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Patch-Based Color Image Denoising using efficient Pixel-Wise Weighting Techniques

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Abstract: Digital color image denoising is a prominent and promising challenge before researchers which has to be overcome. All digital color images contain some degree of noise introduced by the camera when a picture is taken. Image denoising algorithms aim to restore an image in presence of random additive white Gaussian noise (AWGN). Color image denoising is a standard inverse problem. In this paper, an efficient pixel wise weighting techniques for color image denoising based on patch is implemented and simulated using MATLAB tool. The normal, standard and mobile camera color images sets are taken for simulation. Simulation results demonstrate that the WEPLL technique performs well as compared to EPLL technique.
***Keywords**: AWGN, EPLL, WEPLL, QP, MSE, PSNR, Weighting.*

I. INTRODUCTION

Digital color images play a key role in satellite television (TV), events casual documentation, visual communication, computer tomography and in the areas of research. This has made an always increasing insist for accurate and visually pleasing color images. Presence of a minute amount of noise is detrimental when a high accuracy is essential, so the presence of noise has to be removed in order to further process the image. The most popular noises such as additive white Gaussian noise (AWGN), speckle noise, impulse noise, and poisson noise will degrade the image during image formation, recording or transmission phase. Image denoising refers to the recovery of a digital color image that has been degraded by noise. The denoising is an essential and the primary pre-processing step that has to be carried out prior to further processing such as image segmentation, image feature extraction, object recognition, texture analysis, etc [1]. The removal of noise will causes blurring of the images and introduces artifacts. The idea behind denoising is to suppress the noise present in image quite efficiently at the same time retaining and keeping the edges and other image features intact as much as achievable. Conventionally, the problem through image restoration is to reduce presence of undesirable distortions and noise in an image, at the same time preserving and retaining the most significant features like homogeneous regions, discontinuities, edges and textures. The chance of introduction of noise in digital color images became a key challenge in image processing. Thus denoising the image in order to recover the original image for processing became an essential. The major sources of noise in digital images are imperfect instruments, problem with data acquisition process, Interference natural phenomena, transmission and compression. Noisy image introduces an undesirable visual quality and also lowers the visibility of low contrast objects. Consecutively to improve and recover the fine features of image, denoising is necessary. In the literature, there are a variety of image denoising techniques available for noise removal from an image.
The image denoising techniques are mainly classified into two; i) spatial domain filtering technique and ii) transform domain filtering technique. The removal of noise from image by using spatial filters is called as spatial domain filtering. The transform domain filtering technique utilizes wavelet based noise removal scheme.

II. RELATED WORK

There are many number of state-of-the-art image denoising techniques[1], [2], [3], [4], [5], [6], [7], [8], [9].[10],[11] which are based on image patches and denoising methods of these techniques are interpreted as iteration of Filtering and Weighting process. In filtering and weighting process, first, filtering is done to restore the local image patches and then final estimate is calculated by weighting the numerous estimates of the identical pixel from overlapping patches. For filtering, advanced patch based image models[1], [3], [5], [6], are used to generate the filters models such as the sparse coding, the Gaussian Mixture [7], [8], [9] and non local similarity [10]. The weighting methods[11] are rather easy as compared to filtering methods, either by use of simple averaging or by separately weight is derived based on transform coefficients of the resultant image patch itself [4], [5]. These different types of weighting methods are quite optimal, when we consider the estimates for weighting as independent random variables. On the other hand, the estimates can be typically correlated due to overlapping of the patches there by violating the supposition of independence. Therefore, we may further improve the image denoising performance by evaluating the correlation between the

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estimates with the overlapping information. From above proposal, we depict the filtering and weighting process precisely, mean squared error (MSE) is examined under different weights, and a bias variance model is derived to estimate it precisely. The use of weight optimization and overlapping information in the proposed model will gives the smallest MSE. Also a novel weighting method is proposed to solve the optimization difficulty in the bias variance model using Quadratic Programming (QP). Further the proposed weighting techniques can be introduced into two algorithms such as Expected Patch Log Likelihood (EPLL) and Weighted Expected Patch Log Likelihood (WEPLL).

III. PROPOSED WORK

We propose a color image denoising model as shown in Fig.1. We use the standard color images as inputs to this model which are often taken from internet. Four different color images are used in this work. In the literature of image denoising, noise is frequently assumed to be AWGN.

