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An Adaptive Image Mixed Noise Removal Algorithm Based On MMTD

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ABSTRACT

Combination of both Gaussian Noise and Salt & pepper Noise is known as Mixed Noise. It is an ever-present noise model in the image. Based on the variance of Gaussian Noise and density of Salt & pepper Noise, it adaptively alters the detection window size. Salt & pepper Noise is also known as Impulse Noise where as Gaussian Noise is also known as Bell Shaped Noise. MMTD means Measure of Medium Truth Degree. Then it defines the conception and establishes the relation between grey level and truth interval of Quality levels. Finally, it uses distance ratio function to calculate the similarity degree between the centre pixel and the normal neighbourhood pixel in the considered detectable mask(window)and which removes the noisy pixel. By sample simulation using MATLAB and PSNR evaluation, it shows the adaptive image mixed noise removal algorithm (Adp MMTD) gives a good performance in removing Mixed Noise.

Keywords: MMTD, MATLAB, NLM, BM3D, Peak-Value Signal-to-Noise

I. INTRODUCTION

Gaussian noise and Salt-Pepper noise combination is one of the most ever-present noise model in the image. Since noise is the important factor to reduce the image quality, noise removal is a fundamental problem in image processing. Noise removal aims to extract clear information from the noise corrupted observation image while preserving all possible details such as edges, textures and etc. Although image noise removal has been studied for years and the problem rectification recently proposed methods got a lot of achievement, most of the algorithms provides good noise reduction results for such types of noise. But noise particularly mixed noise is reduced by these methods which results of blurring.

Basically, we have plenty of Noise removal techniques and algorithms such as Wiener, Median, Mean filters and so on. They are little popular because of their easy implementation and understanding, but their performances are not good in some applications. Earlier research work focused on various smoothness, such as anisotropic filtering, mathematical morphology, Markov random field, total variation, or image decompositions on fixed bases such as Fourier, wavelets and so on. Although they may be very different in tools, it must be emphasized that a wide range of share the same basic remark: de-noising is achieved by averaging techniques. Most of the smoothness algorithms compare the grey level in a single point but take little consideration on the geometrical configuration in a whole neighbourhood. It is result in the blurring and lack of conception of structure in the reconstructed image. For taking any advantage of geometrical information, Bauds exploited image self-similarities between local parts and proposed the technique called Non-Local Mean(NLM) filtering. In this filtering technique, every mask element is computed as, the weighted average of sum of all its similar elements in that considered image. Actually, those weights are determined by the similarity between patches. Non-Local Mean Filter, which is a filter for image de-noising. This method replaces a noisy pixel by the weighted average of all its similar image neighbourhood pixel elements with weights reflecting the similarity between local neighbourhoods of the pixel being processed and the other pixels are patched. The NLM filter algorithm has become a bench mark proven to be asymptotically optimal and in fact it has a drawback of time consuming , complex and more over it is highly impossible for providing good results under higher amount of density .

Image de-noising is also based on the effective filtering in 3D transform domain, which is nothing but BM3D Filtering. In this project we proposes the blocks within the image are should be considered as patches or simply mask and utilize the block-matching concept by searching for blocks which are similar to the currently processed one. What actually BM3D means Block Matching With 3D Image. In this BM3D means, we have to take any image as our reference image and then proceed with that technique procedure. The blocks which are going to be processed must be stored after and attached together to form a 3D array structure. Due to the similarity between patches, the blocks in the masking window exhibits a high amount of correlation. We overcome this correlation by using a 3D de-correlating unitary transforms and prevent the noise properly and shrink its transform coefficients. Here also we have to use similarity concept to measure the distance between two considered pixels. we have to perform comparison procedure between centre pixel and the neighbourhood pixel, because of measure of medium truth degree. The subsequent inverse 3D transform procedure is also there in order to estimates all blocked patched blocks. After repeating this procedure for all blocks with in the reference window, simply we compute the final result as a weighted average of all its overlapping block-estimates. In MATLAB coadding point of view also its analysis is so difficult. we can consider both variance density of certain noises and we should find both Mean square and Peak Signal to Noise Ratio values. These methods NLM and BM3D filtering measure of uncertain problem.

techniques achieved better noise removal results in some applications. But in fact, they are more complex and time-consuming not useful for high density of noise. Sometimes this procedure is unable to predict the conception of the reference image such as edges, textures and etc.

