# An Adaptive Image Mixed Noise Removal Algorithm Based on MMTD

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***Abstract*—Mixed noise composed by Gaussian noise and Salt-Pepper noise is an ever-present noise model in the image. This paper proposes an adaptive image mixed removal algorithm based on measure of medium truth degree(MMTD). According to the feature and density of noise, it adaptively alters the detection window size. Then it defines the predicates and establishes the relation between gray level and truth interval of predicates. Finally, uses the distance ratio function to measure the similarity degree between the considered pixel and the normal pixel in the detection window and to remove the noise pixel. By sample simulation and classic PSNR evaluation, it shows the adaptive image mixed noise removal algorithm (AdpMMTD) brings about a good performance in removing mixed noise and preserving fine details.**

***Keywords—image noise removal; measure of medium truth; mixed noise;distance ratio function***

## I. INTRODUCTION

Mixed noise composed by Gaussian noise and Salt-Pepper noise is an ever-present noise model in the image. Since noise is the important factor to degrade 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 as much as possible details such as edges, textures and etc. Although image noise removal has been studied for decades and the sophistication of the recently proposed methods got a lot of achievement, most algorithms can provide excellent noise-reduction capabilities for certain types of noise. But noise especially mixed noise is reduced by these methods as a result of blurring.

On the one hand, the classic noise removal algorithms such as Mean filter, Median filter, Wiener filter and so on, are quite popular because of their easy implementation and understanding, but their performances are not very good in some applications. So some scholars sill made their efforts to improve the performance of the classic algorithms at present[1]-[5]. On the other hand, many novel theories and new methods are introduced into image noise removal. Early research work focused on various smoothness, such as anisotropic filtering[6]-[8], mathematical morphology[9], Markov random field[10], total variation[11], or image decompositions on fixed bases such as Fourier[12], Wavelets[13] and so on. Even though they may be very different in tools, it must be emphasized that a wide class share the same basic remark: denoising is achieved by averaging. Most of the smoothness algorithms compare the gray level in a single point but take little consideration on the geometrical configuration in a whole neighborhood, which may result in the blurring and lack of preservation of structure in the restored image. In order to take advantage of geometrical information, Buades exploited image self-similarities between local parts and proposed the Non-Local Means(NLM) filtering[14] in which 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 patches. The NLM algorithm is proven to be asymptotically optimal under a generic statistical image model and inspires many scholars to continue to study[15].Among them,by grouping the nonlocal similar patches into a 3D cube and applying transform based shrinkage, the block matching with 3D filtering (BM3D) method[18] has become a benchmark for Gaussian noise removal[19].One of the shortcoming of BM3D is that it can't get the desirable result to some other kinds of noise. In addition, more recent approaches have been presented ,such as learned sparse models[20], fields of experts[24],and so on. These methods achieved better noise removal results than NLM and BM3D in some applications. But in fact they are more complex and time-consuming.

From the point of uncertainty and inaccuracy appearing in the image processing, this paper presents an adaptive mixed noise removal algorithm based on medium logic which is a mathematical tool to deal with fuzzy and uncertain problem. The complexity of image information and the strong relations among image pixels are evident, and problems with uncertainty and inaccuracy appear in the image processing. There are many noise removal algorithms based on fuzzy logic which yielded good results[25]. But the results of fuzzy noise removal algorithms are highly dependent on the membership functions which are decided by subjective experience. In order to get more objective and scientific measure of uncertain problem, Wujia Zhu and Xi'an Xiao established medium principle[27]. In medium logic, a kind of truth grade function which possesses quantitative form was presented by Long Hong in 2006[29]. The quantitative method is called as measure of medium truth degree, namely MMTD. From then on ,some image noise removal algorithms based on MMTD

This work is supported by the National Natural Science Foundation of China (No.61170322, 61073115,61373065 and 61302157.)

appeared[31].These methods showed good performance under some circumstance, but in high intensity of noise, especially in mixed noise the performance of these algorithms should be improved. This paper presents an adaptive mixed noise removal algorithm based on MMTD. According to the feature and density of noise, it adaptively alters the detection window size. Then it defines the predicates and establishes the relation between gray level and truth interval of predicates. 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 testing and simulation, the results demonstrate that the proposed algorithm can do better in smoothing mixed noise while preserving details than other ones do in subjective aspect and objective aspect.

The remainder of this paper is organized as follows. Section II briefly introduces the medium mathematic. Section III presents the detail of the adaptive image mixed noise removal algorithm. Section IV reports experimental results and discussions. Section V concludes the paper.

