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Research on Denoising Salt and Pepper Noise Based on Edge Classification

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ABSTRACT

Present denoising algorithms of salt and pepper noise have many problems, such as high time complexity, neglect of the image edge and drawbacks of the details management. In order to get rid of these problems, this paper presents an algorithm of denoising salt and pepper noise based on edge classification. The algorithm first applies mesh division to denoising algorithms of salt and pepper noise. The edge mesh and non- edge mesh are processed by different methods. Experimental results showed the proposed algorithm could obtain higher Peak Signal-to-Noise-Ratio value and protect the edges of images. The research in this paper would have great significance to improve the quality of image.

Key words: salt-pepper noise; mesh generation; edge mesh; image edge

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INTRODUCTION

Information-rich images are important media and means in transporting information. The way to access and process image data has become the focus of present image studies. However, lack of ideal interference-free detection environment in reality means that images will inevitably carry various noises for the duration of acquisition, processing, transportation, and storage. Noise jamming brings grey scale distribution mutation to the originally uniformly and continuously changing images, and gives rise to illusory edges or broken outlines for product images as well. As a result, image quality as a whole deteriorates. This may lead to image blur that affects visual perception on the one hand, and impede geometrical parameter acquisition for product edges on the other hand. Meanwhile, in follow-up image processing, great difficult will arise concerning edge detection, image segmentation, as well as shape identification and classification. Common types of noise include Gaussian noise, Gamma (Ireland) noise, Rayleigh noise, exponential distribution noise, uniform distribution noise, and salt-pepper noise. Adjacent image pixels usually have great correlation and approximate grey values. Nevertheless, since there is a discrepancy between grey values for neighboring salt-pepper noise pixels, any image detail with a spot of salt-pepper noise may be severely damaged. Thus, salt-pepper noise is a noxious matter to images.

Among algorithms of salt-pepper noise removal at home and abroad, the conventional median filtering algorithm [1] tended to generate errors and image edge blur. The document hence presented a modified algorithm of salt-pepper noise elimination. An improved extremum and median (IEM, for short) filtering algorithm was introduced by document [2], which treated any point whose central pixel was equal to the maximum or minimum grey value in the window as a noise point. This measure achieved much better effects than the traditional median filtering algorithm, but had a higher false identification rate. Later, document [3] proposed an adaptive weighed window salt-pepper denoising method on the basis of extremumdenoising idea, which introduced the concept of grey value difference and devised pixel weighs for denoising performance enhancement. But this method increased time complexity to a large extent. Compared to median filtering algorithm, the weighed mean filtering method [4] employed more information of signal points, but gained mere effect on images with even noise distribution. On this basis, document [5] put forward an adaptive switch weighted median (ASWM, for short) filtering algorithm that conducted hierarchical noise detection and processed noise points by weighted median as well, whereas complicated situations could not be handled with this algorithm because multiple levels of detection had to be done in a fixed window. For the adaptive median filtering algorithm [6], the size of denoising windows was decided by degrees of noise interference, but the latter one was difficult to identify. The corresponding improved adaptive median filtering algorithm (IRAMF, for short) [7] chose window sizes according to noise; however, when the window was enlarged, computation volume rocketed. Document [8] proposed a similarity function based adaptive weighed filtering algorithm. By adaptive weighed noise elimination with characteristics of detail preservation, this method offset shortcomings of local extremum false identification for salt-pepper noise detection algorithm. Document [9] introduced a new-type high-density salt-pepper noise filtering algorithm, which had fine denoising effect on nothing but high-density silt-pepper noise and was endowed with high time complexity as well.

Two main problematic aspects for present salt-pepper noise filtering algorithms are: (1) high time complexity and overly detailed computation. The requirements for real-time image processing hence cannot be satisfied. (2) Overlook of image edge conditions, and insufficient detail processing, which cause edge blur for denoised images. To address the above two issues, the paper presented an algorithm of edge classification based salt-pepper noise removal on the foundation of mesh generation. By partitioning edge meshes and non-edge meshes, the paper differentiated denoising methods between them.