From the point of uncertainty principle and inaccuracy appearing in the image processing, this project proposes an adaptive image mixed noise removal algorithm based on medium logic. Actually, Medium is a mathematical tool, which deals with fuzzy and uncertain problems. The complexity of any reference image considerations and the strong relations among pixels of image are evident. The problems are mostly happened because of uncertainty and inaccuracy appear in the image processing. As we discussed earlier many noise removal algorithms based on fuzzy logic which yielded good results and similarity degree is nothing but Medium Logic only. But the results of fuzzy noise removal algorithms are highly sophisticated and are dependent on the membership functions. These member ship functions are decided by subjective experience. For getting more objective and scientific

This quantitative method is called as measure of medium truth degree, namely MMTD. From then on, some image noise removal algorithms based on MMTD appeared. These methods yields best performance under some circumstances, like in high intensity of noises, especially in mixed noise the performance of these algorithms should be improved a lot. This project proposes how mixed noise can be removed adaptively by using some noise removal algorithm based on MMTD. According to the feature and density of noise, it adaptively alters the detection window size. Finally, uses the distance ratio function to measure the similarity degree between the considered pixel and the normal pixel in the detection window. Based on this similarity degree, it removes the noise pixel and restores the image. By sample testing and simulations, the final results demonstrates that the proposed algorithm can perform better in smoothing mixed noise while preserving details such as textures and edges other in subjective aspect and objective aspect.

II. ADAPTIVE IMAGE MIXED NOISE REMOVAL ALGORITHM

Image noise is random (not present in the object imaged) variation of brightness or colour information in images, and is usually an aspect of electronic noise. It can be produced by the sensor and circuitry of a scanner or digital camera. Salt-and-pepper noise is a form of Noise, it is also known as Impulse Noise. It is a high density of noise.It presents itself as sparsely occurring white and black pixels. It contains Black pixels in Bright regions and bright pixels in dark regions. An effective noise reduction method for this type of noise is a median filter or a morphological filter. Gaussian noise is statistical noise having a probability density function (PDF) equal to that of the normal distribution.

A. Noise model :

Let x be a noisy original image, y be the output image and n be the noisy pixel yi,j, original pixel xi,j and ni,j the pixel at location (i,j)in the y, x and n respectively.

$$y_{i,j} = x_{i,j} + n_{i,j}$$

In order to distinguish more noise models For a Gaussian noise corrupted observation, yi,j can be described as,

$$y_{i,j} = x_{i,j} + nG_{i,j}$$

Where nGi,j follows Gaussian distribution with zero mean and variance б2 . For a Salt-and-Pepper impulse noise polluted observation, yi,j can be described as:

$$y_{i,j} = \begin{cases} x_{\min} & \text{with probability } t/2 \\ x_{\max} & \text{with probability } t/2 \end{cases}$$

Where [xmin , xmax] is the range of the yi,j, and t is the probability of the pixel corrupted by the impulse noise, 0≤t ≤1. Normally, the probabilities of the noisy pixel whose value appears to be xmin and xmax are the same. For a mixed noise yi,j can be described as:

$$y_{i,j} = \begin{cases} x_{\min} & \text{with probability } t/2 \\ x_{\max} & \text{with probability } t/2 \\ x_{i,j} + nG_{i,j} & \text{with probability } p \end{cases}$$

B.Adaptively adjust the detection window size :

The adaptive mixed noise removal algorithm (AdpMMTD), is based on the test for the presence of noise at the center pixel in a detection window. As we know, the size of detection window affects the result of noise removal. Small filter window limits inhibition capability of noise but can preserve the image details better, on the contrary, large filter window strengthens the inhibition capability of noise but loses much more details which results in blur. Furthermore, using a fixed window size in the whole image is not very reasonable. For example, classic filters and previous MMTD noise removal algorithms use the fixed widow size to detect the center pixel, they have good performance in removing low density of noise but show ineffectiveness in removing high density of noise. With respect to the density of noise and the feature of different parts of image, the proposed algorithm adaptively varying the detection window size to improve the noise removal ability. We start from a 3×3 windows. If the median pixel in this window is the extreme pixel, we enlarge the detection window size. The step is repeated and stopped when the median pixel is not the extreme pixel or the window size reaches to a given maximum window size which is related with the intensity of noise. The larger the intensity, the larger the maximum window size is needed. If the median pixel in the detection window is between the maximal pixel and the minimal pixel, then use this window to consider the center pixel the probability to be a normal pixel or the noise. Firstly, according to the feature of noise, decide the ranges of grey level of normal, noise and transition. Then use MMTD to scale the similarity between the considered center pixel and the grey level range of normal pixel. If the center pixel lies in the normal range, it is reserved. If it lies in the noise and transition areas, it is replaced by a weighted median pixel and its neighbours.