## II. THE MEDIUM MATHEMATIC SYSTEM

The medium mathematic system is a mathematical tool which deals with fuzzy and uncertain problem. Medium principle was established by Wujia Zhu and Xi'an Xiao in 1980s who devised medium logic tools[27] to build the medium mathematic system[28], the corner stone of which is medium axiomatic sets.

### A. Basic Symbols in Medium Mathematic System

In medium mathematic system [28], predicate (conception or quality) is represented by *P*, any variable is denoted as *x*, with *x* completely possessing quality *P* being described as *P(x)*. The "╕"symbol stands for inverse opposite negative and it is termed as "opposite to". The inverse opposite of predicate is denoted as ╕*P*. Then the concept of a pair of inverse opposite is represented by both P and ╕*P*. Symbol "~" denotes fuzzy negative which reflects the medium state of "either-or" or "both this-and that" in opposite transition process. The fuzzy negative profoundly reflects fuzziness.

### B. Measure of Medium Truth Degree

There has been a large body of literature on the theories research of medium mathematic and got much theoretical achievement. But in application, we care about how to use a quantitative form to get the truth degree of *x* related to *P* or ╕*P*. Until 1996,scholar Long Hong has presented a distance ratio function *h(x)*[29][30] to scale the medium truth degree. It is a kind of the definition of truth grade function possesses quantitative form which can be processed by computers. The method is called as measure of medium truth degree, namely MMTD.

According to the concept of super state, the numerical value area of generally applicable quantification is divided into five areas corresponding to the predicate truth scale, namely ╕+*P* , ╕*P* ,~*P*, *P* and +*P*, as shown in Fig.1. In "True" numerical value area T, $\alpha_T$ is $\varepsilon_T$ standard scale of predication P ; In "False" numerical value area F, $\alpha_F$ is $\varepsilon_F$ standard scale of predication ╕*P* .

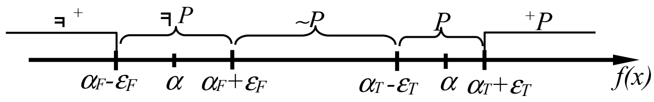


Fig. 1 Relation between numerical value areas and predicate

Individual truth scale in each numerical value area can be obtained by the distance ratio function $h_T(f(x))$(or $h_F(f(x))$) which relates to P(or ╕*P* ).

$$h_T(f(x)) = \begin{cases} \frac{-d(f(x),\alpha_F-\varepsilon_F)}{d(\alpha_T-\varepsilon_T,\alpha_F-\varepsilon_F)} & f(x) < \alpha_F - \varepsilon_F \\ 0 & \alpha_F - \varepsilon_F \le f(x) \le \alpha_F + \varepsilon_F \\ \frac{d(f(x),\alpha_F+\varepsilon_F)}{d(\alpha_T-\varepsilon_T,\alpha_F+\varepsilon_F)} & \alpha_F + \varepsilon_F < f(x) < \alpha_T - \varepsilon_T \\ 1 & \alpha_T - \varepsilon_T \le f(x) \le \alpha_T + \varepsilon_T \\ \frac{d(f(x),\alpha_F+\varepsilon_F)}{d(\alpha_T+\varepsilon_T,\alpha_F+\varepsilon_F)} & f(x) > \alpha_T + \varepsilon_T \end{cases} \tag{1}$$

Where *d* is the Euclidean distance in one dimension. Similarity, we can get the $h_F(f(x))$. The higher the $h_T(f(x))$,the higher the truth degree of *f(x)* related to *P* is.

The measuring of truth scale of disperse set *X* which relates to *P* (or ╕*P*)can be scaled by the additive truth scale $A_T(x)$ (or $A_F(x)$)[29] and the average additive truth scale $A_{TM}(x)$( or $A_{FM}(x)$) [29] of set which relate to P (or ╕*P*).

## III. ADAPTIVE IMAGE MIXED NOISE REMOVAL ALGORITHM

Noise is unavoidable during image acquisition, processing and transmission, and often exhibits as the random variation of brightness or color in images. In most cases, noise can be modeled as some kinds of distribution.

### A. Noise model

Let *y* be a noisy observation image, *x* be the real clean image and *n* be the noise. Denote noisy pixel $y_{i,j}$, original pixel $x_{i,j}$ and $n_{i,j}$ the pixel at location *(i,j)*in the *y*, *x* and *n* respectively.

$$y_{i,j} = x_{i,j} + n_{i,j} \tag{2}$$

The two most common types of image noise are Gaussian noise and Salt-and-pepper impulse noise. In order to distinguish different noise, give some more specified noise models in the follows.

