Adaptive Image De-noising Algorithm in Intersecting Cortical Model

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Abstract—Because the classic intersecting cortical model (ICM) and the traditional image de-noising algorithm exist the deficiencies-the image collection, transmission and conversion are often subjected to impulse noise interference, thus affecting the quality of the image, therefore we improved the framework structure and related parameters of the ICM and proposed the adaptive image de-noising algorithm. Through improving the intersecting cortical model (ICM), we use the timed matrix information of the improved IICM to determine the specific location of the pixels polluted by the impulse noise, and then use the adaptive image de-noising algorithm to complete the de-noising process of the noise pixels on the basis of the improved ICM structure. Finally we made a detailed experimental validation and comparison. The experiments show that the improved intersecting cortical model (ICM) and the adaptive image de-noising algorithm have the superior impulse noise filter performance than the classic de-noising algorithm and can improve the image quality.

Index Terms—Adaptive Image, Mean Square Error, Peak-to-peak Signal-to-Noise Ratio, Impulse Noise

I. INTRODUCTION

Multi-sensor image is often interfered by the imaging device and the impulse noise in the external environment in the collection, transmission and conversion process, and the pixels polluted by this type of noise usually presents in the way that there are significant differences between the brightness value of themselves and their neighborhood pixels and in the visual effects their will also appear a certain degree of black-and-white light and dark points, which not only greatly reduce the image quality, but also bring a big inconvenience to image segmentation, image fusion, and a series of follow-up work [1-3]. Moreover, the presence of impulse noise will also bring a lot of interference to the image recognition, which can easily cause the wrong or omitting justice of the decision-making system [4-7]. So how to effectively remove the impulse noise in the source image has become a top issue in the field of image preprocessing field.

Current dominant image de-noising algorithm is divided into two categories: one image de-noising algorithm is based on the multi-scale and multi-resolution transform, in which the representatives are the Discrete Wavelet Transform de-noising Algorithm, Contourlet Transform de-noising Algorithm and the Non-Subsampled Contourlet Transform, NSCT de-noising Algorithm being popular in recent years which has the most ideal effect, but the final de-noised images derived from the above algorithms all contain scratch like false information; the other image de-noising algorithm is based on the artificial neural network. Currently, the most widely used and has the better de-noising effect is the Pulse Coupled Neural Networks PCNN algorithm, but abnormally complex neurons frame structure and the presence of a large number of parameters to be determined is the unavoidable question [8-10]. The Intersecting Cortical Model, ICM is a new visual cortex model that has the important biological background, compared with the PCNN, it has less unknown parameters and the computational complexity is significantly reduced, and has a superior image processing performance. But when using into the image de-noising, the complicated parameter settings such as the number of iterations, the attenuation coefficient, and amplitude constant are still the bottleneck restricting its performance.

On the other hand, in recent years, there are several superior performance impulse noise removal algorithms at home and abroad, for example, although Kenny's adaptive fuzzy median filter algorithm has better de-noising effect, there are still defects in parameter setting and operation time; Srinivasan proposed to arrange the pixels of $3 \times 3$ window in order to obtain the minimum (maximum) value and the median value, in order to determine whether a pixel is polluted and calculate gray value of the correction pixel; Lv Zongwei and others adopted the gray average value of the non-noise pixels within the $3 \times 3$ window as the correction value of the noise pixels which achieved a relatively better effects and has a shorter running time [11-17]. However, the above two algorithms both adopted the fixed-size regional window to analyze each pixel, and did not adjust adaptively the size of de-noising window according to the gray value distribution of the actual pixel of the image, which means they have the poorer flexibility, so the image de-noising effect should still to be improved.

This thesis develops under this background. It deeply analyzes the classic ICM and knows its deficiency in the model framework, then improve it to get a new kind of ICM (IICM), and then use IICM’s timed matrix information to determined the location of the pixels polluted by the pulse noise, finally it puts forward the
adaptive image de-noising algorithm based on the ICM and completes the de-noising processing of the noise pixels. The simulation section in the following part compares the algorithm mentioned in this thesis, more superior impulse noise processing algorithms appeared in recent years, with several kinds of the classic ones, and the result shows that the de-noising algorithm proposed in this thesis achieved a good de-noising effect and has the obvious advantage in performance.