RELATIVE DEFINITIONS

Definition 1: edge mesh, namely meshes containing image edge pixels. This concept comes into being to serve for preservation of image details and edge characteristics, facilitating faster and better edge pixel processing. In general, it is highly likely that areas with marked changes in grey values fall into image edges. Here is the way to identify edge meshes: Prewitt operator [10] is employed in detecting edges of the original image $f(x, y)$, and the detected image edge is defined as $f^{'}(x, y)$. With certain width in most cases, inspected edges are edge regions in other words. However, there is no need for precise location in the paper, instead, the task is to find out edge meshes in images. Therefore, it is deemed in the paper that meshes containing edge regions are edge meshes, and non-edge meshes without edge regions.

Definition 2: noise location. It is expressed as follows, and N_{ij} denotes pollution of S_{ij} noise.

$$N_{ij} = \begin{cases} 1, & \max\{W_D(S_{ij})\} - \delta \geq S_{ij} \text{OR } S_{ij} \leq \min\{W_D(S_{ij})\} + \delta \\ 0, & oterwise \end{cases} \quad (1)$$

where $W_D(S_{ij})$ represents the preset S_{ij} -centered neighborhood, δ is a range parameter, $\min\{W_D(S_{ij})\}$ denotes the minimum grey value among pixels in window $W_D(S_{ij})$, and $\max\{W_D(S_{ij})\}$ denotes the maximum grey value among pixels in window $W_D(S_{ij})$.

Definition 3: Peak signal-noise ratio (PSNR, for short), the most frequently-used measurement parameter of image fidelity. The larger PSNR is, the closer to the original image the denoised image is. PSNR is expressed as

$$P_{PNSR} = 10\lg \frac{M \times N \times 255^2}{\sum_{m=1}^{M}\sum_{n=1}^{N}\left[F(m, n) - F^{'}(m, n)\right]^2}, \quad (2)$$

whereM and N denote image sizes, $F(m, n)$ represents the grey value of the original image, and $F^{'}(m, n)$ represents the grey value of the denoised image.

DESCRIPTION OF THE ALGORITHM OF MESH GENERATION FOR IMAGES

Figure 1 shows the proposed adaptive algorithm of mesh generation for images in the paper. The basic thought is: pixels of the grey scale images to be generated are referred to in determining mesh sizes and its numbers. Then, image pixels are partitioned into different meshes, each of which decides the pixel's neighborhood. And each pixel is located at the center of its neighborhood. This measure assures the accuracy of pixel generation. Since each pixel corresponds to one mesh, the amount of task to calculate the grey values can be reduced as there is no necessity to conduct a second pixel traversal for the image. Here are steps for the algorithm:

Determine the pixel of the grey scale image to be generated, which was assumed as $n \times m$ for this time. Correspondingly, a $n \times m$ two-dimensional array was generated as $Array - P$, where each unit (represented by P) in it was a container to house a pixel.

Traverse image pixels for the edge values: $max(x)$ 、 $\min(x)$ 、 $max(y)$ 、 $\min(y)$ 。

Calculate side lengths($xlength = max(x) - \min(x)$ and $ylength = max(y) - \min(y)$) of the unit, and choose the larger one $L = \max(xlength, ylength)$ for calculation of $L/n, L/m$. Determine the unit length as $t = \min(L/n, L/m)$ （corresponded to the pixel form, and each unit in the mesh was square）.

Take L as the total mesh length, and produce a square with L as the length. Set the initial location along the X direction to be $start\_x = min(x)$.

Traverse the image. Conduct computation on each point P: $tn = (p[x] - start\_x)\%\ t + 1$ and $tm = (p[y] - start\_y)\%t + 1$, where "%" denoted exact division.Then, put each point P in the container of the unit $Array - P[tn][tm]$.

For the above algorithm, a mere 2n number of cycles was done to image pixels (if there were n pixels). Meanwhile, as the square length was determined to be L, and the minimum length was taken for partition, this algorithm thus obtained more even distribution of meshes, and laid foundation for the following step of salt-pepper noise removal.