For a Gaussian noise corrupted observation, $y_{i,j}$ can be described as:

$$y_{i,j} = x_{i,j} + nG_{i,j} \tag{3}$$

Where $nG_{i,j}$ follows Gaussian distribution with zero mean and variance $\sigma^2$.

For a Salt-and-Pepper impulse noise polluted observation, $y_{i,j}$ can be described as:

$$y_{i,j} = \begin{cases} x_{\min} & with\ probability\ t/2 \\ x_{\max} & with\ probability\ t/2 \end{cases} \tag{4}$$

Where [$x_{min}$ , $x_{max}$] 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 $x_{min}$ and $x_{max}$ are the same.

For a mixed noise composed by Gaussian noise and Salt-and-Pepper noise, yi,j can be described as:

$$y_{i,j} = \begin{cases} x_{\min} & with\ probability\ t/2 \\ x_{\max} & with\ probability\ t/2 \\ x_{i,j} + nG_{i,j} & with\ probability\ p \end{cases} \tag{5}$$

Where $p$ is the probability of the Gaussian corrupted pixel,$t$ is the probability of Salt-and pepper corrupted pixel.

### 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 an normal pixel or the noise. Firstly, according to the feature of noise, decide the ranges of gray level of normal, noise and transition. Then use MMTD to scale the similarity between the considered center pixel and the gray 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 neighbors.

### 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 $x_{i,j}$ is a normal pixel, where $(i,j)$ is the coordinate of the center pixel in the detection window. $\neg Q_L(x)$ and $\neg Q_R(x)$ represent that the pixel $x_{i,j}$ is a noise, and transition $\sim Q_L(x)$ and $\sim Q_R(x)$ represent that the pixel $x_{i,j}$ 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 ($\neg Q_L(x)$, $\sim Q_L(x)$, $Q(x)$, $\sim Q_R(x)$ and $\neg Q_R(x)$), and establish the standard scales $\alpha_{FL}$, $\alpha_{FR}$which relate to $\neg Q_L(x)$ and $\neg Q_R(x)$, as shown in Fig. 2. [a,b] denoted as Set A is the gray partition of normal pixels in the neighborhood of the pixel $x_{i,j}$.

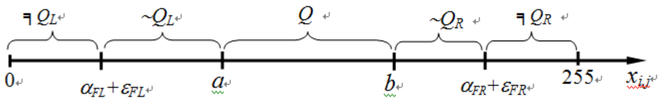


Fig. 2. Relation between gray level and predicate noise, normal and transition

According to Fig.2 the distance ratio function $h(x_{i,j})$ which relates to $Q(x)$ can be expressed as follows:

$$h(x_{i,j}) = \begin{cases} 0 & 0 \le x_{i,j} \le \alpha_{FL} + \varepsilon_{FL} \\ \dfrac{|x_{i,j} - (\alpha_{FL} + \varepsilon_{FL})|}{|a - (\alpha_{FL} + \varepsilon_{FL})|} & \alpha_{FL} + \varepsilon_{FL} < x_{i,j} < a \\ 1 & a \le x_{i,j} \le b \\ \dfrac{|x_{i,j} - (\alpha_{FR} + \varepsilon_{FR})|}{|b - (\alpha_{FR} + \varepsilon_{FR})|} & b < x_{i,j} < \alpha_{FR} + \varepsilon_{FR} \\ 0 & \alpha_{FR} + \varepsilon_{FR} \le x_{i,j} \le 255 \end{cases} \tag{6}$$

The value of the distance ratio function $h(x_{i,j})$ determines the degree between the pixel and the normal pixel. When it equals to 1,it means that the center pixel $x_{i,j}$ is a normal pixel. The closer to 1,the higher probability of the pixel $x_{i,j}$ being a normal pixel. When it equals to 0, it means that the pixel $x_{i,j}$is a noise. The closer to 0,the higher probability of the pixel $x_{i,j}$ being a noise pixel.

### D. Restore the considered center pixel

The mixed noise composed by Gaussian noise and Salt-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 $\sigma^2$. 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. From the point of improving the visual effect, we decide the range of normal pixels mainly according to the feature and density of Salt-and-pepper. 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.