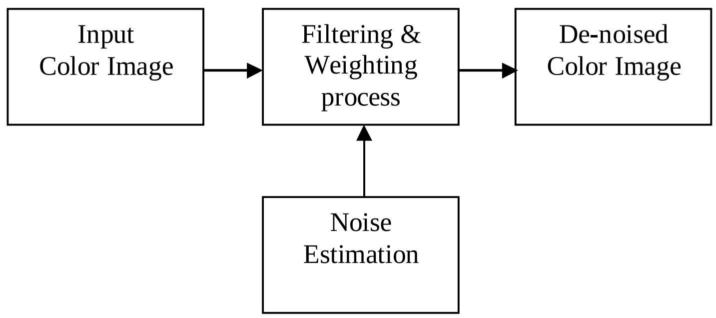

Fig.1. Proposed Block Diagram of Color Image Denoising

Noise estimation step is applied to estimate noise level form a single color image. For estimating the noise level from a single color image, we need to identify whether local image variations are because of the noise, color, texture, or lighting variations from the color image itself. The original image signal has to be known in order to estimate noise level, which can be estimated using a color denoising technique. An extremely sophisticated prior model for color images is required for estimation of noise level accurately. In F&W step, first, filtering operation is done to restore the local image patches and then final estimate is computed by means of weighting the multiple estimates of the same pixel from overlapping patches. The output of F&W process is denoised color image.
This proposed work is divided into three different models.

1) Degradation Model.
2) Bias-Variance Model.
3) QP Based Weighting Technique.

A. The Degradation Model

We firstly formulate the degradation model for color image denoising.

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

Where x denotes the (vectorized) clean color image taken from the source, y denotes its noisy color image, and the parameter n- denotes the additive white Gaussian noise with variance σ^2. The modeling of noise in numerous cases can be gaussian distribution and this noise includes,

1) Image sensor noise.
2) Photon detector shot noise

In the currently available literature of various images denoising, noise is regularly assumed to be zero Mean Additive White Gaussian Noise.

B. The Bias-Variance Model:

The bias variance model is proposed to find and characterize the correlation of the restored image estimates in the filtering and weighting process. The bias variance model is able to approximate the MSE under different weights authentically by using the information set of overlapping the restored patches. Thereby, optimization of the weights for bias variance model is almost equal to reducing the real MSE. We can represent the F&W process for each pixel i as:

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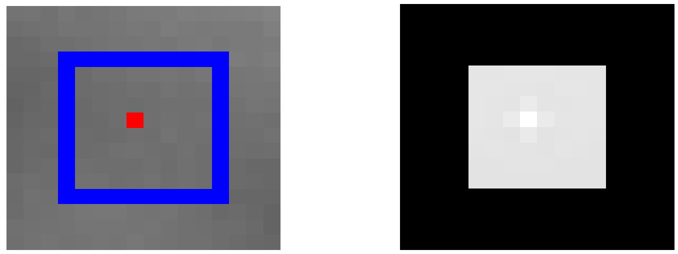
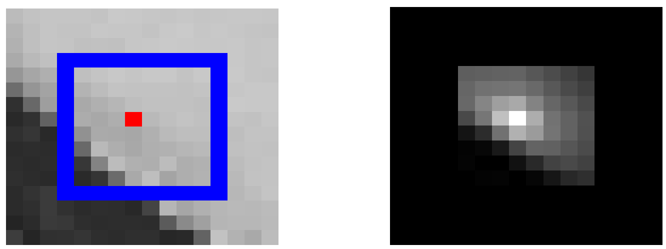


x **P$_{i,k}$**

(a) A smooth image region



x **P$_{i,}$**

(b) A region consist of an edge

Fig.2. the two examples of x and $P_{i,k.}$ The image of x, the red color point denotes pixel, blue color block indicates the k-th local region. For the image of $P_{i,k.,}$ lighter the pixel is, the larger the matching element in $P_{i,k.}$.

C. Filtering within the Local Region.

If there are m_i local regions (also called as patches) that share a pixel 'i' in the *k*-th region, x_i is expected as

$$\hat{x}_{i,k} = \mathbf{p}_{i,k}^T \mathbf{y} + c_{i,k} \tag{2}$$

Where ($P_{i,k,}C_{i,k}$) represents a low pass global filter. Several image denoising techniques calculates ($P_{i,k,}$ $C_{i,k}$) in different ways and the values are just somewhat different [7].

