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A Review- Patch Based Image Denoising Using Pixel-Wise Weighting Approach

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Abstract: Many of the Patch based image denoising algorithms filter overlapping image patches and aggregate multiple estimates for the same pixel via weighting. Current weighting and filtering approaches assume the restored estimates as independent random variables, which is not convenient with the reality. In this paper, we consider the correlation among the estimates and propose model to estimate the Mean Squared Error under various weights of the image patches. This model identifies the overlapping information of the patches, and then use the optimization to try to minimize the MSE. We propose a new weighting approach based on Quadratic Programming, which can be embedded into various denoising algorithms.

Keywords: Patch based, Mean Squared Error (MSE), Weighting, Bias variance model, Filtering, Weighting.

I. INTRODUCTION

Image denoising is the most basic image processing problems it aims to recover an image under random additive white Gaussian noise. Various image denoising algorithms are based on image patches. Their denoising methods can be interpreted as an iteration of called Filtering and Weighting process. In this process, local image patches are firstly restored through filtering, and then multiple estimates of the same pixel from overlapping patches are weighted to calculate the final estimate. For the filtering method, advanced patch based image models have been applied to generate the filters, e.g., the sparse coding model [2], the Gaussian Mixture Model [3], and the non-local similarity model [4].

The weighting methods are somewhat easy as compare to filtering methods, either using simple averaging or deriving the weight separately based on certain transform coefficients of the corresponding image patch itself [4], [5]. This type of weighting methods are optimal when the estimates for weighting are independent random variables. However, the estimates can be mostly correlated due to overlapping of the patches, which violates the assumption of independence.

Therefore, we may further improve the denoising performance by examine the correlation among the estimates using the overlapping information. Based on the above idea, we describe the F&W process precisely, examine the MSE under various weights, and derive a bias variance model to estimate it accurately. We also show that optimizing the weight under the proposed model yields the minimum MSE with the help of the overlapping information. We propose a new weighting approach to solve the optimization problem under the bias variance model via Quadratic Programming (QP). We also introduce the proposed weighting approach into the K-SVD algorithm and the EPLL algorithm. Finally, Section V concludes the letter.

II. LITERATURE REVIEW

In 1984, new method for removing various noises from images was proposed. This filtering scheme is based on replacing the central pixel value by mean value of all pixels inside a sliding window. The new concepts of thresholding which is shown to improve the performance of the generalized mean filter are introduced in this paper.

This threshold is derived using a statistical theory. The performance of the proposed filter is compared with that very commonly used median filter by filtering noise from the corrupted real images. The hardware complexity of the two types of filters is compared indicating the advantages of the generalized mean filter [6].

By 1988, two algorithms using adaptive-length median filters are proposed for improving impulse noise removal performance for image processing. The algorithms achieved significantly better image quality than median filters when the images are corrupted by impulse noise. One of the algorithms, when realized in hardware, requires rather simple additional circuitry. Both algorithms can easily be integrated into efficient hardware realizations for median filters [7].

In 1992 Fresh introduced the wavelet and inverse wavelet transforms of self-similar random processes. It showed that, after suitable rescaling, the wavelet transform at a given position becomes a stationary random function of the logarithm of the scale argument in the transform [8]. Appropriate wavelets and their corresponding band-pass filters were selected for image processing. A multichannel optical processing system with two gratings was set up to obtain image representation and image reconstruction [9].

In 2000 for impulsive noise reduction of an image without the degradation of an original signal an adaptive centre weighted median filters was developed. The weight in this filter is decided by the weight controller based on counter propagation networks. This controller classifies an input

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vector into some cluster according to its feature and gives the weight corresponding to the cluster [10].

A new operator was introduced by Yuksel in year 2006 for removing noise from digital images. The proposed operator was a hybrid filter constructed by combining four centre weighted median filters (CWMF) with a simple adaptive neuro fuzzy inference system (ANFIS). The results showed that the proposed operator significantly outperforms the other operators and efficiently removes noise from digital images without distorting image details [10].

