MIXED GAUSSIAN-IMPULSE NOISE REMOVAL BY WEIGHTED ENCODING WITH SPARSE NONLOCAL REGULARIZATION

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ABSTRACT

The main objective of this project is to remove the mixed noise from images by weighted encoding with sparse nonlocal regularization (WESNR). In the existing system, the detection based methods are used for removing the mixed noise. This is done by detecting the location of the impulse noise pixels and removing the mixed noise. While performing this method, it becomes less effective when the additive white gaussian noise (AWGN) or impulse noise (IN) is strong. In the proposed system, WESNR method is used for removing the mixed noise. Instead of detecting location of the impulse noise pixels explicitly , the proposed method uses soft impulse pixel detection via weighted encoding is used to remove the mixed noise AWGN+IN simultaneously. The image sparsity prior and nonlocal self-similarity prior are integrated into a regularization term. The proposed method removes mixed noise of AWGN+SPIN(Salt and Pepper Impulse Noise) and AWGN+RVIN(Random Valued Impulse Noise)+SPIN. The proposed system achieves high performance in terms of quantitative measures and visual quality.

Index Terms: Mixed noise, weighted encoding, Additive white Gaussian noise(AWGN),Impulse noise(IN)

I. INTRODUCTION

During image acquisition and/or transmission, noise will be more or less introduced. Denoising (or noise removal) is a fundamental problem in image processing, aiming to estimate the original image from its noise-corrupted observation while preserving as much as possible the image edges, textures and fine scale details. The prior knowledge of noise distribution plays an important role in noise removal. Two types of commonly encountered noise are additive white Gaussian noise(AWGN) and impulse noise (IN). AWGN is often introduced due to the thermal motion of electron in camera sensors and circuits . IN is often introduced by malfunctioning pixels in camera sensors, faulty memory locations in hardware, or bit errors in transmission.

An image corrupted by IN will have a portion of its pixels replaced by random noise values with the remaining pixels unchanged. Two types of widely encountered IN are salt-and pepper impulse noise (SPIN) and random-valued impulse noise (RVIN). An image corrupted by SPIN shows dark pixels in bright regions and bright pixels in dark regions. Nonlinear filters such as median filters have been dominantly used to remove IN. However, one shortcoming of median filters is that the image local structures can be destroyed, making the denoised images look unnatural. This problem becomes serious when the IN density is high. Various improvements of median filters have been proposed to better preserve the image local structures . Among them, the weighted median filter , the center-weighted median filter and the multistate median filter do not distinguish whether the current pixel is a noise pixel or not, and they tend to over-smooth the fine scale image details.
At each pixel of an image corrupted by AWGN, a value independently sampled from a zero-mean Gaussian distribution is added to the pixel gray level. Traditional linear filtering methods such as Gaussian filtering can smooth noise efficiently but they will over-smooth the image

edges at the same time. To solve this problem, nonlinear filtering methods have been developed.

Filtering Methods

1. Linear filtering
2. Non Linear filtering
3. Non local means filtering

Linear Filtering

Traditional linear filtering methods such as Gaussian filtering can smooth noise efficiently but they will over-smooth the image edges at the same time. To solve this problem, nonlinear filtering methods have been developed.

Non Linear Filtering

Non linear filters such as median filters have been dominantly used to remove IN. However, one shortcoming of median filters is that the image local structures can be destroyed, making the denoised images look unnatural. Various improvements of median filters have been proposed to better preserve the image local structures . Among them, the weighted median filter , the center-weighted median filter and the multistate median filter do not distinguish whether the current pixel is a noise pixel or not, and they tend to over-smooth the fine scale image details. The wellknown bilateral filter (BF) is good at edge preservation. It estimates each pixel as the weighted average of the neighboring pixels but the weights are determined by both the intensity similarity and spatial similarity.

Non Local Means Filtering

The nonlocal means (NLM) filtering method can be viewed as a significant extension of BF based on the fact that similar pixels in an image can be spatially far from each other. In NLM, each pixel is estimated as the weighted average of all its similar pixels in the image, and the weights are determined by the similarity between them. By grouping the nonlocal similar patches into a 3D cube and applying transform based shrinkage, the BM3D method has become a benchmark for AWGN removal.

Fig.1 Noisy Image

II. PROPOSED METHOD

The architecture design of the proposed method is shown in fig.2. Select the input image for removing the mixed noise. The input image is of RGB image and size would be less than 512 X 512. The original input image is noise less image because in real world all the digital image is noise free image. So that reason we add the noise in input image. In our proposed system, we added three types of noise they are white Gaussian noise, Salt and Pepper noise, Random valued noise. Using five quality image will help to extract the PCA dictionary. The dictionary will help to reconstruct the image after removing the noise pixel in the image. The Weighted encoding with sparse non local regularization algorithm is used in the proposed system for removing the mixed Gaussian and impulse noise. After the noise removing process is done, the PSNR value will help to identify the image restoration value noise removal image and at the same time, it denote the accuracy of the algorithm.