This thesis mainly dose the extension and innovation work in the following aspects:

It analyzes the classic Intersecting Cortical Model (ICM) and finds that there exist defaults in the frame structure and parameters determination. It improves the electronic nerve components of the classic ICM and uses the thinking in the new image de-noising algorithm based on the PCNN timed matrix for reference, then it introduces the timed matrix T to determine adaptively the iteration times. On the above foundation, it put forward the Adaptive Image de-Nosing Algorithm and gives the detailed steps. First of all, we improved the Intersecting Cortical Model (ICM), and gained the Timed matrix information on basis of the improved ICM, then determined the specific location of the pixels polluted by the impulse noise. We used the adaptive image de-noising algorithm to do the de-noising process on these pixels, and then gave the specific steps of the adaptive image de-noising algorithm.

To further verify the correctness and effectiveness of the Adaptive Image de-Nosing Algorithm in improving ICM, it does detailed experimental validation and comparison to several classic de-noising algorithms and the experimental results show that compared with former algorithms, The density of the impulse noise increases, the decline of PSNR index and the rise of MSE index of the algorithm proposed in this thesis are relatively slowly, which reflects the superior robustness of the algorithm proposed in this thesis. With the density of the impulse noise increases gradually, especially after more than 50%, the index values of the rest algorithms occur unusually dramatic changes, while the change of indexes of the PSNR and MSE is relatively flat. At the same time, the greater the density of the impulse noise of the original image is, the contrast of the two corresponding index values of the algorithm proposed in this thesis with the rest algorithms will be more obvious. The adaptive image de-noising algorithm has the more superior pulse noise filtering performance than the previous classical de-noising algorithms which improves the quality of the image.

II. ICM AND ITS FRAME STRUCTURE

A. Classic ICM Structure and Its Frame Default

ICM is directly from the mammals’ research results on the visual cortex neurons cells and gets the artificial neuron model from the simulation of mammalian visual activities. ICM uses the multiply coupling characteristics of linear addition and nonlinear multiply which belongs to the biological neuron only, at the same time it takes into account that when the view of the mammalian optic system achieves the appropriate stimulus, the adjacent neurons will send the pulse at the same time. Figure 1 shows the structure of a basic ICM neurons and its discrete mathematical expression is as follows:

\[ F_y(n) = fF_y[m-1] + s_y + w_y[y(n-1)] \]  \hfill (1)

\[ y_y[n] = \begin{cases} 
1 & \text{if } F_y[n] > \theta_y[n-1] \\
0 & \text{then} 
\end{cases} \]  \hfill (2)

\[ \theta_y[n] = g\theta_y[n-1] + h y_y[n] \]  \hfill (3)

In which, the subscript \((i, j)\) is the coordinate of each pixel; \(w_y\) is the link matrix between neurons, \(y_y\) is the output value of the corresponding, which is either 1 or 0; \(F_y, S_y, \theta_y\) respectively represents the dendrites state value corresponding pixel value of the input image and the dynamic threshold of the neuron; \(f\) and \(g\) respectively represents the dendritic attenuation coefficient and the threshold attenuation coefficient of the corresponding iteration; \(h\) is the threshold amplitude constant; \((f, g)\) and \(h\) are all scalar factors, and meet \(g < f < 1\), in order to ensure that a dynamic threshold value will be lower than the state value of neurons as the iteration continues. Usually \(h\) is a big scalar value to ensure that after ignition each neuron can quickly enhance its dynamic threshold value to ensure that the neural will not be activated in the next iteration.

Similar to the PCNN, when used to process the images, ICM is corresponding to a single-layer two dimensional partial linked network and the number of its neurons is corresponding to the numbers of the pixels of the images. However, different to the classic PCNN model, which also has the biology background, ICM abandons the former’s complex link input branches and the producing mechanism of the internal activities, which makes the pulse propagation behavior of the whole biological neuron model more clearly and greatly reduces the computational complexity while reserved the effectiveness of the brain’s visual cortex model. However, the ICM framework still has its own defects: (a) It is still a problem that difficult to overcome that how to choose the number of the iterations times \(n\). If the value of parameter \(n\) is too small, it is easy to cause the non-sufficient send of the ICM neuron pulse; on the contrary, if the number of iteration times \(n\) is too large, it can easy to cause the deterioration of the image processing effects and greatly increase the system overhead; (b) The determination of the approximate range

