maximum window size. The maximum window size of the condition is ignored and the window is expanded if no uncorrupted pixels are found. In this case, window expansion is repeated until one uncorrupted pixel is found. Basically, this step is an adaptation from the filtering process and is reported to perform well even under high noise densities.The BDND filter is proven to operate effectively under different impulse noise models. However, two main observations can be made about its filtering step. First, expanding the window until the number of uncorrupted pixels is at least half the number of pixels in the window may impose additional blurring in the output image. The impact of this is clearly noticeable under high noise densities. Second, the filtering step relies on computing the median value of the uncorrupted pixels found in the window without any regard to the spatial relationship of these pixels to the noisy pixel, and the deviation of the pixels' intensities from the median value. This also affects the quality and the sharpness of the edges in the filtered image.

The first observation is related to the way filtering is performed in the BDND algorithm which starts by using a 3 × 3 filtering window that is centered on the noisy pixel. However, the size of this window is considered insufficient for filtering under two conditions: i) the number of uncorrupted pixels Nu is less than half of the number of pixels in the window Nh, where Nh = 1/2 (WF ×WF) and WF is the window width, ii) if the number of uncorrupted pixels is zero. In case any of these conditions is violated for the current window, the window is expanded outward by one pixel in all directions. For the first condition, expansion is allowed as long as the size of the window is less than or equal to a maximum window size of Wmax ×Wmax. Such approach in expanding the filtering window could be useful in providing a better estimate for the value of the noisy pixel. However, the strict condition of requiring the number of uncorrupted pixels to be greater than half the number of pixels in the window is easily violated under high noise densities. Thus, with high noise densities the filtering window is expected to be expanded and most likely it will reach the maximum size. The direct impact on increasing the window size is the possible loss of correlation between the pixel values inside the filtering window. This may directly affect the value that replaces the noisy pixel, which

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may lead to blurring and unnecessary distortion in the filtered image.

To demonstrate the idea, consider the 5 × 5 image shown in Fig. 1(a), which contains an edge along the 45° diagonal that separates between two smooth regions. Suppose that this image is corrupted with 60% impulse noise as shown in Fig. 1(b), with the noisy pixels indicated by (*). These noisy pixels are assumed to be detected reliably by the detection step of the BDND algorithm. When the filtering step of the BDND algorithm is applied on the central pixel with a 3 × 3 window, then the set of uncorrupted pixels Vu in the window is simply {18, 20, 151}. This implies that Nu is 3, which is less than half the number of pixels in the window (Nh = 4.5). This violates the first condition that is imposed on the size of the filtering window, since Nu is less than Nh. If Wmax is set to 3, then the filtering window is expanded to 5 × 5 since WF equals Wmax. Given this new window, the set of uncorrupted pixels Vu is {18, 20, 20, 21, 22, 151, 151, 152, 152, 153}. This means that the number of uncorrupted pixels Nu is 10, which still less than half the window size (Nh = 12.5). Thus, the condition is violated again. However, the current window size is greater than Wmax, so window expansion stops. Of course, the second condition for window expansion is false since the number of uncorrupted pixels is not zero. Consequently, the filtered value of the pixel under consideration Xij is replaced by a new value Yij, which is simply the median of the uncorrupted pixels found in the filtering window using

$$Y_{ij} = \text{median}\{X_{i-s,j-t} | (s,t) \in W \wedge X_{i-s,j-t} \in V_u\}$$

where

$$W = \{(s,t) | -(W_F - 1)/2 \leq s,t \leq (W_F - 1)/2\}.$$

For the example image given in Fig. 1(b), this implies that the output value for the center pixel after filtering is 86, which is far away from the original pixel value. Additionally, this implies that the edge position between the two regions is displaced by one pixel.

The main reason for such a problem in the BDND algorithm results from the condition imposed on expanding the filtering window which requires the number of uncorrupted pixels to be at least half the window size. However, such requirement is hard to satisfy under high noise densities. Actually, expanding the window in such circumstance may not solve the problem since the number of required uncorrupted pixels increases nonlinearly when the window is expanded. As a result, the maximum window size is usually reached with high noise densities, which in turn results in additional blurring and edge displacement in the filtered image.

In order to address this problem, we propose the following modification to the window expansion process in the BDND algorithm. Basically, the condition is modified to take into consideration the estimated noise density P that is determined

from the detection step of the algorithm and the total number of pixels NT in the filtering window, such that while the number of uncorrupted pixels Nu is less than 1/2(1−P)NT and WF is less than or equal to Wmax, then the filtering window is expanded by one pixel outward in all directions. The term (1-P) basically is the percentage of uncorrupted pixels that are expected to be found in the filtering window. Including this term in the condition makes it adaptive to the noise density. In other words, when the noise density increases, the condition is loosened since the expected number of uncorrupted pixels decreases. This in turn reduces the occasions of window expansion. This is unlike the BDND algorithm that uses a fixed threshold of 1/2(WF ×WF) regardless of the noise density.