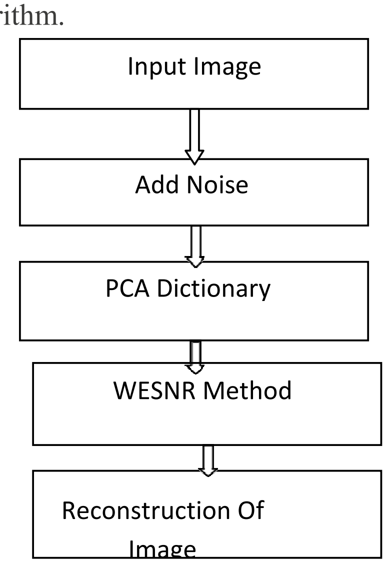

Fig.2Design of the proposed method

Modules

a. Adding noise
b. PCA Dictionary
c. Denoising using WESNR method
d. Reconstruction of image

a. Adding noise

The original input image is noise less image because in real world all the digital image is noise free image. So that reason we add the noise in input image. In our proposed method three types of noises are added they are white Gaussian noise, Salt and Pepper noise, Random valued noise. The RVIN and SPIN both are the impulse noise in real world that created by the electronic circuits. The property of the both noise is add black and white pixels in randomly added the image pixels. In real world the white Gaussian noise created by low lighting and low brightness. The property of the white Gaussian noise is adding white pixels in image pixels. In proposed method we add noise in image based on that properties. The white Gaussian noise is created by generate the white pixels randomly in the original image. The SPIN and RVIN is added in same manner to create the black and white pixels mix in the original image. After adding the noise we calculate the PSNR value to estimate the noise level in the input image.

Adds noise of a given type to the intensity image I, using J= imnoise(I,type). Type is a string that specifies any of the types of noise.J= imnoise(I,type,parameters),depending on type you can specify additional parameters to imnoise. All numerical parameters are normalized they correspond to operations with images with intensities ranging from 0 to 1. J= imnoise(I,'Gaussian',M,V) adds Gaussian white noise of mean m and variance v to the image I. The default is zero mean noise with 0.01 variance. J= imnoise(I,'Salt & pepper',d) adds salt and pepper noise to the image I, where d is the noise density. The default for d is 0.05. The mean and variance parameters for gaussian noise types are always specified as if the image were of class double in the range [0, 1]. If the input image is of class uint8 or uint16, the imnoise function converts the image to double, adds noise according to the specified type and parameters, and then converts the noisy image back to the same class as the input.

b. PCA Dictionary

Using five quality image will help to extract the PCA dictionary. The dictionary will help to reconstruct the image after removing the noise pixel in the image. Linear Discriminant Analysis (LDA), Independent Component Analysis and PCA are some of the techniques used for feature extraction, among them PCA is one of the feature extraction method in this project, we use that algorthim for it's powerful method in image formation, Data patterns, similarities and differences between them are identified efficiently. The other main advantage of PCA is dimension will be reduced by avoiding redundant information, without much loss. Better understanding of principal component analysis is through statistics and some of the mathematical techniques which are Eigen values, Eigen vectors.

PCA is a useful statistical and common technique that has found application in fields such as image recognition and compression. Principal Component Analysis (PCA) is a mathematical procedure that uses linear Transformations to map data from high dimensional space to low dimensional space. The low dimensional space can be determined by Eigen vectors of the covariance matrix. The following things expressed the PCA features that is help to extract the dictionary and reconstruct the noise removal image.

c. WESNR method

The proposed noise removing algorithm called as Weighted encoding spare Nonlocal regularization algorithm. It is newly developed algorithm for removing mixed noise in one process. In this ,the process done by update the residual value in the image. The residual value initialized by noise image SPIN noise removal image. The SPIN noise is removed by adaptive median filter. Median filtering follows this basic prescription. The median filter is normally used to reduce noise in an image, somewhat like the mean filter. However, it often does a better job than the mean filter of preserving useful detail in the image. This class of filter belongs to the class of edge preserving smoothing filters which are non-linear filters. This means that for two images A(x) and B(x).

$$\text{Median}[A(x)+B(x)] \neq \text{median}[A(x)]+\text{median}[B(x)]$$

These filters smooth the data while keeping the small and sharp details. The median is just the middle value of all the values of the pixels in the neighborhood. Note that this is not the same as the average (or mean) instead, the median has half the values in the neighborhood larger and half smaller. The median is a stronger "central indicator" than the average. In particular, the median is hardly affected by a small number of discrepant values among the pixels in the neighborhood. Consequently, median filtering is very effective at removing various kinds of noise. Adaptive median filter changes size of Sxy (the size of the neighborhood) during operation. That adaptive median filter helps to improve the initialize the residual by subtracting the original image to noise image. Then we calculated the weighted vectors of Noise removal image. Then set the iteration values to reputation of process. The initial residual and PCA dictionary and weighted will give the input of the WESNR than the values are updated and the PCA dictionary used to reconstruct the image at every iteration than residual will update the iteration. After the iteration will be over the noise is remove in the image.