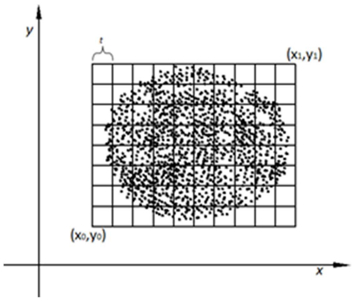


Figure 1: The proposed adaptive algorithm of mesh generation for images

DESCRIPTION OF THE ALGORITHM OF EDGE CLASSIFICATION BASED SALT-PEPPER NOISE REMOVAL

On the basis of the above mesh generation algorithm, the paper proposedthe algorithm of edge classification based salt-pepper noise removal. The fundamental idea is: under the guidance of Definition 2, traverse the mesh for noise points. If there was no points whose pollutant was $N_{ij} = 1$, no image processing was needed in the mesh; if there was noise points in peripheral meshes (marked as W), one should decide whether W was edge meshes according to Definition 1. If identified as non-edge mesh, Wshould undergo calculation in the linear classifier for the mean value among different types, and use the most approximating mean value to replace the noise point. If M was identified as edge mesh, the median M_{ij} of pixels in W should be compared with the grey value of the noise point. If the grey value was larger, one ought to search for pixels neighboring the noise point as a priority or for meshes neighboring the mesh containing the noise point as an alternative until k pixels had been found whose grey values exceeded M_{ij} ; the average grey value of the k pixels was marked as $A_{ij}^{'}$, and $A_{ij}^{'}$ was employed to substitute the noise point. If the grey value of the noise point was smaller than M_{ij} , one ought to find k pixels neighboring the noise point whose grey values were smaller than M_{ij} ;calculate $A_{ij}^{'}$, and $A_{ij}^{'}$ was employed to substitute the noise point. The flow chart of the algorithm is shown in Figure 2.

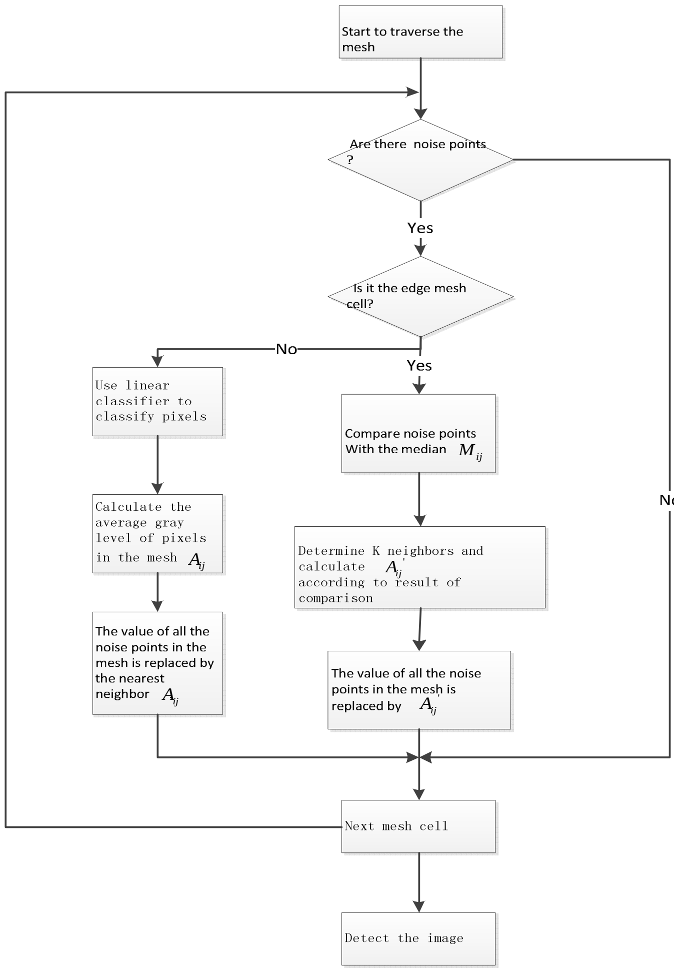


Figure 2 Flow chart ofthe algorithm of edge classification based salt-pepper noise removal

