

Weighted Encoding Technique for Removal of Mixed Noise in an Image

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ABSTRACT: In today's modern age, digital images are used to transmit visual information, but the drawback is that images get corrupted with different noises after transmission. Image denoising technique recovers original high quality image from noisy image. Many detection based methods for mixed noise removal, including AWGN and IN noise have been proposed in recent years of research. This proposed method uses weighted encoding technique to remove AWGN & IN simultaneously. Using basis of PCA, the algorithm uses the dictionary which effectively explains the content of image. The proposed method, gives promising results with higher PSNR.

KEYWORDS: Mixed noise removal, adaptive median filtering, PCA dictionary.

I. INTRODUCTION

During transmission, digital images are often distorted by noise. In day to day life, we come across many applications based on image processing like digital cameras, traffic monitoring, forensic investigations and many more. But due to improper handling of instruments, poor image sensors of cameras and other natural and environmental phenomenon, images are corrupted with noise. To obtain original transmitted image from degraded image the task of image denoising technique, keeping the original details of the image intact. Image denoising deals with removing of such noise along with its detail preservation thus retaining all possible important signal features. Many methods have been proposed, but they are not self adaptive and can remove small amount of noise. In this paper we desire to implement a model which will remove the noise so as to get close to original image.

Noise is unwanted information affecting quality of an image. Noise can be added to the image through various sources like camera defects, poor transmission or acquisition. Usually two types of noise encountered are AWGN and IN noise. AWGN is introduced due to motion in camera sensors. IN noise is introduced through faulty pixel, poor functioning of memory. Thus few pixels are replaced by random noise pixel, leaving remaining pixels unaltered. SPIN and RVIN are also experienced in IN noise.

For efficient transmission, noise removal is a major concern. Thus filtering plays an important role for removing noise. Recently various filtering methods have been used with different algorithms. Initially in first step, noise present in the image is detected, and then after filtering methods like mean filter, median filter, bilateral median filter, switching median filter, adaptive median filter, etc. are used. However, this two phase strategy partially fails when AWGN and IN have high density of noise.

Gaussian filtering is one of the typical filtering methods used for smoothening noisy image but in the meantime over-smoothening causes loss of image edges. To overcome this problem, for edge preservation bilateral filtering is used. In this nonlinear filtering method, each pixel is estimated as weighted mean of neighbouring pixel. But these weights are dictated by closeness of spatial and intensity. Median filter is used in many filtering methods, but results in unnatural image due to loss of image features. Many improvements are made in median filters so as to retain the features of original image; one of them is adaptive median filtering. In adaptive media filter, window size increases adaptively until correct median value is obtained. Then this median value is replaced by noisy pixel.

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In this model, we present a simple and effective mixed noise removing method. This model doesn't involve pixel detection step, rather each noisy patch is encoded to remove mixed noises simultaneously using pre-learned dictionary. As we observe, the distribution of mixed noise is very complex; with heavy tail and doesn't have any parametric model. The conventional l_2 -norm method suits to remove Gaussian noise distribution, but it is unable to suppress mixed noises whose non-Gaussian distribution is complex. In the presented paper, using weighted encoding residual, the final encoding residual follows Gaussian distribution, thus suppressing mixed noise. Weighted encoding with sparse representation is combined, to minimize the noise to the maximum value and to get higher PSNR.

II. RELATED WORK

Comparing different filtering methods in [3], it is found the adaptive median filtering proves best for removal of impulse noise. Usually, the difference between median of nearby pixels and current pixel is calculated. This difference classifies whether the pixel is noisy or not. Switching based median filter is applied on pixels which are labelled as noise free to estimate value of noisy pixels, thus noise is reduced. The window size of filter changes adaptively depending on the number of noisy pixels in the present filtering window. But this approach involves more computational overheads. To overcome these drawbacks, revised scheme is introduced in [4]. In this method, only noise free pixels participate in the filtering, giving better result along with preservation of image details.