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of values of four coefficients \( w, f, g, h \) is still inseparable from the human subjective experience as well as a large number of simulation experiments, and a set of parameter values is often only suitable for one or a class of applications, when it is used on other occasions, the effect will be bad.(c) The mathematical expression corresponding to the classic ICM neuron dendrites state value \( F_n \) has a complex structure, for it not only relates to the pixel value \( s \) corresponding to the image, the link matrix \( w \) between neurons, binary output \( y \) of the corresponding neurons, but also needs to determine the dendritic attenuation coefficient \( f \) of the corresponding iteration and neuron dendrites state value in the previous iteration cycle, which is not good for the computer operation, nor good for our in-depth understanding of the operation mechanism of the model; (4) formula (3) uses the threshold attenuation coefficient \( g \) to complete the threshold attenuation mode which is multiplicatively subordinate to the attenuation of the threshold value \( \theta \), but this mode can not make the threshold value cover the entire range, and it is easy to produce decimals which is not conducive to the algorithm running and even unnecessary, so we consider that we can use an additive threshold attenuation mode instead.

**B. IICM and Determination of Related Parameters**

To solve the above-mentioned defects, this thesis improves the classic ICM in the following aspects: (a) It further simplifies the connection modulator portion and ignores the memory function of the dendritic input state of each neuron \((i, j)\) in the classic ICM and retains only the external input \( s \) as well as the neurons integrate information in the neighborhood after the previous iteration; (b) It makes improvements on the threshold function \( \theta \) by replacing the traditional threshold attenuation coefficient \( g \) with the monotonically decreasing linear function; (c) Reference matrix based on PCNN It uses the thinking in the new image de-noising algorithm based on the PCNN timed matrix proposed by Liu Qing for reference-introducing the timed matrix \( T \) to determine adaptively the number of iteration times. Because the ignition timing and ignition frequency of each neuron is mostly determined by the gray value of the pixel linked to the neuron and the time information, thereby eliminating the blind select of the parameter \( n \). Figure 2 shows the structure of the IICM neuron. Formula (4) - (7) mathematically describe the IICM neurons.

![Figure 2. The structure of the IICM neuron](image)

\[
F_n[i,j] = s + w_y(y[n-1])
\]  

\[
y_y[n] = \begin{cases} 
1 & \text{if } F_y[n] \geq \theta_y[n-1] \\
0 & \text{otherwise}
\end{cases}
\]  

\[
\theta_y[n] = \theta_x[n-1] - \Delta + hy_{y[n]}
\]  

\[
T_y[n] = \begin{cases} 
\text{if neuron } ij, \text{ first ignition and } y_y = 1 \\
T_y[n-1], \text{ other}
\end{cases}
\]  

The formula (6) adjusts the step length \( \Delta \) to ensure that the dynamic threshold of each neuron has a linear attenuation trend; the threshold amplitude constant \( h \) is usually a large number, in order to ensure that the ignition frequency of each neuron is no more than once which provides the premise for the timed matrix operation in the formula (7).

The timed matrix \( T \) in the formula (7) and the neuron output matrix \( Y \) is of the equal size, and its elements \( T_y \) is associated to \( y_y \) and record the ignition time of each pixel and corresponding to the IICM neurons. There are three aspects need to be described: (1) If the neuron \((i, j)\) is never ignited, its corresponding value \( T_y \) will always be 0; (2) If neurons \((i, j)\) is ignited for the first time in one iteration, then set the \( T_y \) to be the corresponding number of iterations; (3) If the neuron \((i, j)\) is ignited but no for the first time, then the corresponding \( T_y \) value will remain the same number of iterations of the first time. In the timed matrix \( T \) generated by the formula (7), the pixels which have smaller changes of gray-scale in the original processed images will have the same or similar ignition time, and the connection modulator of the IICM does the integration process to the two-valued information of the neurons in the neighborhood, so \( T \) not only records the time information of each neuron, but also stores the space and other relevant information associated with the ignition time of each neuron, which provides a basis for the subsequent image processing; Besides, the timed matrix \( T \) can adaptively determine whether the iteration process is ended according to the feedback of the output matrix \( Y \) of the whole image, once all the elements in \( Y \) are not 0, it indicates that all the neurons in the image are all ignited and the iteration process is ended and the matrix element value in the matrix \( T \) is the total iteration number of the IICM.

In the actual IICM parameter setting process, as the external input value of the image, \( S \) is usually a pixel value, so there is no need to manually set it; the link weight matrix \( W \) directly determines the influence degree of the output pulse of the adjacent neurons to the neuron \((i, j)\), and it usually takes a square region with the size of \( n \times n \), in which \( n \) is an odd number not less than 3, \( n \) preferably larger value, and if the image gray level distribution and the texture are relatively simple, then \( n \) can be a larger value. The parameter \( \Delta \) will determine the linear attenuation rate of the threshold, in the IICM, \( \Delta \) can be set to 6. The threshold amplitude constant \( h \) is used to limit that each neuron can ignited at
most once, so we just need to give it a larger value to meet the requirements. This thesis mainly involves 256-level gray scale images, so h can be set to 600.

