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Additive Noise Removal for Color Images using Wavelet Based Fuzzy Filter

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Abstract: Noise removal is an important step for an image retrieval system to remove the unwanted information present in the image using filtering techniques for web based applications. Web images are often degraded by additive noise. The goal of smoothing the image is to remove the noise while retaining the image features such as color, texture, shape and so on. The denoising technique yields a better quality image. Denoising can be done through filtering which can either be linear filtering or non-linear filtering. Linear filters do not eliminate additive noise as they have a tendency to blur the edges of an image. On the other hand, nonlinear filter is suitable for dealing with additive noise. These filters operate on small size windows and replace the value of the central pixel. Compared to other nonlinear techniques, wavelet based fuzzy filters have the ability to combine edge preservation and smoothing. In this study, wavelet based fuzzy filter is used to filter the images and the result proved better in terms of Peak Signal to Noise Ratio (PSNR) and Structural SI Milarity (SSIM) when compared other filters.

Key words: Median, wiener, fuzzy filter, wavelet based fuzzy filter, peak signal to noise ratio, SSIM

INTRODUCTION

Digital noise is a common problem in digital cameras today. Even if noise is not so, obviously visible in a picture, some kind of image noise is bound to exist. The noise causes due to some factors such as optical and mechanical property of camera, lighting condition, scanner resolution and so on. There are many kinds of filters used to remove the noise such as median filter, wiener filter, fuzzy filter and wavelet based fuzzy filter.

Wavelet based fuzzy filter is used for a variety of applications, including compression, gray-level or color image denoising, object tracking and texture analyzing. When taking pictures with a digital camera, an electronic sensor (also known as a Charge Coupled Device (CCD)) built from many tiny pixels is used to measure the light for each pixel. The result is a matrix of pixels that represent the photo. With any other electronic sensor the CCD is not perfect and includes some noise. Normally, web images are often degraded by additive noise. The additive noise, otherwise called Gaussian is independent of the pixel values in the original image. It is a good model for the thermal noise (Johnson-Nyquist Noise) with photo-electronic sensors. It is an idealized form of white noise which is caused by random fluctuations in the image. In color cameras, more noise created in the blue channel compared to red and green channel because of amplification. Amplifier noise is a major part of the noise of an image sensor (Bacchelli and Papi, 2007; Huang *et al.*, 2005; Dabov *et al.*, 2007). In Gaussian noise, each pixel in the image will be changed from its original value by a small amount. Let f[m,n] be the original image, f'[m,n] be the noise digitized version and [m,n] be the noise function which returns random values coming from an arbitrary distribution. Then, the additive noise is given by the Eq. 1:

$$f'[m,n]= f[m,n]+ \sigma[m,n] \quad (1)$$

Where:
m = The number of rows and
n = The number of columns

The goal of denoising is to remove the additive noise while retaining as much possible important features. Denoising can be done through wavelet based fuzzy filtering. This filtering technique yields a better quality image for the purpose of web application (Chen *et al.*, 2005; Saeedi *et al.*, 2010; Deng *et al.*, 2007).

Non local means and its variants proposed for image denoising (Wu *et al.*, 2013a). The contributions are novel formulation of the center pixel weights problem from a statistical shrinkage perspective, construct the james-stein shrinkage estimator in the center pixel weights context and a new local james stein type center pixel weight that is locally tuned for each image pixel. Non local means denoising is proved in terms of peak signal to noise ratio and structural similarity. Shrinkage problem of image denoising method is proposed the additive white Gaussian noise (AWGN) model (Basu, 2002). The contribution is to derive the closed-form of the optimal shrinkage that minimizes the Stein's Unbiased Risk Estimator (SURE) and thus allows direct blockwise shrinkage without additional optimizations. Simulation results show that the proposed method boosts the denoising performance for a variety of image denoising techniques including the moving average filter, the median filter, the wiener filter, the bilateral filter, the probabilistic non-local means and the block matching 3D filter in terms of higher Pixel Signal Noise Ratio (PSNR) and Structural Similarity Index (SSIM).