D. Weighting to Local Regions

The final estimate of x_i is derived by weighting the estimates m_i as

$$\hat{x}_i = \sum_{k=1}^{m_i} w_{ik} \hat{x}_{i,k} \tag{3}$$

Where $w_{i,k}$'s denotes weights, $w_{i,k}$'s are non-negative and summation is equal to 1.

E. Mean Square Error (MSE)

The two image similarity metrics (evaluation metrics) such as Mean Square Error (MSE) and peak signal noise ratio (PSNR) is used to assess the performance of the proposed image denoising algorithm.

MSE is expressed as

$$\begin{aligned} \mathrm{MSE}(\hat{\mathrm{x}}(\mathrm{w})) &= \frac{1}{M}\left(\hat{x}_i(\mathrm{w}_i) - x_i\right)^2 \\ &= \frac{1}{M}\left(\mathrm{w}_i^T\left(\mathrm{P}_i^T \mathrm{x} + \mathrm{c}_i\right) - x_i + \mathrm{w}_i^T \mathrm{P}_i^T \mathrm{n}\right)^2 \end{aligned} \tag{4}$$

Where M is the number of pixels in 'x' and 'w' is denoted as the concatenation of all w_i's.

F. Peak signal-to-noise ratio (PSNR)

Peak signal to noise ratio (PSNR) is defined as it is the ratio of maximum signal power and corrupting noise power**.** The proposed denoising techniques performance is evaluated by calculating its mean and standard deviation in terms of the PSNR in decibels (db). Also this two metrics are examined as goal assessments for evaluating the overall quality of the denoised color images. PSNR is the factor that judges whether a technique is providing good denoising scheme or not. Its value should be Maximum as much as possible. The higher the value means, the image quality will be higher. PSNR plays a decisive role in digital image processing areas. To evaluate the quality of recovered images, the recovered color images are compared against an original color image in terms of PSNR. The PSNR can be computed as follows.

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{(2^n-1)^2}{\mathrm{MSE}}\right) \tag{5}$$

Where *n* represent the number of bits per pixel and it is integer number, *n* = 8 for grey-scale images.

In an RGB color image, the pixel values are triples containing the amount of light color images, so typically require 24 bits per pixel, or 8 bits for each of in which case 32 bits are associated with each pixel. Then the PSNR is as

$$\mathrm{PSNR} = 20\log_{10}\left(\frac{255}{\mathrm{MSE}}\right) \tag{6}$$

Where MSE represents mean squared error among the original noise free image sequence and the denoised image sequence. There are two types of Evaluation such as Quantitative Evaluation and Qualitative Evaluation. In Quantitative Evaluation PSNR is utilized as a similarity metric to objectively assist the difference between the original and denoised images. The results are computed by measuring the differences between the original images and the denoised ones. The qualitative evaluation is subjective, where the quality of the denoised color images is addressed via the visual perception. Additive white Gaussian noisy images are chosen to perform this evaluation.

1) *The QP Based Weighting Technique:* We propose a weighting technique [9], [11] using Quadratic Programming (QP) for optimizing weights by means of protecting the overlapping information of restored patches.

This weighting technique contains two profiles

*a)*The approximation profile will optimizes f(w) with an approximation matrix $Q_{i.}$

*b)*The practical profile will calculates the optimal weight like a linear combination of two weights; each reduces components of bias and the variance separately, with a practically resultant combination coefficient.

A new weighting technique to solve the optimization difficulty under the bias variance model using Quadratic Programming (QP) is known as Weighting Expected Patch Log Likelihood (WEPLL).

G. Approximation Profile

The Q_i contains unidentified pixel values x. so, prior to optimizing f(w), we must approximate Q_i primary based on y and (P_i, c_i)'s. Let us assume Qi to be a diagonal matrix $\hat{Q}_i$, still we maintain the overlapping information set of patches in $P^T_i P_i$. The Q_i has k-th diagonal entry which is given as

$$(\mathbf{Q}_i)_{kk} = (x_i - \mathbf{p}_{i,k}^T\mathbf{x} - c_{i,k})^2. \tag{7}$$

We approximate it as

$$(\hat{\mathbf{Q}}_i)_{kk} = \left(\bar{x}_i - \mathbf{p}_{i,k}^T\mathbf{y} - c_{i,k}\right)^2 + \varepsilon, \tag{8}$$

Where

$$\bar{x}_i = \frac{1}{m_i}\sum_{k=1}^{m_i}\hat{x}_{i,k} = \frac{\mathbf{1}^T(\mathbf{P}_i^T\mathbf{y} + \mathbf{c}_i)}{m_i} \tag{9}$$

ε is a small parameter to make sure the entry to be positive.