The ascending median vector value is also used for noise detection. The noise is identified by the difference between value of pixel and the threshold value. Using advanced version of bilateral filter [5], the filter is applied to noisy pixels which are classified using an efficient detector. This method mainly concentrates on removal of IN and Gaussian noise, but fails to filter Poisson noise which is also included in Universal noise. An extension to BF is non local means (NLM) filtering method [12], weights are assigned according to the similarity between the similar pixels of the image. Further advancement in NLM is BM3D method, in which nonlocal similar patches are grouped in the form 3D cube. The results obtained in this model are compared with the results obtained in [7].

The improved impulse detector [8] depends on the difference between current and neighbouring pixels with four main directions. This method is combined with weighted median filter named as directional weighted median filter. This filter suppresses high level of noise preserving the image features even works for corrupted colour images. This method uses only four main directions, thus the performance lags due to insufficient information regarding the image. Images corrupted by impulse noise and blur are restored in [9] using two-phase approach. Initially pixels corrupted by impulse noise are identified, considering remaining pixels as noise free. Thenafter, deblurring and denoising techniques are applied using noise free pixels by variational method. This method gives better result for SPIN but RVIN result is comparatively low.

In [10], image patches with similar content are used for PCA calculation, thus preserving the image features efficiently, also finding the components like missing colour. In [11], small image patches are removed using K-SVD algorithm. Trained dictionary is obtained from database of high quality images which is based on sparse representation. Using this algorithm, AWGN noise is removed. This method works well for images for filling in the missing pixels and image compression. But this merit proves unscalable for large image patches. To handle large database of images, sparse decomposition is done over the dictionary for sparse representation of image. K-SVD based denoising algorithm using dictionary of colour images is explained in [18]. Further the work is carried out to preserve the image features in various applications like inpainting. The algorithm used in the paper involves initially coding of sparse, updating of dictionary and then reconstruction of image.

In [14], dictionary is obtained for each cluster of image. PCA is applied to the cluster to learn the dictionary. More efficient sparsity coding is introduced to have faithful reconstruction of images. The model proposed in [15], provides efficient solutions for image processing using sparse representation. These methods can be used in various applications like denoising, compression, deblurring, etc. for more satisfactory results. A K-LMS algorithm obtained using K-means clustering is used to update the dictionary with the threshold value; denoised image can be obtained effectively. This method gives better results, but selection of threshold value becomes tedious [16].

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III. PROPOSED METHODOLOGY

A simple and effective weighted encoding based methodology is proposed to encode noisy patch using PCA pre-learned dictionary from the set of five high quality images. The following Figure 1 shows block diagram of the proposed model.

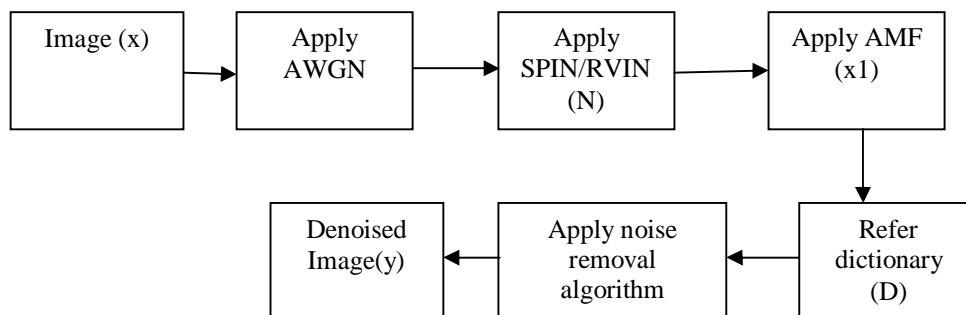


Figure 1: Block diagram for proposed method

The 5 high-quality images as shown in Figure 2, from [15] are used to obtain the dictionaries. K-means clustering is applied to large number patches from the five images are grouped into 200 clusters. PCA technique is applied to the clusters to get the dictionary D.