For this algorithm, different methods were used to process edge meshes and non-edge meshes. Specifically,

Since the pollutant of P_{ij} was $N_{ij}=1$, P_{ij} was regarded as a noise point.The set of all grey values of non-noise points in the mesh $G(P_{ij})$ was marked as $G_D(P_{ij})$, $G_D(P_{ij})=\{P_{mn}|N_{mn}=0, P_{mn}\in G(P_{ij})\}$.

If $G(P_{ij})$ was a non-edge mesh, the eigenvector $x=(x_1, x_2, \cdots x_d)^T$ represented the linear array of all salt-pepper noise-free grey values. The expression of the ith linear identification function was:

$$g_i = w_{i1}x_1 + w_{i2}x_2 + \cdots + w_{id}x_d + w_{i0} = \sum_{k=1}^{d} w_{ik}x + w_{i0}$$

$$g_i(x) = W_i^T x + w_{i0}, i = 1, 2, \cdots, \mathrm{d} \quad (3)$$

Where $W_i = [w_{i1} \cdots w_{id}]^T$ was the weight vector, and w_{i0} was the threshold weight.

Identification function： $g(x) = g_1(x) - g_2(x)$,

Decision level: $g(x) = g_1(x) - g_2(x) = 0$

The mesh pixel was classified into two types.

Calculate the average grey value A_{ij} of pixels in each of the two types of $G(P_{ij})$, $A_{ij} = average\{G_D(P_{ij})\}$. Replace P_{ij} with the most neighboring value of A_{ij}, and record G_{ij} as the grey value of P_{ij}. No treatment was done on the rest pixels, thus $G_{ij}=A_{ij}$。

Calculate the median M_{ij} of points in the mesh, $M_{ij} = (G_{\max} + G_{\min}) / 2$, where $G_{\max}$ denoted the maximum grey value of all non-noise points in the mesh, and $G_{\min}$ denoted the minimum grey value of all non-noise points in the mesh.

If $G(P_{ij})$ was an edge mesh, G_{ij} and M_{ij} were compared to determinate neighborhood k of P_{ij}.When $G_{ij} > M_{ij}$, neighborhood k of P_{ij} was equal to the grey values of all non-noise points which were larger than M_{ij}; similarly, when $G_{ij} < M_{ij}$, all of the grey values of neighborhood k of P_{ij} were smaller than M_{ij}.

Calculate the average grey value A_{ij}' of the neighborhood k of P_{ij}, and substitute G_{ij} with A_{ij}', namely $G_{ij}=A_{ij}'$.
1)-3) were the denoising algorithm for non-edge meshes, and 4)-6) for edge meshes. In the process of image pixel denoising under mesh generation, efforts have been spared to take neighborhood size into account, thus reducing time complexity. Noise removal in edge meshes ensures more proper treatment on edge pixels, and can also preserve image details and edge characteristics better.

ANALYSIS OF TIME COMPLEXITY FOR THE ALGORITHM

There are two parts in the proposed algorithm of edge classification based salt-pepper noise removal. For the mesh generation part, 2n cycles were done to image pixels (if there were n pixels), thus the time complexity was equal to $O(n)$. For the denoising part, there are two sub parts, the edge mesh denoising method and the non-edge mesh denoising method.The most time-consuming part in the non-edge mesh denoising method is to partition mesh pixels linearly, with the time complexity of $O(h)$, where h denotes the number of pixels in non-edge meshes.Similarly, the most time-consuming part in the mesh denoising method is to search for neighborhood k of noise points in meshes, with the time complexity of $O(m)$, where m denotes the number of pixels in non-edge meshes. Since it is impossible that m exceeds n, thus $O(m)$ is smaller than $O(n)$. To be concluded, the time complexity of the algorithm of edge classification based salt-pepper noise removal is $O(n)$.