In this approximation the optimal weight i

$$\mathbf{w}^* = \arg\min_{\mathbf{w}}\sum_{i=1}^{M}\mathbf{w}_i^T\left(\hat{\mathbf{Q}}_i + \sigma^2\mathbf{P}_i^T\mathbf{P}_i\right)\mathbf{w}_i \tag{10}$$

Subject to $w_i >= 0$, $1^T w_i = 1$ for i=1,…..,M.

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Each w_i which can be solved separately and independently through QP. The Lagrangian multiplier process using $1^T w_i=1$ may leads to a negative elements in w_i, that is constraining $w_i >=0$ to be a non-trivial [11].

H. Practical Profile.

Approximation profile[11] in an additional generalized linear combination framework can be understood. We can see w* that in Equation No.(10) can be approximated by

$$\mathbf{w}(\lambda) = (1-\lambda)\mathbf{u} + \lambda\mathbf{v}, \tag{11}$$

with a certain λ€ [0,1] , where

$$\mathbf{u} = \arg\min_{\mathbf{w}} \sum_{i=1}^{M} \mathbf{w}_i^T \hat{\mathbf{Q}}_i \mathbf{w}_i \tag{12}$$

$$\mathbf{v} = \arg\min_{\mathbf{w}} \sum_{i=1}^{M} \mathbf{w}_i^T \mathbf{P}_i^T \mathbf{P}_i \mathbf{w}_i \tag{13}$$

under the same constraints as in Equation No. (10).

The optimal weight is computed as w (λ*) during the practical profile, where λ*ε R is a practically erudite real scalar that produces the least averaged MSE on a training color image set. When $\hat{\mathbf{Q}}_i$ is a superior approximation of Q_i, λ* possible within [0,1] so that the approximation and practical profiles can improve the image denoising performance. If not so, λ* can be negative. The only practical profile achieve properly in this case. In practice, Q_i's are quite likely to be always a positive scalar times the identity matrix, which denotes to be an averaging weight. In practical profile by setting λ*=0 makes the original algorithm as a special case [8],[9],[10].

IV. SIMULATION RESULTS & DISCUSSIONS

The implementation and simulation of proposed denoising techniques for color image denoising is carried out using MATLAB tool. In this simulation, we test the proposed weighting approach under two representative image denoising algorithms EPLL, and WEPLL. Here, the details about MATLAB simulation to evaluate effectiveness the proposed denoising technique for color images and the result are presented. The simulation is performed on three single image dataset such as normal color image set, standard test color image set and mobile camera color image set. The original images of this dataset are presented in Fig.3 through Fig.6, Fig 8 through Fig.11 and Fig.13 through Fig 16. In this simulation, two image similarity metrics (evaluation metrics) such as MSE, and PSNR are examined as goal assessments for evaluating the overall quality of the denoised color images.

A. Normal Images taken from Internet

The simulation is performed on single image dataset comprises of four different normal color images that are taken from internet. Simulation results indicate that the PSNR gain of WEPLL and EPLL is enhanced by under a range of noise levels.

Fig.3.Input Color Image 1, Denoised using EPLL and Denoised using WEPLL

Fig.4.Input Color Image 2, Denoised using EPLL and Denoised using WEPLL

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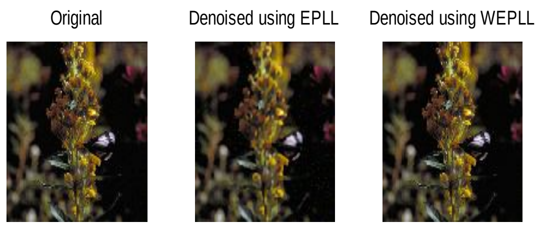

