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Image De-Noising Based on Simple Total Least Square

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ABSTRACT: Noise is a random variation of image intensity and appear as grains in the image. There are many methods suggested for de-noising.Image de-noising involves the manipulation of the image data to produce a visually high quality image. In this paper we suggested new filterfor de-noise based on simple total least square. The simple total least square is the process of finding the smallest difference between the square of pixel and the square of 8-neighbors pixels. The proposed algorithm tested with (Salt and pepper, Speckle, Gaussian and Poisson noise) with different concentration of noise and gives promised results. Also proposed algorithm compared with other de-noising algorithms and the results were better.

KEYWORDS: de-noising, STLS, noise filter, image processing

I. INTRODUCTION

Image de-noising is an important image processing task, both as a process itself, and as a component in other processes. Very many ways to de-noise an image or a set of data exists. The main properties of a good image de-noising model is that it will remove noise while preserving edges. The goal of the noise reduction is how to remove noise while keeping the important image features as much as possible [1].

Image de-noising is a hot research issue in the field of digital image processing. Image de-noising is very important on guaranteeing the effectiveness and robustness of other image processing algorithms in the industry image process procedures, such as image registration, image segmentation.[2].

Image de-noising problems arise when an image is corrupted by additive white Gaussian noise which is common result of many acquisition channels, whereas image in-painting problems occur when some pixel values are missing or when we want to remove more sophisticated patterns, like superimposed text or other objects, from the image [3].

It has proved that the spatial domain smoothing is effective to remove the additive Gaussian noise in the noisy image. The key idea is to replace the intensity value of each pixel by a weighted average of all intensity values of its neighborhood. The weight can be computed via the Gaussian filter or the box filter. The basic idea of the Gaussian filter is that the value of the pixels of its neighborhood is given different weighting which is defined by a spatial Gaussian distribution.[4]

Removing noise from the original signal is still achallenging problem for researchers. There have beenseveral published algorithms and each approach hasits assumptions, advantages, and limitations.

Estrada suggested probabilistic algorithm for image noise removal. He showed thatsuitably constrained random walks over small image neighborhoods provide a goodestimate of the appearance of a pixel, and that a stable estimate can be obtained with a small number of samples. [5]

Guoshen introduced an image de-noising algorithm, arguably the simplest among all the counterparts, but surprisingly effective. The algorithm exploits the image pixel correlation in the spacial dimension as well as in the color dimension. The color channels of an image are first de-correlated with a 3-point orthogonal transform. Each de-correlated channel is then de-noised separately via local DCT (discrete cosine transform) thresholding: a channel is decomposed into sliding local patches, which are de-noised by thresholding in the DCT domain, and then averaged and aggregated to reconstruct the channel. The de-noised image is obtained from the de-noised de-correlated channels by inverting the 3-point orthogonal transform.[6].



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Firasproposed approach to suppress noise from the image is conducted by applying the interquartile range (IQR) which is one of the statistical methods used to detect outlier effect from a dataset. A window of size kxk was implemented to support IQR filter. Each pixel outside the IQR range of the kxk window is treated as noisy pixel. The estimation of the noisy pixels was obtained by local averaging. The essential advantage of applying IQR filter is to preserve edge sharpness better of the original image.[7]

II. IMPLEMENTING SIMPLE TOTAL LEAST SQUARE (STLS)

Suppose that we have a window of nine holes as in Fig. 1. this window moving on the entire image from left to right and top to down. At each time the STLS will be determined, according to its result the value at the center of the window will be change.

| А | В | С |
|---|---|---|
| D | S | Е |
| F | G | Н |

Fig. 1: STLS mask

The STLS determined by the following relation according to the mask in Fig. 1:

 $R = (E - S)^{2} + (H - S)^{2}(G - S)^{2} + (F - S)^{2} + (D - S)^{2} + (A - S)^{2} + (B - S)^{2} + (C - S)^{2}$

such that (**R**) represent the value of the simple total square differences. We start to increase the value at the center by one and then check the value of (**R**) if this value (**R**) become less than its previous value then we continue to increase the center value at each step with one until we get value of (**R**) equal to zero or greater than the previous one, at this step we get the final value of the (**S**) and we have to change the old value of (**S**) with new one. Otherwise, if from the first step when increasing (**S**) with one we get value of (**R**) greater than its previous value, at this case we change the process to decrease the (**S**) value by one and continue to decreases (**S**) with one at each step until we get (**R**) value greater than the previous, which mean end of process and get the final value to (**S**). The best result is when we get (**R**) equal to zero.

III. THE RESULTS

A. Visual Results

In the Fig. 2. We test algorithm to remove noise from Lena image after highly noisy with salt and pepper noise. The result image is very similar to origin image. Same thing for image in Fig. 3. when Lena noisy with Gaussian noise.



Fig. 2: A. origin image. B. noisy image with salt & pepper noise. C. image after de-noising using STLS.

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Fig. 3: A. origin image. B. noisy image with Gaussian noise. C. image after de-noising using STLS.