Compared to other existing algorithms, the algorithm of edge classification based salt-pepper noise removal takes priority in the aspect of time complexity.For instance, the time complexity of mean filtering algorithm is $O(m \times n)$ [11], and that of the conventional median filtering algorithm is $O(n^2)$ [12]. For the improved IEM filtering algorithm, the most time-consuming part is to calculate neighborhood when each pixel needs to be traversed, thus the time complexity approximates $O(n^2)$; although weight is added to the weighed mean filtering algorithm, its time complexity is not affected and, instead,remains to be $O(m \times n)$; Noise acts as the model center of the ASWM filtering algorithm; therefore, when the noise density is high, a double traversal is a must, which results in more time complexity than $O(n)$. For the adaptive median denoising algorithm, it costs much time to order pixels in windows, and the theoretically minimum time complexity for ordering n pixels is $O(n \times \ln n)$ [13]; in the IRAMF algorithm, as different windows are enlarged, computation volumes increases drastically, thus the time complexity exceeds $O(n \times \ln n)$. All in all, the time complexity $O(n)$ of the proposed algorithm of edge classification based salt-pepper noise removal in the paper is smaller than that of any other existing salt-pepper denoising algorithms.

RESULTS

Simulation tests were done for the proposed salt-pepper denoising algorithm in the matlab software on Intel(R) PENTIUM(R) PC with a dominant frequency of 2.7 GHz and 4.0 GB RAM. Considering time complexity and denoising effects of the aforementioned algorithms, the paper chose the improved IEM filtering algorithm, the improved IRAMF algorithm, and the ASWM filtering algorithm as a comparison. The popular image of Lena was selected to be the basis of image comparison. With the intention to verify the proposed algorithm’s denoising effects and image detail preservation capacity, the paper opted for PSNR and image edges as experimental parameters. The difference between denoised images and original images was mainly employed as the objective evaluation standard in measuring image quality. PSNR is the most commonly-used measurement parameter of image fidelity, and image edges are one of the important attributes for a substance. Both of them describe or identify the substance and provide valuable information for explanation. Therefore, the paper conducted two tests on PSNR and image edges. Experimental results show that the proposed algorithm of edge classification based salt-pepper noise removal in the paper achieves high PSNR and preserves image details well.

Experiment 1 the objective experiment With PSNR as the comparative parameter, this experiment added salt-pepper noise to the original image to from noise-polluted images with the noise ratios of 0.1、0.2、0.3、0.5、0.6、0.7 and 0.8, respectively. Figure 3 compares PSNR of the four algorithms, namely the proposed algorithm in the paper, the improved IEM filtering algorithm, the improved IRAMF algorithm, and the ASWM filtering algorithm.

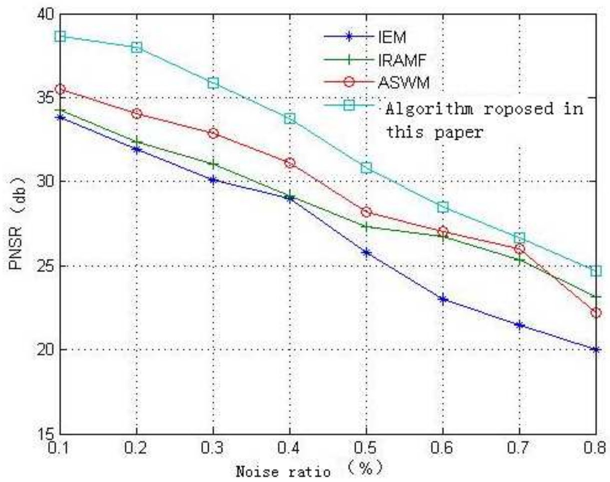


Figure 3 comparison between PSNR of the four algorithms

As can be seen from Figure 3, PSNR fluctuates greatly for the improved IEM filtering algorithm and the ASWM filtering algorithm, with lower values when noise ratios are high; PSNR for the IRAMF algorithm stays more stable, but is lower than that of the proposed algorithm in the paper, whose PSNR is the highest among the four algorithms. The reason is that after mesh generation, the computed median of linearly classified pixels in non-edge meshes approaches the ideal denoised value still further, and that the edge mesh based denoising method allows for image edge by preserving edge information. In other words, the denoising effect of the proposed algorithm in the paper outbalances that of any other three denoising algorithm inasmuch as the edge classification measure is taken in salt-pepper noise removal.