Fig.5.Input Color Image 3, Denoised using EPLL and Denoised using WEPLL

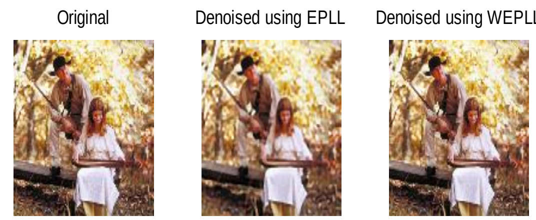

Fig.6.Input Color Image 4, Denoised using EPLL and Denoised using WEPLL

The simulation results of four normal images are shown in Fig.3 through Fig.6 and which shows that the improvement is very significant in presence of random noise. Fig.3 through Fig.6 shows the images with improved visual quality by using WEPLL technique. Table.1 shows the PSNR gain in dB for four different normal color images using EPLL and WEPLL Technique. Fig.7 the graph of PSNR Gain v/s λ for normal color images shows the PSNR gain of WEPLL technique is more than EPLL technique. Hence, the denoising performance of WEPLL technique is improved over EPLL technique.

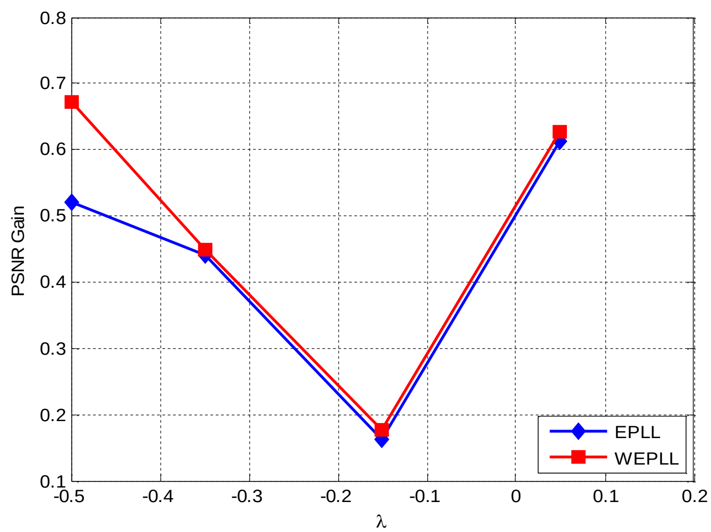

Fig.7 the Graph of PSNR Gain v/s λ for normal images for four normal color image

Image\Angle	PSNR Gain EPLL(db)	PSNR Gain WEPLL(db)
1	0.5199	0.6713
2	0.4415	0.4489
3	0.1634	0.1764
4	0.6121	0.6270

Table 1 PSNR Gain Comparison of EPLL and WEPLL Technique for four normal color images

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B. Standard Test color Images taken from Internet

The simulation is performed on single standard test image dataset comprises of four different standard test color images that are taken from internet source:

http://www.hlevkin.com/06testimages.htm

https://homepages.cae.wisc.edu/~ece533/images/

The simulation results of four standard test color images are shown in Fig.8 through Fig.11 and which shows that the improvement is very significant in presence of random noise.