III. PROPOSED SCHEME

This paper improves the classic ICM. The ICM not only has less and more easily to set number of parameters than former algorithms and enhance the operating efficiency; but also can adaptively determine the number of iterations times n according to the actual situation of the image processing, but also eases the contradiction between the number of iterations times and image processing effects to some extent.

This thesis mainly discusses the bipolar pulse noise, which is also called the salt and pepper noise. The salt and pepper noise can be positive or negative. Because the pulse interference is usually larger than the intensity of the image signal, therefore, in an image, the pulse noise is usually digitalize as the maximum value (pure black or pure white). Due to this result, in a gray scale image, the negative pulses are usually appear as a black spot (pepper) in images. For the same reason, the positive pulses are often appear as a white dot (salt and pepper) in the images. Which means a or 0 (black) and 255 (white) for an 8-bit image. As a result, in the 256-level gray image, there are only two values: 0 and 255 for the pixel gray value polluted by the impulse noise. Unless specified mentioned in this thesis, the pulse noises are all mean the bipolar pulse noise and the gray images are all the 256-level gray scale images.

Besides, when an image is interfered by the external pulse noise, we can directly observe the gray scale value of each pixel to estimate the pollution degree of the whole image, but the efficiency of this algorithm is very low and no intuitive enough. The de-nosing algorithm proposed in this thesis is based on the regional window, therefore we can set a regional suspected pollution coefficient \( \eta \) to estimate the noise of each regional window of the whole image. The formula (8) gives the mathematical expression of \( \eta \).

\[
\eta_i = \frac{k_i}{n \times n}
\]

where, \( k_i \) is the timed matrix element value corresponding to each pixel in the \( n \times n \) regional window which takes pixel point \( (i, j) \) as the center. \( T_i \) is equal to 1 or equal to the number of pixels of the maximum element value \( T_{\text{max}} \) of the entire image timed matrix and this kind of pixels are known as the suspected polluted pixels, \( n \) is the radius of the regional window, and it is usually the odd number. Obviously, \( 0 \leq \eta_i \leq 1 \).

According to the ICM, we can gain the timed matrix \( T \), if \( T_i \) - the value of the matrix element is neither 1 nor the maximum value \( T_{\text{max}} \) of the matrix \( T \), then it shows that the gray value of the pixel \( (i, j) \) is neither 0 nor 255, then directly output the pixel; if \( T_i \) is equal to 1 or the maximum element value of the matrix \( T \), then we regard the pixel \( (i, j) \) as the suspected polluted pixel. If \( \eta_i \neq 1 \), then adopt median filtering method to the non-suspected polluted pixels in the \( n \times n \) regional window and then give the result to the final image; otherwise, if \( \eta_i = 1 \), then maybe all the pixels in the \( n \times n \) regional window are polluted by the pulse noise, if so, we should extend the regional window \( n \times n \) to \( (n+2) \times (n+2) \) and test \( \eta \) again, until \( \eta_i \neq 1 \), then adopt median filtering method to the non-suspected polluted pixels in the new produced regional window and then give the result to the final image.

The specific steps of the adaptive image impulse noise removal algorithm based on the IICM are as follows:

Input: Source image \( A \) with the size of \( M \times N \) polluted by the impulse noise;

Output: The final image \( B \) processed by the adaptive image impulse noise removal algorithm based on the IICM;

Steps:

Step 1: Initialize the timed matrix \( T \) as a zero matrix with the size of \( M \times N \), then use the improved ICM formula (4) - (7) in Section 2.2 to obtain the timed matrix \( T \) of the source image \( A \) and gain the maximum value \( T_{\text{max}} \) of the elements in \( T \);

Step 2: Calculate the regional suspected polluted coefficient \( \eta_i \) of each pixel in image \( A \) according to the calculation of the timed matrix \( T \), in which \( 1 \leq i \leq m, 1 \leq j \leq n \);