Experiment 2 the subject experiment

To verify the denoising effect of the proposed algorithm in the paper, the author provided a comparison between the original image and the noise-polluted images with the noise ratios of 0.2, 0.5 and 0.8, respectively, in Figure 4. Figure 5-7 shows the denoised images with the noise ratios of 0.2, 0.5 and 0.8, respectively that underwent the four algorithms.

(a) (b) (c) (d)

Figure 4: The original Lena image and the salt-pepper noise-polluted images with the noise ratios of 0.2, 0.5 and 0.8, respectively

(a) IEM (b) IRAMF (c) ASWM (d) the proposed algorithm in the paper

Figure 5: Denoising effects of the four algorithms on the salt-pepper noise-polluted image with the noise ratio of 0.2

(a) IEM (b) IRAMF (c) ASWM (d) the proposed algorithm in the paper

Figure 6: Denoising effects of the four algorithms on the salt-pepper noise-polluted image with the noise ratio of 0.5

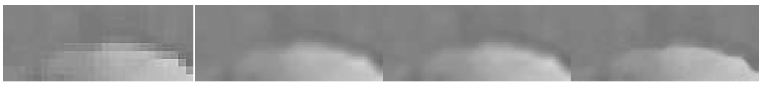
(a) IEM (b) IRAMF (c) ASWM (d) the proposed algorithm in the paper

Figure 7: Denoising effects of the four algorithms on the salt-pepper noise-polluted image with the noise ratio of 0.8

As can be seen from Figure 5-7, when the noise ratio is as low as 0.2, all of the four algorithms can eliminate all noises on the one hand, and preserve image details on the other hand; however, there is still a few noises left for the improved IEM filtering algorithm. When the noise ratio is 0,5, the denoising effects for the improved IEM filtering algorithm and the the ASWM filtering algorithm are weakened, and the denoising performance for the IRAMF algorithm begins to be lowered down, the image becoming blurred. When the noise ratio is as high as 0.8, all of the four algorithms lose image details to different degrees, but the proposed algorithm in the paper has the best denoising effect in comparison with other three ones. In summary, no matter what the noise ratio is, the noise removal capacity for the proposed algorithm in the paper is superior to that for the rest algorithms.

During the process of noise elimination, the problem of edge blur is inescapable for existing salt-pepper denoising algorithms. Figure 6-7 proves that the proposed algorithm in the paper can comparatively preserve image edge information well under medium and large noise ratios. To verify the ability for it to protect image edge from being blurred under small noise ratios, the paper targeted at the hat part of the original Lena image as shown in Figure 8, and compared the corresponding denoised images under the action of the four algorithms in Figure 9.

Figure 8: The hat part of the original Lena image



(a) IEM (b) IRAMF (c) ASWM (d) the proposed algorithm in the paper

Figure 9: The hat part of the denoised Lena images

As can be seen from Figure 9, the image with small noise ratios can be denoised better by the proposed algorithm in the paper than by the rest algorithms. To sum up, no matter what the noise ratio is, the noise removal capacity for the proposed algorithm in the paper is superior to that for the rest algorithms.

CONCLUSION

To address problems in existing algorithms of salt-pepper noise removal, the paper presented an algorithm of edge classification based salt-pepper noise removal on the foundation of mesh generation, differentiating denoising methods for edge meshes from those for non-edge meshes. Test results show thatafter eliminating salt-pepper noise, the proposed low time-complexity algorithm of salt-pepper noise removal in the paper assures image quality and preserves image edge information well. The author intends to undertake research on an optimized algorithm for detail-rich images in the foreseeable future.

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