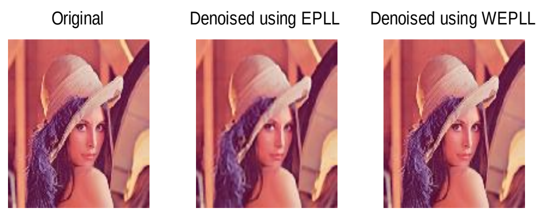

Fig.8.Input Lena Color Image1, Denoised using EPLL and Denoised using WEPLL

Fig.9.Input Peppers Color Image, Denoised using EPLL and Denoised using WEPLL

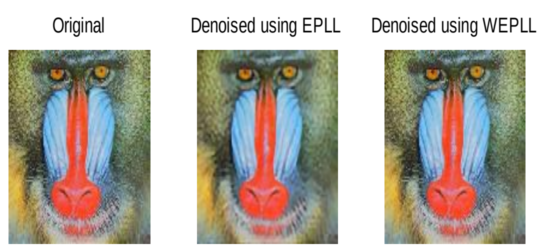

Fig.10. Input Baboon Color Image, Denoised using EPLL and Denoised using WEPLL

Fig.11. Input Barbara Color Image, Denoised using EPLL and Denoised using WEPLL

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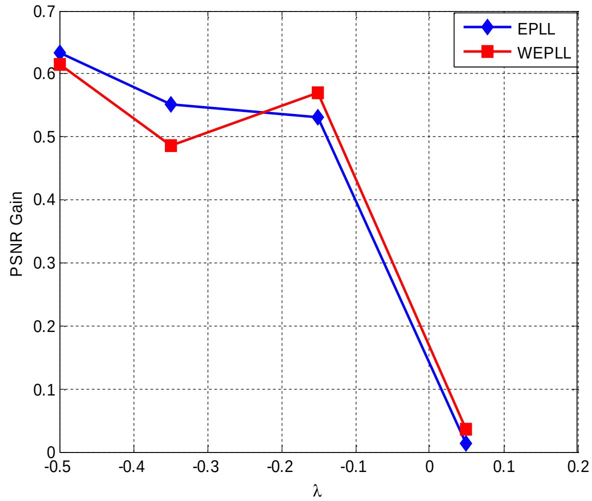

Fig.12 the Graph of PSNR Gain v/s λ for standard test color images

Image\Angle	PSNR Gain EPLL(db)	PSNR Gain WEPLL(db)
Lena	0.6331	0.6146
Peppers	0.5506	0.4868
baboon	0.5316	0.5701
Barbara	0.0136	0.0361

Table 2 PSNR Gain Comparison of EPLL and WEPLL Technique for standard test color images

Fig.8 through Fig.11 shows the images with improved visual quality by using WEPLL technique. Table 2, shows the PSNR gain in dB for four different standard test color images using EPLL and WEPLL Technique. Fig.7 the graph of PSNR Gain v/s λ for standard test color images shows the PSNR gain of WEPLL technique is more than EPLL technique. Hence, the denoising performance of WEPLL technique is improved over EPLL technique.

C. Color Images taken using mobile camera

The simulation is performed on single image dataset comprises of four different color images that are taken using mobile camera.

Fig.13.Input Color Image 1, Denoised using EPLL and Denoised using WEPLL

Fig.14.Input Color Image 2, Denoised using EPLL and Denoised using WEPLL

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Fig.15.Input Color Image 3, Denoised using EPLL and Denoised using WEPLL

Fig.16.Input Color Image 4, Denoised using EPLL and Denoised using WEPLL

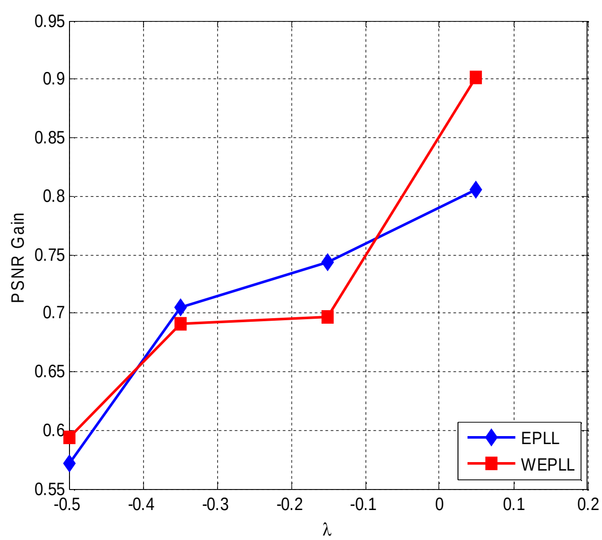

Fig.17 the Graph of PSNR Gain v/s λ for mobile camera color images

Image\Angle	PSNR Gain EPLL(db)	PSNR Gain WEPLL(db)
1	0.5717	0.5943
2	0.7044	0.6915
3	0.7435	0.6963
4	0.8060	0.9012

Table 3 PSNR Gain Comparison of EPLL and WEPLL Technique for mobile camera color images

The simulation results of four mobile camera color images are shown in Fig.13 through Fig.16 and which shows that the improvement is very significant in presence of random noise. Fig.13 through Fig.16 shows the images with improved visual quality by using WEPLL technique. Table 3, shows the PSNR gain in dB for four different mobile camera color images using EPLL and WEPLL Technique. Fig.17 the graph of PSNR Gain v/s λ for mobile camera color images shows the PSNR gain of WEPLL technique is more than EPLL technique. Hence, the denoising performance of WEPLL technique is improved over EPLL technique.