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.

$$B = X - \max(X) - \min(X) \tag{7}$$

$$A = [\min(B), \max(B)] \tag{8}$$

The higher the density of noise is, the more extreme pixels are in the window. The normal range should wipe off more extreme pixels, we can repeat the following step (13),until get the appropriate range.

$$A = [\min(A - \max(A) - \min(A)), \max(A - \max(A) - \min(A))] \tag{9}$$

The relation between the gray value and the predicate is illustrated in fig. 3

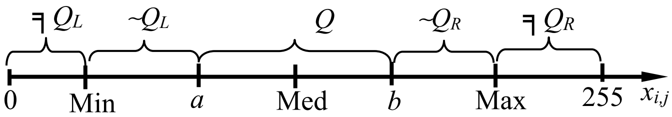


Fig. 3. Relation between gray level and predicate salt-pepper noise ,normal and transition

According to the fig.3 the distance ratio function $h(x_{i,j})$ which can scale the similarity between the center pixel and the normal pixel is as:

$$h(x_{i,j}) = \begin{cases} 0 & 0 \le x_{i,j} \le \min \\ \dfrac{|x_{i,j} - \min|}{|a - \min|} & \min < x_{i,j} < a \\ 1 & a \le x_{i,j} \le b \\ \dfrac{|x_{i,j} - \max|}{|b - \max|} & b < x_{i,j} < \max \\ 0 & \max \le x_{i,j} \le 255 \end{cases} \tag{10}$$

If the pixel $x_{i,j}$ is regarded as a normal pixel, it is reserved. A solution for Gaussian noise reduction is to process the image by its individual pixels based upon the appearance of its immediate neighbor pixels. Its noise reduction properties depend upon the fact that the neighborhood involved in the smoothing is large enough, so that the noise gets reduced by averaging. The better salt-and-pepper noise reduction is use the median value to replace the corrupted pixel. With respect to both reduction of Gaussian noise and Salt-and-pepper noise, if the pixel $x_{i,j}$ is a noise, it is replaced by the mean of its neighbors and the median pixel. If the pixel $x_{i,j}$ is between a normal pixel and a noise, it is replaced by the weighted sum of original value of $x_{i,j}$ and the mean of the its neighbors and the median value. There is no doubt that the weight is very important parameter in the restoration algorithm. Since the distance ratio function $h(x_{i,j})$ can scale the similarity between the pixel $x_{i,j}$ and the normal ones, we use the value of the distance ratio function $h(x_{i,j})$as the weight.

To sum up, the new image restoration algorithm can be expressed as follows:

$$x'_{i,j} = h(x_{i,j}) \times x_{i,j} + (1-p) \times (1 - h(x_{i,j})) \times Med(A) + p \times \overline{x_{k,l}} \tag{11}$$

Here $x'_{i,j}$ is the gray value of the restored image at the point coordinate $(i,j)$, M × N is the size of the detection window. Where $\overline{x_{k,l}}$ is the mean of the other pixels except the center pixel and Med(A) is the median pixel in the detection window. $p$ is the probability of Gaussian noise and $(1-p)$ is the probability of Salt-and-pepper noise.

$$\overline{x_{k,l}} = \frac{\sum_{k,l \in C} x_{k,l}}{M \times N - 2} \tag{12}$$

Where set C includes the pixels in the detection window except the center pixel and median pixel.

### *E. Computation of the mixed noise removal algorithm*

The computation of the new algorithm is implemented in following steps:

①Adaptively 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.

②Decide 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

③ Use distance ratio function(expression 10) to scale the similarity degree between the center pixel and the normal pixel using distance ratio function.

④ According to expression(11), compute the value of restored image at the center point.

⑤Traverse 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.

## IV. 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.I-table.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. PSNR is defined as:

$$PSNR = 10 \times \log_{10} \frac{x_{Max}^2}{\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (x_{i,j} - x'_{i,j})^2} \tag{13}$$

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Where: $x_{i,j}$ , $x'_{i,j}$ denotes the gray value of original image and restored image at coordination $(i,j)$ respectively; M and N denotes the width and height of the image, $x_{Max}$ is the pear-gray-value of the image.