The images in Fig. (4 and 5) are pepper image and Baboon image both noisy with salt and pepper and the results were highly similar to origin images.



A B C Fig. 4: A. origin image. B. noisy image with salt & pepper noise. C. image after de-noising using STLS



Fig. 5: A. origin image. B. noisy image with salt & pepper noise. C. image after de-noising using TLS



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B. Compare (STLS) with other methods

The PSNR for STLS algorithm compared with PSNR for other noise removing methods such as (Median, Gaussian, Morphology, Average, Motion, Disk). The following tables showed the PSNR when application suggested method on RGB images (Lena, Baboon and Pepper images) compared with PSNR for other methods with different types of noise (Salt and pepper, Speckle, Gaussian and Poisson) and different density of noise.

Table1:comparing PSNR for different filters(Median, Gaussian ,Morphology, Average, Motion, Disk, STLS), at different salt and pepper noise density, using Lean image.

| Noise | PSNR | | | | | | | | |
|---------|--------|----------|------------|---------|--------|--------|-------|--|--|
| density | Median | Gaussian | Morphology | Average | Motion | Disk | STLS | | |
| 0.01 | 60.57 | 64.20 | 60.93 | 60.45 | 59.66 | 59.23 | 73.22 | | |
| 0.001 | 64.09 | 67.38 | 65.13 | 63.17 | 61.11 | 60.511 | 82.99 | | |
| 0.0001 | 65.47 | 68.26 | 66.96 | 63.88 | 61.32 | 60.71 | 94.94 | | |

Table2:comparing PSNR for different filters (Median, Gaussian, Morphology, Average, Motion, Disk, STLS), at different speckle noise density, using Lean image.

| Noise | PSNR | | | | | | | | |
|---------|--------|----------|------------|---------|--------|-------|-------|--|--|
| density | Median | Gaussian | Morphology | Average | Motion | Disk | TLS | | |
| 0.01 | 60.63 | 64.26 | 63.01 | 60.55 | 59.70 | 59.28 | 73.46 | | |
| 0.001 | 64.22 | 67.38 | 66.22 | 63.21 | 61.11 | 60.52 | 83.26 | | |
| 0.0001 | 65.46 | 68.27 | 67.21 | 63.85 | 61.32 | 60.70 | 93.10 | | |

Table3:comparing PSNR for different filters (Median, Gaussian, Morphology, Average, Motion, Disk, STLS), at different Gaussian noise density, using Lean image.

| Noise | PSNR | PSNR | | | | | | | | |
|---------|--------|----------|------------|---------|--------|-------|-------|--|--|--|
| density | Median | Gaussian | Morphology | Average | Motion | Disk | TLS | | | |
| 0.01 | 58.27 | 61.93 | 59.97 | 58.32 | 57.98 | 57.67 | 68.33 | | | |
| 0.001 | 62.63 | 66.05 | 64.51 | 62.14 | 60.64 | 60.12 | 78.14 | | | |
| 0.0001 | 65.07 | 68.91 | 66.88 | 63.67 | 61.27 | 60.65 | 88.05 | | | |

Table4:comparing PSNR for different filters (Median, Gaussian, Morphology, Average, Motion, Disk, STLS), at Poisson noise, using Lean image.

| PSNR | | | | | | | | | | |
|--------|----------|------------|---------|--------|-------|-------|--|--|--|--|
| Median | Gaussian | Morphology | Average | Motion | Disk | STLS | | | | |
| 61.48 | 64.99 | 63.29 | 61.22 | 60.13 | 59.67 | 75.26 | | | | |



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Table5:comparing PSNR for different filters (Median, Gaussian, Morphology, Average, Motion, Disk, TLSS), at different salt and pepper noise density, using Pepper image.

| Noise | PSNR | | | | | | | | | |
|---------|--------|----------|------------|---------|--------|-------|-------|--|--|--|
| density | Median | Gaussian | Morphology | Average | Motion | Disk | TLS | | | |
| 0.01 | 60.38 | 63.99 | 60.69 | 60.41 | 59.79 | 59.18 | 73.18 | | | |
| 0.001 | 63.84 | 67.02 | 64.79 | 63.08 | 61.51 | 60.50 | 82.89 | | | |
| 0.0001 | 65.02 | 67.75 | 66.55 | 63.68 | 61.78 | 60.67 | 93.65 | | | |

Table6:comparing PSNR for different filters (Median, Gaussian, Morphology, Average, Motion, Disk, STLS), at different Spackle noise density, using pepper image.

| Noise | PSNR | | | | | | | | | |
|---------|--------|----------|------------|---------|--------|-------|-------|--|--|--|
| density | Median | Gaussian | Morphology | Average | Motion | Disk | TLS | | | |
| 0.01 | 60.85 | 64.41 | 63.21 | 60.73 | 60.06 | 59.40 | 74.07 | | | |
| 0.001 | 64.13 | 67.12 | 66.14 | 63.19 | 61.56 | 60.53 | 84.04 | | | |
| 0.0001 | 65.07 | 67.75 | 66.84 | 63.70 | 61.78 | 60.68 | 93.88 | | | |