Step 3: Do the element sampling from the \( n \times n \) regional window for the element \( T_{ij} \) in the timed matrix \( T \):

a. If \( T_{ij} \) meets \( T_{ij} \neq 1 \) and \( T_{ij} \neq T_{\text{max}} \) in the \( n \times n \) regional window of \( T_{ij} \), then the gray value \( A_{ij} \) of the source pixel in the final image \( B \) will not change, that is to say \( A_{ij} = B_{ij} \), then turn to Step4;

b. If \( T_{ij} \) meets \( T_{ij} = 1 \) or \( T_{ij} = T_{\text{max}} \) in the \( n \times n \) regional window of \( T_{ij} \), then the pixel \( A_{ij} \) in the source image \( A \) is the suspected polluted pixel. If \( \eta_i \neq 1 \), then adopt the median filtering to the non-suspected polluted pixels in the \( n \times n \) regional window and then add the result to the image pixel \( B_{ij} \), then turn to Step4;

c. If \( T_{ij} \) meets \( T_{ij} = 1 \) or \( T_{ij} = T_{\text{max}} \) in the \( n \times n \) regional window of \( T_{ij} \), then the pixel \( A_{ij} \) in the source image \( A \) is the suspected polluted pixel. If \( \eta_i = 1 \), then extend the \( n \times n \) regional window to \( (n+2) \times (n+2) \), then calculate \( \eta \) again, if \( \eta_i \neq 1 \), then adopt the median filtering to the non-suspected polluted pixels in the new regional window and then add the result to the image pixel \( B_{ij} \), then turn to Step4; then continue to extend the window of the original region until it meets \( \eta_i \neq 1 \), then turn to Step4;

Step 4: Step 3 If all the elements \( T_{ij} \) are processed, the algorithm is over; otherwise return.

IV. EXPERIMENTAL RESULT

In order to verify the reasonable effectiveness of the algorithm proposed in this thesis, this thesis uses the Matlab7.1 software to make the impulse noise processing simulation experiment to the standard test images Lena and Peppers. These two images are both the 256 gray scale image with the size of 512×512.
This thesis will compare five superior de-noising algorithms proposed in recent years with algorithm (A6) proposed in this thesis: the 3x3 classic standard method of median filter MEDF (A1), de-noising method based on the PCNN image (A2), image de-noising method (A3) proposed by Eenny KVT, image de-noising method (A4) proposed by Srinivasan KS, and image de-noising method (A5) proposed by Lv Zongwei. The parameters in A2-A5 are set in accordance with the given data in source corresponding material and link right matrix W is set to be [0.707 10.707; 101; 0.707 10.707]. A is 6 and the threshold amplitude constant h is 600 of the algorithm proposed in the thesis.

The subjective evaluation method can be used to test the image de-noising effect, but it is easily to be affected by the factors such as the visual characteristics, mental state and so on of the evaluator. Therefore, this thesis adopt the Mean Square Error and the Peak-to-peak Signal-to-Noise Ratio as the quantitative evaluation criteria.

a. Mean Square Error, MSE is used to evaluated the difference degree between the processed image and the source one. The smaller the MSE value is, the closer these two images are and the better the process effect is. The ideal value is 0. Its expression is:

\[
MSE = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} [F(i,j) - P(i,j)]^2}{MN}
\]  

(9)

b. Peak-to-peak Signal-to-Noise Ratio, PSNR is the logarithm decibels expression of the Mean Square Error among the image pixels which can reflects whether the changes before and after the image data processing as well as the noise before and after data changes have been effectively suppressed to a certain extent. The bigger the PSNR value is, the better the de-noising effect is and the higher the quality of the processed image will be. Its expression is:

\[
PSNR = 10\log_{10} \frac{255 * 255}{MSE}
\]  

(10)

In which (i, j) is the coordinate of the image pixels; F is the source image; R is the image after de-noising processed; MxN is the size of the image.

This thesis take the standard Lena the Pepper figures with the size of 512 × 512 as the source images and adds 10%, 20%, 30%, 40%, 60% of the noise pulses respectively, then adopts five de-noising algorithm from A1 to A5 and the de-noising algorithm A6 to make the comparison. All of the algorithms take the PSNR and MSE as the evaluation standard of the performance. The experimental data is shown in Table 1 and Table 2.

Figure 3(a) Figure 3(h), Figure 4(a) Figure 4(h) give the source images, images polluted by the 60% impulse noise as well as the Lena and Peppers images processed by six de-noising algorithms respectively.