In WESNR, the weights W are introduced in the data fidelity term and they are updated in the iteration process. W initialize the dictionary and noisy image. W are with real values and the pixels corrupted by IN will be assigned small weights.This is to reduce their effect on the encoding of y over the dictionary so that clean images can be reconstructed. WESNR reconstructs much cleaner and sharper image edges.It provides more pleasant denoising results than the other competeting methods.There is no explicit impulse pixel detection and it uses soft impulse pixel detection.We encode each noise pixel corrupted patch over a prelearned dictionary to remove IN and AWGN simultaneously.

$$\acute{\alpha} = \arg\min_{\alpha}\{\|W^{1/2}(y-\Phi\alpha)\|^2 + \lambda\|\alpha-M\|1\}$$

where W is a diagonal weight matrix and its element Wii is to be automatically determined and assigned to pixel i.

One simple and appropriate choice of Wii is Wii=exp(ae2)

$$W_{ii}=\exp(ae^2)$$

where a is a positive constant to control the decreasing rate of Wii.

In this project, we solve it via the iteratively reweighted scheme for its simplicity. Let V be a diagonal matrix. We first initialize it as an identity matrix, and then in the (k + 1)th iteration, each element of V is updated as

$$v^{(k+1)} = \lambda / ((\alpha^{(k)} - \mu)^2 + \varepsilon^2)^{1/2}$$

$$\hat{\alpha}^{(k+1)} = (\Phi^T W \Phi + V^{(k+1)})^{-1} (\Phi^T W$$

$$-\Phi^T W \Phi \mu) + \mu$$

In the case of AWGN+SPIN noise removal, we apply AMF(Adaptive median filter) to y to obtain an initialized image and then initialize e as

$$e^{(0)} = y - x^{(0)}$$

In the case of AWGN+RVIN+SPIN noise removal, AMF cannot be applied to y to initialize x.

We initialize e as

$$e^{(0)} = y - \mu y .1$$

d. Reconstruction of image

After the noise removing process the PSNR value will help to identify the image restoration value noise removal image and same time, it denote the accuracy of the algorithm. The term peak signal-to- noise ratio (PSNR) is an expression for the ratio between the maximum possible value (power) of a signal and the power of distorting noise that affects the quality of its representation. Because many signals have a very wide dynamic range, (ratio between the largest and smallest possible values of a changeable quantity) the PSNR is usually expressed in terms of the logarithmic decibel scale. Image enhancement or improving the visual quality of a digital image can be subjective. Saying that one method provides a better quality image could vary from person to person. For this reason, it is necessary to establish the effects of image enhancement algorithms on image quality. Using the same set of tests images, different image enhancement algorithms can be compared systematically to identify whether a particular algorithm produces better results. The metric under investigation is the peak-signal-to-noise ratio. If we can show that an algorithm or set of algorithms can enhance a degraded known image to more closely resemble the original, then we can more accurately conclude that it is a better algorithm.

For the following implementation, let us assume we are dealing with a standard 2D array of data or matrix. The dimensions of the correct image matrix and the dimensions of the degraded image matrix must be identical. The mathematical representation of the PSNR is as follows:

$$\mathrm{PSNR} = 20\log10\left(\frac{MAX_f}{\sqrt{MSE}}\right)$$

III. EXPERIMENTAL RESULTS

The proposed system is implemented using MATLAB and it is evaluated for removing the mixed Gaussian and impulse noise in the image. The performance of the algorithm is measured with test images: Lena, Boat, Peppers. The figure3 is for adding the noise like additive white Gaussian noise, salt and pepper impulse noise and random valued impulse noise in the image. The figure4 shows the PSNR value for the noisy image. The figure represents the creation of PCA dictionary. The figure4 shows the removal of random noise in the image. The figure5 shows the removal of white noise and the iteration is in progress for removing the mixed noise. This iteration would take 7-12 iterations. The figure6 shows the denoised image and having the high PSNR value for the noise removed image compared to the original image. The figure represents the graph that is plotted against the PSNR values with the number of iterations