From above discussions, we observe the for mixed noise removal, AMF is used to reduce SPIN widely. Thus to make a fair comparison, for AWGN+SPIN/RVIN we still use AMF to obtain x1. Further algorithm is applied image x1, so as to reduce mixed noise and to obtain original image with effective results. In this noise removal algorithm, the mixed noise of image (n) is suppressed by weighting the encoding residual. Residuals (r) are the values obtained after comparison of denoised image after iteration and image (x). For mixed noise, the residual is initialised as,

$$r^{(0)} = n - \mu_i \cdot 1 \quad (1)$$

Where μ_i is the selected dictionary for patch y_i can be calculated as,

$$\mu_i = D_i^T \hat{x}_i \quad (2)$$



Figure 2: High-quality images

The residuals (r) for assigning weights (w) can be done in two ways. The residuals obtained from the pixels caused by AWGN are assigned with weights close to 1. The residuals obtained at other pixels corrupted by IN are assigned with smaller weights. Weights (w) and coding vector (α) is updated by iterating the value of i. the weight (w) is updated using coding residual (r). The weights (w) can be initialised as,

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$$W_{ii} = \exp(-ar_i^2) \quad (3)$$

Algorithm:

Input: Dictionary D, noisy image n;

Initialize r by Eq. (1)

Initialize w by Eq. (3);

Initialize μ to 0.

Output: Denoised image y.

Loop: Iterate on k= 1,2,...K;

1. Compute $\alpha^{(K)}$;
2. Compute $y^{(K)} = D\alpha^{(K)}$ and update the nonlocal coding vector μ ;
3. Compute the residual $r^{(K)} = n - y^{(K)}$;
4. Calculate the weights w by $r^{(K)}$ using Eq. (1);

End

Output the denoised image $y = D\alpha^{(K)}$

IV. EXPERIMENTAL RESULTS

A sufficient number of experiments are conducted to present the performance of the proposed model. Considering mixed noise, with standard deviation of AWGN varies as $\sigma = 5, 10, 15$, the RVIN ratio as $r = 5\%, 10\%, 15\%$ and the SPIN ratio as $s = 30\%, 40\%, 50\%$ respectively. For these specifications, experiment is conducted on commonly used images as shown in Figure 3.



Figure 3: Test images (a) Barbara (b) Fingerprint (c) Couple (d) Boat (e) Peppers

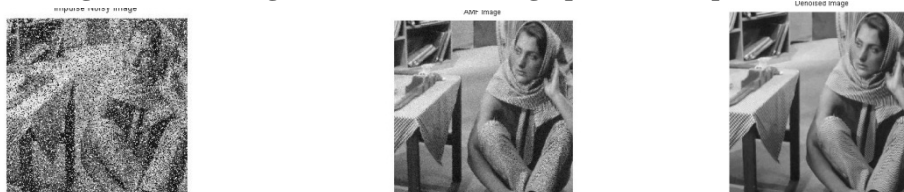


Figure 4: Result images (a) Noisy Image (b) AMF Image (c) Denoised Image

Figure 4 shows result images, when methodology is applied on Barbara image when noise ($\sigma = 10$; $r = 10\%$; $s = 40\%$) is applied. Observing the result images we can understand and conclude that algorithm is efficient in removing the noise to the maximum extent. From Table 1, shows comparison of denoising results by different methods used earlier for different images. From this, we can conclude that the proposed method achieves higher PSNR value consistently.

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Table 1: PSNR (dB) results of mixed noise removal ($\sigma = 10$; $r = 10\%$; $s = 40\%$)

Image	NLM	BM3D	Weighted Encoding Technique
Barbara	27.87	26.88	32.54
Fingerprint	23.64	19.94	27.12
Couple	25.36	23.74	29.43
Boat	25.37	23.84	28.31
Peppers	27.53	26.81	30.01

Also, pre-learned compact PCA dictionaries are used in this method, so the algorithm runs faster than the other denoising methods. Comparatively, the algorithm has three phases to be optimized, thus making it simpler with only 10 iterations.

V. CONCLUSION

Using weighted encoding technique, for removal of mixed noise, the quality of recovered image is improved. The presented method for removal of combination of Gaussian and impulse noise simultaneously gives better performance result both in terms of quantity and quality. Using set of pre-learned dictionary and weights, image patches are encoded to reduce heavy tail of noise distribution. The adaptive nature of weights decides the intensity of noise. Hence, adaptive weighted encoding denoising technique by suppressing the mixed noise with better PSNR is achieved.

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