From the intuitive perspective, the above six algorithms all obtain a good image de-noising effect, but after careful comparison, we can find that the de-noising effect of A1 is the worst because the corresponding de-noising image still exist a large number of impulse noise points, which interferes the visual effect seriously. Compared with A1, the impulse noise points in A2 are reduced sharply, but the degree of pollution of the whole image is still very serious. In addition, A2 is the image de-noising algorithm based on PCNN, whose de-noising effect is restricted by the set of a large number of parameters to be determined and the iterations times. The effects of algorithms from A3 to A6 are better for they not only filter out most of the pulses noise, but also maintain the important features and details of the source images. But after careful comparison, we can easily find that, compared with the A3-A5, A6 algorithm proposed in this thesis filtered the impulse noise added in the source image more thoroughly and the residual impulse noise points are the least and the feature information of the source image are reserved most completely, besides A6 has a more reasonable level of brightness.

### Table I. THE EXPERIMENTAL DATA OF THE LENA IMAGE DE-NOISING ALGORITHM

<table>
<thead>
<tr>
<th>Filtering Method</th>
<th>Evaluation Index</th>
<th>Impulse Noise Density</th>
</tr>
</thead>
<tbody>
<tr>
<td>ImagNoise</td>
<td>PSNR</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10%</td>
<td>20%</td>
</tr>
<tr>
<td>A1</td>
<td>MSE</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1852</td>
<td>3528</td>
</tr>
<tr>
<td>A2</td>
<td>PSRN</td>
<td>15.32</td>
</tr>
<tr>
<td>A3</td>
<td>PSRN</td>
<td>33.4</td>
</tr>
<tr>
<td>A4</td>
<td>PSRN</td>
<td>36.3</td>
</tr>
<tr>
<td>A5</td>
<td>PSRN</td>
<td>15.9</td>
</tr>
<tr>
<td>A6</td>
<td>PSRN</td>
<td>35.7</td>
</tr>
<tr>
<td></td>
<td>MSE</td>
<td>14.0</td>
</tr>
<tr>
<td>A1</td>
<td>PSRN</td>
<td>32.7</td>
</tr>
<tr>
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<td>13.9</td>
</tr>
<tr>
<td>A3</td>
<td>PSRN</td>
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<tr>
<td>A4</td>
<td>PSRN</td>
<td>12.5</td>
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<tr>
<td>A5</td>
<td>PSRN</td>
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### Table II. THE EXPERIMENTAL DATA OF THE PEPPER IMAGE DE-NOISING ALGORITHM

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<th>Evaluation Index</th>
<th>Impulse Noise Density</th>
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</thead>
<tbody>
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<td>ImagNoise</td>
<td>PSNR</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10%</td>
<td>20%</td>
</tr>
<tr>
<td>A1</td>
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</tr>
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<tr>
<td>A6</td>
<td>PSRN</td>
<td>9.6</td>
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In addition, the intuitive visual effect obtained the validation in an objective evaluation index data. According to the objective evaluation data provided by Table 1 and Table 2, we can find that in the longitudinal perspective, compared with the other five de-noising algorithms, with the density increases of the pulse noise, the PSNR index decline and the MSE index rose more relatively slowly, which reflecting the robustness of the
algorithm proposed in this thesis is superior; from the horizontal perspective, although when the noise density is relatively lower, there is no big difference between the index value of the algorithm proposed in this thesis and other algorithms, and the de-noising effect is almost equal, but with pulse noise density increases gradually, especially after more than 50%, the index value of the rest of the algorithms occurred unusually dramatic changes, while the PSNR and MSE indexes of the algorithm proposed in the thesis change relatively flatter. At the same time, the greater the impulse noise density of the source image is, the more obvious contrast of the two index values corresponding to the algorithm proposed in this thesis with the rest of several algorithms will be.

![Figure 3](image-url) The de-noising effect of the six algorithms for the Lena gray image

![Figure 4](image-url) The de-noising effect of the six algorithms for the Pepper gray image

V. CONCLUSION

This thesis improves the classic ICM theory and put forward the adaptive image de-noising algorithm based on IICM. The IICM greatly improves the parameter setting mechanism of the classic ICM and introduces the timed matrix \( T \) adaptively determine the iteration times. This thesis proposes the adaptive image de-noising algorithm of the IICM, which only deals with the polluted pixels to maximize remain the edge details information of the source image. In addition, it can determine adaptively the size of the de-noising area window according to the degree of pollution of the image to be de-noised which gets rid of the single fixed setting mode of the de-noising regional window in previous algorithms. The simulation result shows that the image de-noising algorithm proposed in this thesis has the superior the pulse noise filtering performance than the previous classic de-noising algorithm.

REFERENCE