A two-phase median filter based iterative method for removing random-valued noise was proposed in 2010. Simulation results indicated that the proposed method performs better than many well-known methods while preserving its simplicity [11]

III.PROPOSED METHOD

1. THE BIAS VARIANCE MODEL

In this section, we first formulate the degradation model of image denoising and describe the F&W process in an analytic way. Then we propose a bias variance model to characterize the correlation of the restored estimates under the F&W process. This new model can estimate the MSE under various weights by exploiting the overlapping information of the restored patches. Therefore, optimizing the weight under this model is nearly equivalent to minimizing the real MSE.

The degradation model of image denoising can be formulated

$$y = x + n \qquad (1)$$

Where x denote the clean image, y is its noisy version, and n represents the additive white Gaussian noise with variance σ^2.

Under the above notations, one can represent the F&W process for each pixel i as

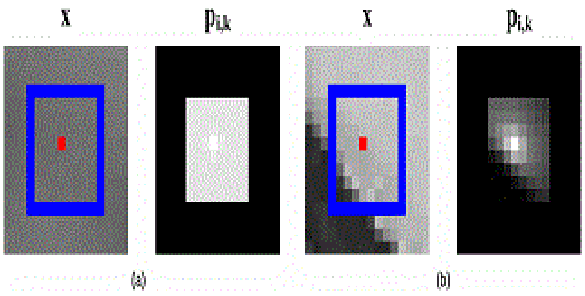

Fig.1

Proposed Block Diagram:

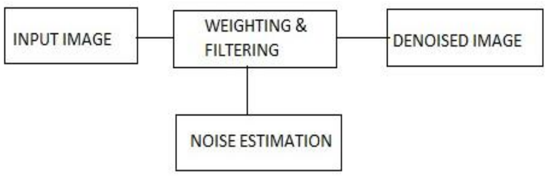

Fig.2

In most of the cases, noise can be modelled as Gaussian distribution, and such noise includes,

1) the noise of an image sensor;
2) the shot noise of a photon detector, which is a type of electronic noise that may be dominant.

Examine the Gaussian noise level from a single image is a very difficult task we need to decide whether local image variations are due to color, texture and lighting variations of the image itself, or due to the external noise. In the image denoising literature, noise is often assumed to be zero mean additive white Gaussian noise (AWGN). An observed noisy image $A_{(i,j)}$ is expressed as:

$$A_{(i,j)} = A_{0(i,j)} + N_{(i,j)} \qquad (2)$$

Where A_0 represents the true image, and N is the signal-independent noise. The amplitude of noise is of Gaussian distribution:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \qquad (3)$$

Filtering with local regions: Suppose there are m_i local regions (also known as patches) that share pixel. In the *k*-th region, x_i is estimated as

$$x_{i,k} = p_{i.k}^T y + c_{i,k} \qquad (4)$$

Where $(p_{i,k}, c_{i,k})$ can be seen as a low-pass global filter. Various denoising algorithms compute $(p_{i,k}, c_{i,k})$ in their own way, but the values are just slightly different. Suppose pixel *i* is at the *l*-th place of the k-th local region, where is a selection matrix, then the patch is

$$(\textstyle\sum + \sigma^2 I)^{-1} (\sum R_{(i,k)} y + \sigma^2 \mu) \qquad (5)$$

Where $\sum$ and μ are the parameter of a Gaussian distribution. In this case, $p_{(i,k)}$ equals to the *l*-th column of

$$\left((\textstyle\sum + \sigma^2 I)^{-1} \sum R_{i,k}\right)^T \qquad (6)$$

Due to the property of $R_{i,k}, p_{i,k}$ is a sparse vector with nonzero elements only in the *k*-th local region, and its *j*-th element reflects the closeness between x_i and x_j. As illustrated in Fig. 1, the *i*-th element of $p_{i,k}$ is always the largest, and if the local region in **x** contains two smooth areas like in Fig. 1(b), the *j*-th element of $p_{i,k}$ is close to 0 when pixel j is in the other area; $c_{i,k}$ is a bias term of the filter.