The mixed noise composed by Gaussian noise and Salt and Pepper noise is an ever-present noise model in the image. Salt and-pepper noise is a form of noise commonly seen on images. It presents itself as sparsely occurring white and black pixels. An image containing this type of noise will have dark pixels in bright regions and bright pixels in dark regions. The Gaussian noise has a zero-mean Gaussian distribution and variance(б2) . It is easier to judge whether a pixel is polluted by salt-and-pepper noise than by Gaussian noise. Generally speaking, Gaussian noise makes image blurring, while Salt and-pepper noise is obvious in the image. In the grey image, the intensity of a pixel is expressed within a given range between a minimum and a maximum. This range is represented in an abstract way as a range from 0 (black) and 255 (white), with any fractional values in between and black pixels whose grey levels are are estimated.

Since the salt-and-pepper noise presents itself as sparsely occurring white and black pixels whose grey levels are extreme, if the center pixel in the detection window is one of the few extreme pixels, it is more like the noise. So we define the range of normal pixels [a,b] as the gray value set except few extreme pixels in the window, denoted as set A. Let X represent the grey level set of pixels in the window, B is the set of pixels which eliminate the maximum pixel and the minimum pixel in the window.

Algorithm:

1. Define the size of detection window (mask). Initially 3x3 mask is taken.
2. Add zeros to the image on all sides, i.e padding. Process of padding is to make an image size which is suitable for convolution.
3. Adaptively adjust the detection window size. Start from a 3×3 windows. If the median pixel in this window is the extreme pixel, enlarge the detection window size. The step is repeated and stopped when the median pixel is not the extreme pixel or the window size reaches to a given maximum window size which is related with the intensity of noise.
4. Decide the normal image gray domain. According to the density and feature of the Salt-and-pepper noise, define the range of normal pixels [a,b] as the gray value set except few extreme pixels in the window.
5. Compute the value of restored image at the center point.
6. Traverse the M╳N image gray level matrix, repeat the above steps in every child window pixels and can get a restored image of denoising the mixed noise.

C. Scale the similarity between the center pixel and normal pixel:

The range of gray level is [0,255] in an grey image, noise can be regarded as a disturbance of gray. Let predicate Q(x) represents that the pixel xi,j is a normal pixel, where (i,j) is the coordinate of the center pixel in the detection window. ╕QL(x) and ╕QR(x) represent that the pixel xi,j is a noise, and transition ~QL(x) and ~QR(x) represent that the pixel xi,j is a pixel between the normal pixel and the noise. Make the every gray level partition of the multi-levels image relate to the different truth interval of the predicate (╕QL(x), ~QL(x), Q(x), ~QR(x) and ╕QR(x)), and establish the standard scales αFL, αFRwhich relate to ╕QL(x) and ╕QR(x), as shown in Fig. 2. [a,b] denoted as Set A is the gray partition of normal pixels in the neighborhood of the pixel xi,j

D. Restore the considered center pixel:

The mixed noise composed by Gaussian noise and SaltPepper noise is an ever-present noise model in the image. Saltand-pepper noise is a form of noise commonly seen on images. It presents itself as sparsely occurring white and black pixels. An image containing this type of noise will have dark pixels in bright regions and bright pixels in dark regions. The Gaussian noise has a zero-mean Gaussian distribution and varianceб2 . It is easier to judge whether a pixel is polluted by salt-and-pepper noise than by Gaussian noise.Generally speaking, Gaussian noise makes image blurring, while Saltand-pepper noise is obvious in the image. From the point of improving the visual effect, we decide the range of normal pixels mainly according to the feature and density of Salt-andpepper. In the grey image, the intensity of a pixel is expressed within a given range between a minimum and a maximum. This range is represented in an abstract way as a range from 0 (black) and 255 (white), with any fractional values in between.

III. EXPERIMENTAL RESULTS

In order to evaluate the effectiveness of the proposed algorithm AdpMMTD,we carry out a series of experiments on some corrupted images. The experimental results of removal of mixed noise composed by different density of Gaussian noise and Salt & Pepper noise are shown as fig.4 and table.Itable.IV. The performance of the new algorithm can be evaluated through both subjective visual and objective quality. Peak-Value Signal-to-Noise (PSNR) is a classic evaluation method to noise removal and restoration of image.