As a matter of fact, this is hard to achieve with high noise densities and small windows.

PROPOSED SYSTEM

- An Enhanced BDND algorithm with 15x15 window size.
- An adaptive switched median filter is incorporated in the existing system.
- This may increase the denoising time. But this is efficient. Because, we add 90% of the noise and observe the performance of the proposed system

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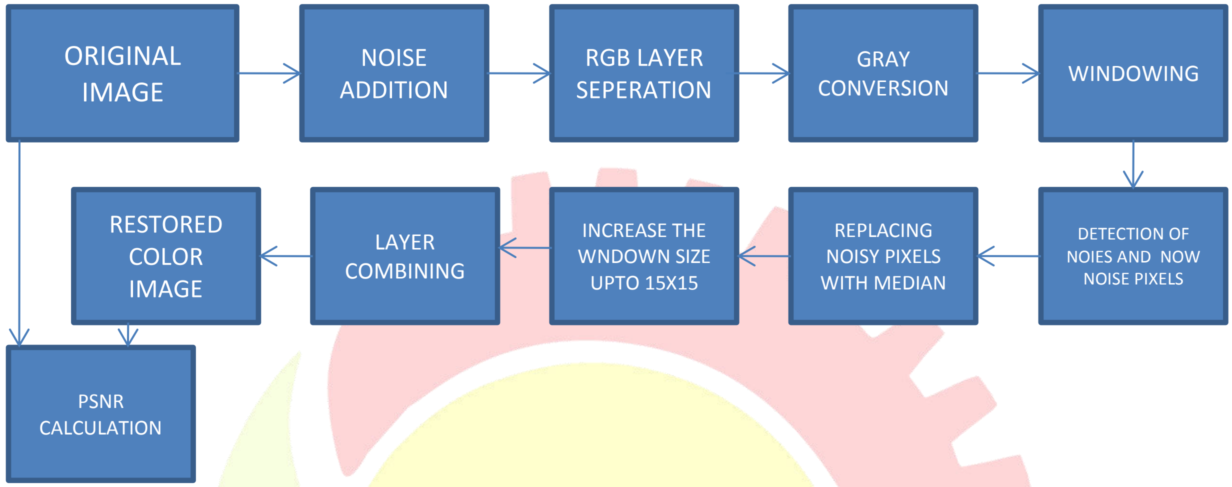

Figure 1. Block diagram of the existing system

In our proposed method the noise estimation is done with linear regression and the filter window is increased to 15x15. This method is likely to give a better PSNR value in our sequence of works as mentioned in the above block diagram.

LINEAR REGRESSION METHOD TO ESTIMATE NOISE BY CURVE FITTING

A large number of procedures have been developed for parameter estimation and inference in linear regression. These methods differ in computational simplicity of algorithms, presence of a closed-form solution, robustness with respect to heavy-tailed distributions, and theoretical assumptions needed to validate desirable statistical properties such as consistency and asymptotic efficiency.

Some of the more common estimation techniques for linear regression are summarized below.

Least-squares estimation and related techniques

- **Ordinary least squares** (OLS) is the simplest and thus most common estimator. It is conceptually simple and computationally straightforward. OLS estimates are commonly used to analyze both experimental and observational data. The OLS method minimizes the sum of squared residuals, and leads to a closed-form expression for the estimated value of the unknown parameter β:

$$\hat{\beta} = (X^TX)^{-1}X^Ty = \left(\tfrac{1}{n}\sum x_i x_i^T\right)^{-1}\left(\tfrac{1}{n}\sum x_i y_i\right).$$

The estimator is unbiased and consistent if the errors have finite variance and are uncorrelated with the regressors[7]

$$E[\mathbf{x}_i \varepsilon_i] = 0.$$

It is also efficient under the assumption that the errors have finite variance and are homoscedastic, meaning that $E[\varepsilon_i^2|\mathbf{x}_i]$ does not depend on i. The condition that the errors are uncorrelated with the regressors will generally be satisfied in an experiment, but in the case of observational data, it is difficult to exclude the possibility of an omitted covariate z that is related to both the observed covariates and the response variable. The existence of such a covariate will generally lead to a correlation between the regressors and the response variable, and hence to an inconsistent estimator of $\boldsymbol{\beta}$. The condition of homoscedasticity can fail with either experimental or observational data. If the goal is either inference or predictive modeling, the performance of OLS estimates can be poor if multicollinearity is present, unless the sample size is large.

In simple linear regression, where there is only one regressor (with a constant), the OLS coefficient estimates have a simple form that is closely related to the correlation coefficient between the covariate and the response.