Table7:comparing PSNR for different filters (Median, Gaussian, Morphology, Average, Motion, Disk, STLS), at different Gaussian noise density, usingPepper image.

| Noise | PSNR | | | | | | | | | |
|---------|--------|----------|------------|---------|--------|-------|-------|--|--|--|
| density | Median | Gaussian | Morphology | Average | Motion | Disk | TLS | | | |
| 0.01 | 58.32 | 61.91 | 60.07 | 58.38 | 58.14 | 57.73 | 68.44 | | | |
| 0.001 | 62.56 | 65.89 | 64.47 | 62.11 | 60.99 | 60.12 | 78.24 | | | |
| 0.0001 | 64.74 | 67.54 | 66.57 | 63.53 | 61.71 | 60.63 | 88.15 | | | |

Table8:comparing PSNR for different filters (Median, Gaussian, Morphology, Average, Motion, Disk, STLS), at Poisson noise, using Lean image.

| PSNR | | | | | | | | | | |
|--------|----------|------------|---------|--------|-------|-------|--|--|--|--|
| Median | Gaussian | Morphology | Average | Motion | Disk | TLS | | | | |
| 61.63 | 65.07 | 63.51 | 61.36 | 60.51 | 59.75 | 75.81 | | | | |



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Table9:comparing PSNR for different filters (Median, Gaussian, Morphology, Average, Motion, Disk, STLS), at different salt and pepper noise density, usingBaboon image.

| Noise | PSNR | | | | | | | | |
|---------|--------|----------|------------|---------|--------|-------|-------|--|--|
| density | Median | Gaussian | Morphology | Average | Motion | Disk | TLS | | |
| 0.01 | 60.02 | 63.85 | 60.58 | 59.93 | 58.69 | 57.90 | 73.40 | | |
| 0.001 | 62.03 | 66.05 | 62.85 | 61.63 | 59.48 | 58.46 | 83.49 | | |
| 0.0001 | 62.40 | 66.47 | 63.32 | 61.89 | 59.57 | 58.52 | 92.72 | | |

Table10:comparing PSNR for different filters (Median, Gaussian, Morphology, Average, Motion, Disk, STLS), at different Speckle noise density, usingBaboon image.

| Noise | | PSNR | | | | | | | | |
|---------|--------|----------|------------|---------|--------|-------|-------|--|--|--|
| density | Median | Gaussian | Morphology | Average | Motion | Disk | TLS | | | |
| 0.01 | 60.12 | 63.97 | 63.37 | 60.04 | 58.75 | 57.92 | 73.79 | | | |
| 0.001 | 62.06 | 66.05 | 63.16 | 61.62 | 59.47 | 58.45 | 83.58 | | | |
| 0.0001 | 62.40 | 66.45 | 61.77 | 61.88 | 59.57 | 58.52 | 93.38 | | | |

Table11:comparing PSNR for different filters (Median, Gaussian, Morphology, Average, Motion, Disk, STLS), at different Gaussian noise density, usingBaboon image.

| Noise | PSNR | | | | | | | | |
|---------|--------|----------|------------|---------|--------|-------|-------|--|--|
| density | Median | Gaussian | Morphology | Average | Motion | Disk | TLS | | |
| 0.01 | 58.03 | 61.77 | 59.65 | 58.08 | 57.47 | 56.91 | 68.30 | | |
| 0.001 | 61.33 | 65.22 | 62.60 | 61.04 | 59.24 | 58.30 | 78.17 | | |
| 0.0001 | 62.31 | 66.34 | 63.31 | 61.81 | 59.54 | 58.51 | 88.10 | | |

Table12:comparing PSNR for different filters (Median, Gaussian, Morphology, Average, Motion, Disk, STLS), at Poisson noise, usingBaboon image.

| PSNR | | | | | | |
|--------|----------|------------|---------|--------|-------|-------|
| Median | Gaussian | Morphology | Average | Motion | Disk | TLS |
| 60.65 | 64.49 | 62.07 | 60.46 | 58.96 | 58.09 | 75.39 |

IV. CONCLUSION

Simple STLS is the process of finding the least difference between the square value of each pixel in the image with the square of its 8-neighbor pixels. This filter scan entire image to make this difference at optimum value. The suggested filter tested with different type of noise and different density of noise, the results were promised. Also the suggested filter compared with other methods and gives good results asshowed in tables (1-12). For future works we suggested to combine this filter with other filters.



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Nidhal El Abbadi, received BSc in Chemical Engineering, BSc in computer science, MSc and PhD in computer science, worked in industry and many universities, he is general secretary of colleges of computing and informatics society in Iraq, reviewer for a number of international journals, has many published papers and three published books, his research interests are in image processing, security, and steganography, He's Associate Professor in Computer Science in the University of Kufa – Najaf, IRAQ.



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