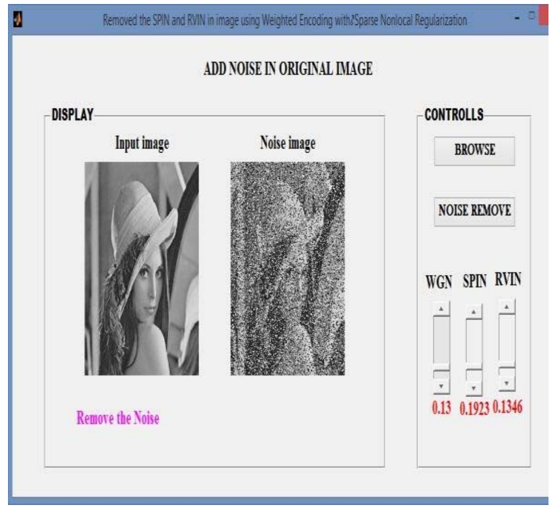

Fig.3 Noise added image

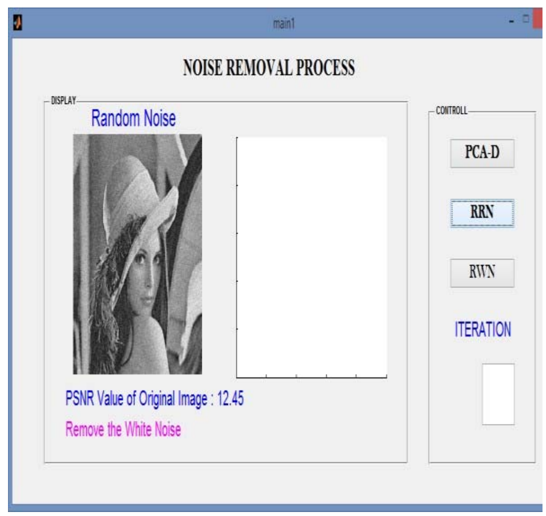

Fig.4 Noise removal process

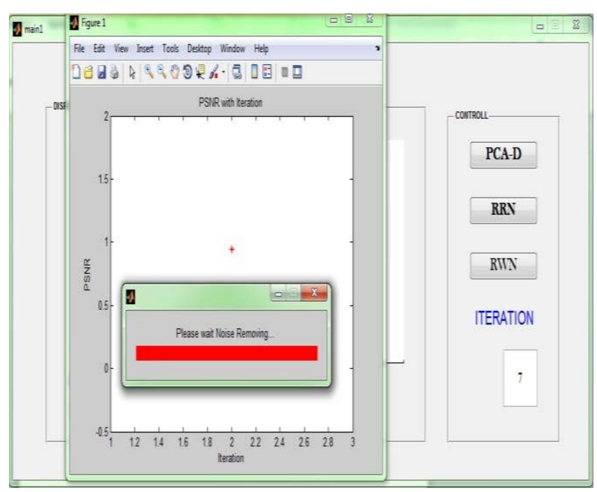

Fig.5 Iteration in progress

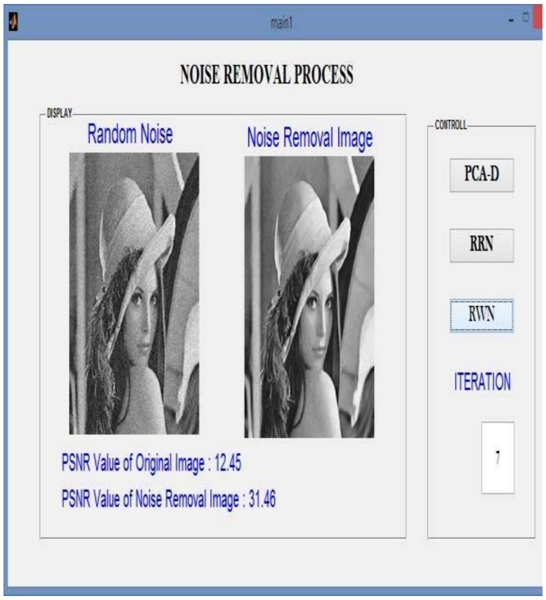

Fig.6 Denoised image

IV. CONCLUSION

The proposed method removes the mixed noise of additive white gaussian noise and impulse noise using weighted encoding technique simultaneously. Denoised image pixels are reconstructed by using the PCA dictionary. The weighted encoding residual are updated during the image pixel is heavily corrupted by noise. Image sparsity prior and nonlocal self-similarity were integrated into a single nonlocal sparse regularization term to enhance the stability of weighted encoding. WESNR reconstructs much cleaner and sharper image edges. The WESNR method can recover the image structure ie) reconstruct the edge and texture features in an image. It provides more pleasant denoising results than the other competeting methods. Achieves high performance compared to other mixed noise removal methods.

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