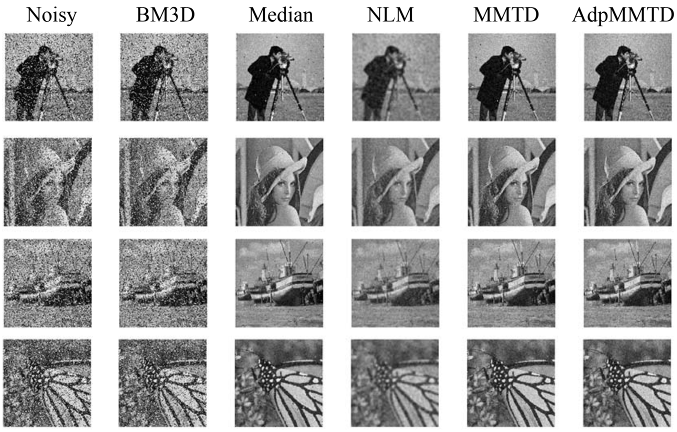


Fig.4. mixed noise removal results

( б$^2$Gaussian=0.005, б$^2$Salt & pepper=0.2).

TABLE I. DENOISING RESULT (PSNR) BY DIFFERENT METHODS
( б$^2$Gaussian=0.004, б$^2$Salt & pepper=0.2)

| | Mean | Median | NLM | MMTD | Adp_ MMTD | BM3D |
|---|---|---|---|---|---|---|
| Cam-man | 18.786 | 22.617 | 19.595 | 23.638 | **24.048** | 12.311 |
| Lena | 20.530 | 26.061 | 23.361 | 25.143 | **25.353** | 12.763 |
| Boat | 20.245 | 24.848 | 22.017 | 24.721 | **24.956** | 12.762 |
| Monach | 19.471 | 23.695 | 19.500 | **24.266** | 23.905 | 12.636 |

TABLE II. DENOISING RESULT (PSNR) BY DIFFERENT METHODS
( б$^2$Gaussian=0.004, б$^2$Salt & pepper=0.3)

| | Mean | Median | NLM | MMTD | Adp_ MMTD | BM3D |
|---|---|---|---|---|---|---|
| Cam-man | 16.979 | 20.077 | 18.289 | 21.741 | **22.950** | 10.470 |
| Lena | 18.561 | 22.275 | 21.538 | 22.923 | **24.492** | 10.902 |
| Boat | 18.471 | 21.570 | 20.725 | 22.391 | **24.040** | 10.967 |
| Monach | 17.637 | 20.772 | 18.469 | 21.801 | **22.259** | 10.741 |

TABLE III. DENOISING RESULT (PSNR) BY DIFFERENT METHODS
( б$^2$Gaussian=0.005, б$^2$Salt & pepper=0.2)

| | Mean | Median | NLM | MMTD | Adp_ MMTD | BM3D |
|---|---|---|---|---|---|---|
| Cam-man | 18.761 | 22.459 | 19.578 | 23.145 | **23.437** | 12.460 |
| Lena | 20.481 | 25.432 | 23.336 | 24.398 | **29.597** | 12.835 |
| Boat | 20.147 | 24.263 | 21.869 | 23.916 | **24.204** | 12.761 |
| Monach | 19.289 | 23.330 | 19.404 | 23.508 | **23.646** | 12.603 |

TABLE IV. DENOISING RESULT (PSNR) BY DIFFERENT METHODS
( б$^2$Gaussian=0.005, б$^2$Salt & pepper=0.3)

| | Mean | Median | NLM | MMTD | Adp_ MMTD | BM3D |
|---|---|---|---|---|---|---|
| Cam-man | 17.071 | 19.987 | 18.426 | 21.274 | **22.414** | 10.594 |
| Lena | 18.532 | 21.980 | 21.508 | 22.371 | **23.782** | 10.978 |
| Boat | 18.370 | 21.203 | 20.680 | 21.874 | **23.357** | 11.204 |
| Monach | 17.597 | 20.239 | 18.424 | 21.324 | **21.838** | 10.782 |

(1) Subjective visual effect. The experiment results as shown in Fig.4 reveal 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, NLM filter, 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.

(2)Better objective quality. The PNSR results in table.I – table.IV. demonstrate that under a high density mixed noise, AdpMMTD outperforms the others.

As we know that some classic noise removal algorithms and sophistication of the recently proposed methods ,such as Mean filter,Median filter,NLM filter and BMD3 are quite popular because for certain types of noise, they provide excellent noise-reduction capabilities. But noise especially mixed noise is reduced by these filters as a result of blurring.The experiments results show that the proposed algorithm AdpMMTD can get more satisfied result.

With the increasing of the Gaussian, outputs of all the filters are blur.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 can not 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.

## V. 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.

## *Acknowledgment*

The authors wish to thank the Associate Editor and the anonymous reviewers for their helpful comments and valuable suggestions regarding this paper.

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