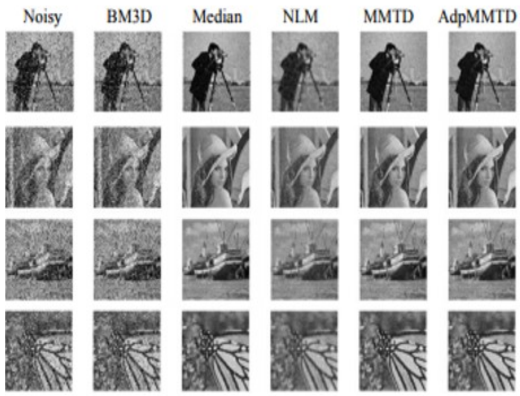

Fig: Mixed Noise Removal Results

The PNSR results in table. I – table -IV. Demonstrate that under a high density mixed noise,AdpMMTD outperforms the other.Subjective visual effect. The experiment results as shown in Fig. reveals that the visual effect of mixed noise removal of the proposed algorithm AdpMMTD is better than that of the others such as Mean filter, Median filter, NLMfilter, BM3D and MMTD filter. NLM and mean filter can remove the mixed noise ,but at the same time, they make the image blurring. The outputs of Median ,MMTD and AdpMMTD are relatively clear. But compared with Median filter and MMTD, AdpMMTD can remove much more mixed noise and preserve as much as possible details, especially to the mixed noise composed by high density Salt-and-pepper and low density Gaussian.

AdpMMTD can get more satisfied result. With the increasing of the Gaussian, outputs of all the filters are blur. In digital Image processing, removing the noise is one of the preprocessing techniques. The image noise may be termed as random variation of brightness or color information.

There are various types of image noise. Here a matlab program to remove 'salt and pepper noise' using median filtering is given. The random occurrence of black and white pixels is ‘salt and pepper noise.There is no doubt that the BMD3 shows excellent performance in removing the Gaussian noise.Compared to BMD3,the AdpMMTD shows less reduction ability to the Gaussian noise. But to the mixed noise,because of its relative less ability to the reduction of Salt-and-pepper noise,the BM3D cannot get satisfied filter result. AdpMMTD consider the medium state of pixels between noise and normal noise,and it shows the best result to remove the mixed noise in these experiments.

The following Tables demonstrates the proposed adaptive MMTD procedure and that corresponding results with suitable variance(Gaussian) and density (Salt & pepper Noise)

TABLE 1: DENOISING RESULT(PSNR)BY DIFFERENT METHODS

(Gaussian=0.004, Salt & pepper=0.2)

Images	Mean	Median	NLM	MMTD	Adp-MMTD	BM3D
Lena	20.216	20.655	22.201	23.301	23.873	12.311
Cameraman	19.132	19.433	20.977	20.325	20.483	12.763
Boat	20.001	20.962	22.672	23.655	23.744	12.762
Butterfly	18.710	18.972	19.844	20.112	20.666	12.636

TABLE 2: DENOISING RESULT(PSNR)BY DIFFERENT METHODS

(Gaussian=0.004, Salt & pepper=0.3)

Images	Mean	Median	NLM	MMTD	Adp-MMTD	BM3D
Lena	16.761	20.077	18.269	22.231	22.984	10.470
Cameraman	18.418	21.364	21.538	24.695	29.860	10.902
Boat	19.231	20.762	20.586	21.838	23.147	10.962
Butterfly	20.953	19.233	19.568	20.659	21.360	10.741

TABLE 3: DENOISING RESULT(PSNR)BY DIFFERENT METHODS

(Gaussian=0.005, Salt & pepper=0.2)

Images	Mean	Median	NLM	MMTD	Adp-MMTD	BM3D
Lena	18.231	22.413	19.629	23.231	22.984	12.471
Cameraman	20.213	24.623	21.860	24.695	29.860	11.902
Boat	19.820	24.632	21.586	23.838	23.147	17.962
Butterfly	21.463	21.034	19.962	24.659	21.360	10.741

TABLE 4: DENOISING RESULT(PSNR)BY DIFFERENT METHODS

(Gaussian=0.005, Salt & pepper=0.3)

Images	Mean	Median	NLM	MMTD	Adp-MMTD	BM3D
Lena	17.637	18.426	22.414	23.231	24.048	11.147
Cameraman	20.462	21.508	22.950	24.695	29.582	10.209
Boat	21.208	21.547	23.978	23.106	25.353	17.324
Butterfly	18.370	19.404	20.418	20.689	23.357	13.548

IV. CONCLUSION

This paper presents an adaptive mixed noise removal algorithm based on MMTD. Conclusions about the method can be drawn as follows:(1)Introduce the measure of medium truth degree to scale the similarity between the noise pixel and normal pixel. (2)Use an adaptively variable detection window to replace the fixed detection window. (3)Both the mean value of its neighbors and the median pixel of the child window are considered to restore the image. The experimental results show that the proposed algorithm AdpMMTD outperforms the Mean,Median,NLM,BD3D,MMTD in mixed noise removal. But to the Gaussian noise, the proposed algorithm does not perform well. In the future, respect to the Gaussian, we want to research on how to give a more reasonable ranges of the normal and noise pixels and restoration algorithm.

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