- **Generalized least squares** (GLS) is an extension of the OLS method, that allows efficient estimation of β when either heteroscedasticity, or correlations, or both are present among the error terms of the model, as long as the form of heteroscedasticity and correlation is known independently of the data. To handle heteroscedasticity when the error terms are uncorrelated with each other, GLS minimizes a weighted analogue to the sum of squared residuals from OLS regression, where the weight for the i^{th} case is inversely proportional to var(ε_i). This special case of GLS is called "weighted least squares". The GLS solution to estimation problem is

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^{\mathrm{T}}\boldsymbol{\Omega}^{-1}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\boldsymbol{\Omega}^{-1}\mathbf{y},$$

where $\boldsymbol{\Omega}$ is the covariance matrix of the errors. GLS can be viewed as applying a linear transformation to the data so that the assumptions of OLS are met for the transformed data. For GLS to be applied, the covariance structure of the errors must be known up to a multiplicative constant.

- **Percentage least squares** focuses on reducing percentage errors, which is useful in the field of forecasting or time series analysis. It is also useful in situations where the dependent variable has a wide range without constant variance, as here the larger residuals at the upper end of the range would dominate if OLS were used. When the percentage or relative error is normally distributed, least squares percentage regression provides maximum likelihood estimates. Percentage regression is linked to a multiplicative error model, whereas OLS is linked to models containing an additive error term.[8]
- **Iteratively reweighted least squares** (IRLS) is used when heteroscedasticity, or correlations, or both are present among the error terms of the model, but where little is known about the covariance structure of the errors independently of the data.[9] In the first iteration, OLS, or GLS with a provisional covariance structure is carried out, and the residuals are obtained from the fit. Based on the residuals, an improved estimate of the covariance structure of the errors can usually be obtained. A subsequent GLS iteration is then performed using this estimate of the error structure to define the weights. The process can be iterated to convergence, but in many cases, only one iteration is sufficient to achieve an efficient estimate of β.[10][11]
- **Instrumental variables** regression (IV) can be performed when the regressors are correlated with the errors. In this case, we need the existence of some auxiliary *instrumental variables* $\mathbf{z}_i$ such that E[$\mathbf{z}_i\varepsilon_i$] = 0. If $\mathbf{Z}$ is the matrix of instruments, then the estimator can be given in closed form as

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^{\mathrm{T}}\mathbf{Z}(\mathbf{Z}^{\mathrm{T}}\mathbf{Z})^{-1}\mathbf{Z}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{Z}(\mathbf{Z}^{\mathrm{T}}\mathbf{Z})^{-1}\mathbf{Z}^{\mathrm{T}}\mathbf{y}.$$

PSNR

The phrase **peak Signal-to-Noise Ratio**, often abbreviated **PSNR**, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

It is most easily defined via the mean squared error (*MSE*). Given a noise-free $m\times n$ monochrome image I and its noisy approximation K, *MSE* is defined as:

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

The PSNR is defined as:

$$\begin{aligned} PSNR &= 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\ &= 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \\ &= 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE) \end{aligned}$$

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RESULTS

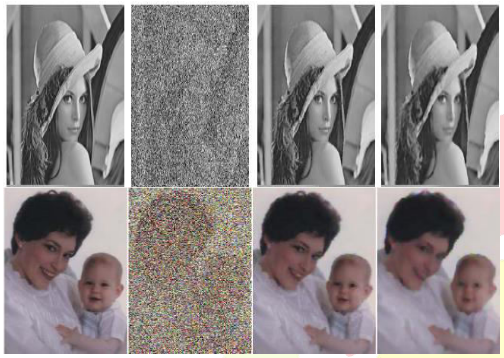

Figure 2 : Denoised image

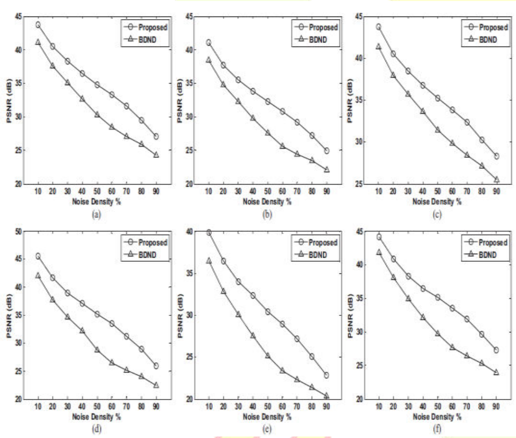

Figure 3 : PSNR variations

This work is highly suitable to

- Satellite image communications
- Internet image transfers.
- For bio medical image processing
- Used as a preprocessing scheme for all image segmentation and recognitions.

Also this work has advantages such as

- This algorithm tolerates upto 90% of the noise.
- PSNR obtained in our algorithm is about 30db.

CONCLUSION

In this work, a detailed study of BDND algorithm and modification in the BDND algorithm is carried out. The expected value of PSNR is above 50 db, and we try to increase the noise level greater than 90% of salt and pepper noise, which is actually 80% in the existing work. Various reference papers had been analysed to compare our novel proposed method. This noise elimination work could be very promising method in all applications like defence communications and bio medical image processing.

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