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V. CONCLUSION AND FUTURE WORK

The proposed bias-variance model and new weighting technique using QP are implemented and simulated using MATLAB successfully. The simulation result shows that the improvement is very significant in presence of random noise and the WEPLL technique perform well as compared EPLL technique. The proposed two profiles for solving this optimization difficulty can be seen as a stepping stone, and improved profiling approach might be proposed with more erudite techniques.

In future we use these weighting techniques for real time video denoising. Also these weighting techniques can be implemented using FPGA.

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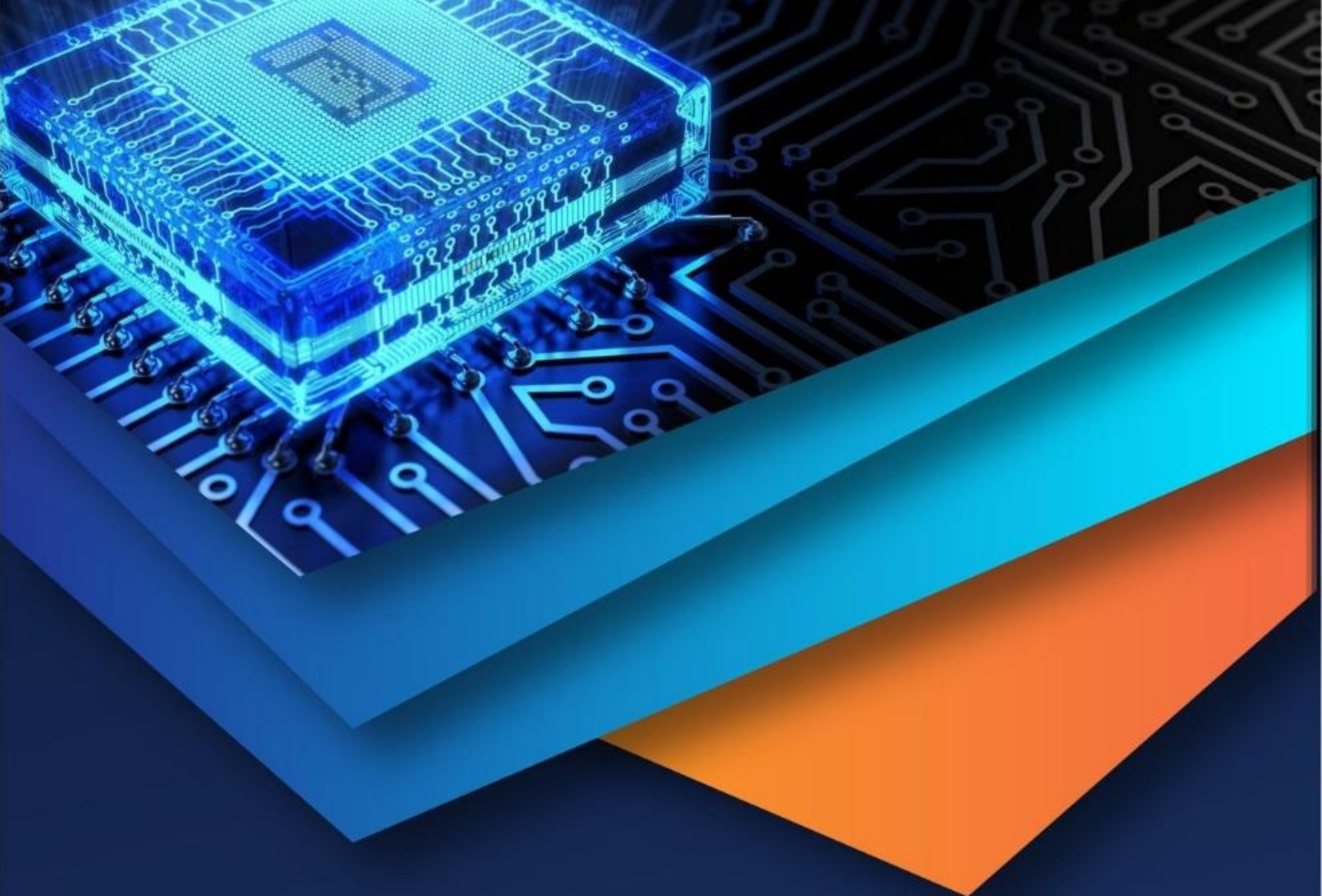

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