Weighting to local regions*:* The estimates m_i are weighted to derive the final estimate of xi as

$$x_i = \textstyle\sum_{k=1}^{m_i} w_{i,k}\, x_{i,k} \qquad (7)$$

Where the weights $w_{i,k}$s are nonnegative and sums to one.

$$x_i = w_i^T (P_i^T y + c_i) \qquad (8)$$

All the denoising algorithms in [1], [2], [3], [4], [5], [6] fit the F&W process quite well. As for the Non-local Means algorithm [11], though it can be seem as a weighting algorithm without filtering, the weights actually reflect the closeness among pixels, which is mainly what $p_{i,k}$'s do under the F&W process. Hence, NLM is more proper to be interpreted as a global filtering process with only one estimate for each pixel

B. Two components in a PSE

Under the F&W process, we assume (P_i, C_i) is computed exactly using the original filtering method of a denoising algorithm. Therefore, x_i is formulated as a function of w_i, and MSE is formulated as

$$MSE\left(\hat{X}(w)\right) = \frac{1}{M}(\hat{x}_i(w_i) - x_i)^2$$

$$MSE\left(\hat{X}(w)\right) = \frac{1}{M}(w_i^T(P_i^T x + c_i) - x_i + w_i^T P_i^T n)^2 \quad (9)$$

Where M is the number of pixels in x and w is denoted as the concatenation of all w_i's. Since $MSE\left(\hat{X}(w)\right)$ is a random variable depend on noise **n**, we propose a bias-variance model, which estimates it by its expectation under **n.** For mathematical derivation simplicity, we assume that (P_i, C_i)'s are independent. Hence, the expectation can be estimated as

$$\hat{E}\left[MSE\left(\hat{X}(w)\right)\right] = \frac{1}{M}\sum\left(Bias^2(\hat{x}_i(w_i)) + Var(\hat{x}_i(w_i))\right) \quad (10)$$

Where

Bias($\hat{x}_i(w_i)$) = $w_i^T(P_i^T x + c_i) - x_i$ is the bias of $\hat{x}_i(w_i)$ to x_i and Var($\hat{x}_i(w_i)$) = $\sigma^2 P_i w_i^T P_i^T n$ is the variance.

In reality, (P_i, C_i)'s are derived from **y**, which makes them still correlated to n. To evaluate the appropriateness of using $\hat{E}\left[MSE\left(\hat{X}(w)\right)\right]$ to $MSE\left(\hat{X}(w)\right)$ approximate, we compute their ratio

$$\gamma(w) = \hat{E}\left[MSE\left(\hat{X}(w)\right)\right] / MSE\left(\hat{X}(w)\right) \quad (11)$$

under various w's. If $\gamma(w)$ is a constant under all w's, then we can conclude that optimizing is equivalent to minimizing the true value of $MSE\left(\hat{X}(w)\right)$. As shown in Table I, under each image and denoising algorithm combination, the values of under an averaging and a uniformly sampled are really close. We only list these two values for illustration due to space limitation, the value of $\gamma(w)$under other w's are also quite close to the presented ones Therefore, we denote the objective function as

TABLE I

$\gamma(w)$ UNDER (IMAGE, DENOISING ALGORITHM) COMBINATIONS. IN EACH COMBINATION, THE LEFT ONE USE AVERAGING **w** AND THE RIGHT ONE USE A UNIFORMLY SAMPLED **w**

Image \ Alg.	K-SVD		EPLL		BM3D	
Lena	0.99	0.98	0.87	0.87	0.96	0.96
Barbara	0.99	0.99	0.93	0.93	0.85	0.85
House	0.99	0.98	0.89	0.89	0.90	0.90
Peppers	0.97	0.97	0.90	0.90	0.88	0.88

IV. CONCLUSION

We propose a bias-variance model to estimate the MSE accurately by examine the correlation among the estimates. The proposed weighting approach optimize the weights by preserving the overlapping information of restored patches. Experimental results show that the PSNR gain of EPLL can be improved by about 0.15 dB under a range of noise levels. The 0.15 dB improvement is promising, since it is independent to which image model is used, especially when the gain from designing new image models becomes less and less. This work setup a novel bias-variance model that formulates the selection of weights as an optimization problem. The proposed profiles for solving this optimization problem can be seen as very good, and better profiling methodology may be proposed with more sophisticated techniques.

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BIOGRAPHY

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