Image denoising approaches are proposed (Tracey *et al*., 2014) that suppress noise while maintaining edge information. The Non Local Means (NLM) algorithm, a widely used patch-based method is a highly effective edge-preserving technique but is sensitive to parameter tuning. A variational approach is used to combine multiple NLM estimates, seeking a solution that balances positivity constraints and gradient penalties against Stein's Unbiased Risk Estimate (SURE). This method greatly reduces parameter sensitivity and improves denoising performance.

Fuzzy random impulse noise is proposed in (Schulte *et al*., 2006) which consist of two fuzzy detection methods and a fuzzy filtering algorithm. This filter is especially developed for reducing all kinds of random valued impulse noise. Its main advantage is that it removes impulse noise very well while preserving the fine image structures. The main disadvantage of the proposed method is its time complexity. A new technique is proposed (Ibrahim *et al*., 2008) to remove impulse noise from highly corrupted images. This method comprises of two stages. The first stage is to detect the impulse noise in the image. Based on the intensity values, the pixels are roughly divided into two classes which are "noise-free pixel" and "noise pixel". Then, the second stage is to eliminate the impulse noise from the image. Hence, the "noise-pixels" are processed. The "noise-free pixels" are copied directly into the output image. This method adaptively changes the size of the median filter based on the number of the "noise-free pixels" in the neighborhood. While filtering, "noise-free pixels" are considered for calculating the median value. One of the advantages of this method is that this method does not need the threshold parameter. As the percentage of noise is high (95%), this method requires slightly longer processing time. A dictionary learning based image decomposition framework is proposed (Huong *et al*., 2005) for single image denoising. It determines the undesirable patterns automatically (e.g., rain streaks or Gaussian noise) from the derived image components directly from the input image. It does not need to collect training image data in advance.

Two-stage Noise Adaptive Fuzzy Switching Median (NAFSM) filter is proposed for salt-and-pepper noise detection and removal. Initially, the detection stage utilizes the histogram of the corrupted image to identify noise pixels. These detected "noise pixels" are then subjected to the filtering action while "noise-free pixels" are retained and left unprocessed. Then, the NAFSM filtering mechanism employs fuzzy reasoning to handle uncertainty present in the extracted local information which are introduced by noise. Meanwhile, the inherited switching median behavior speeds up the filtering process and at the same time preserving image details by selecting only "noise pixels" for processing. An efficient algorithm for adaptive noise reduction is proposed in (Fathi and Naghsh-Nilchi, 2012) which combine the optimal linear interpolation and adaptive thresholding methods in the wavelet packet thresholding function. The performance of the proposed noise reduction algorithm is measured in terms of peak signal to noise ratio. The computational cost of the proposed method is modest and so, it is suitable for many image processing applications. The disadvantage is that this method is applied only for gray scale images. Probabilistic nonlocal means (data-adaptive) method is proposed (Wu *et al*., 2013b) for image denoising. This technique analyzes images on a patch-by-patch basis. It derives all theoretical statistics of patch-wise differences for Gaussian noise. It is less sensitive to parameter changes and has a better ability to retain weak edges. The dictionary learning method is proposed (Shao *et al*., 2014) which is divided into three categories: spatial domain, transform domain and dictionary learning based. Spatial domain methods include local and nonlocal filters which exploit the similarities between either pixels or patches in an image. Both transform domain and dictionary learning based methods consider transforming images into other domains, in which similarities of transformed coefficients are employed. Results in computational burden and artifacts are quite noticeable.

Different types of noise reduction methods can be found in the literature. All of these methods have some drawbacks, i.e., sensitive to parameter changes, artifacts, time complexity and so on. The main difference between the proposed wavelet based fuzzy filter method and other noise reduction methods is that it suppresses the additive noise very well while fine details and edges do not lose much sharpness and also It can be applied to all kinds of color images corrupted with noise (e.g., Gaussian noise) without introducing artifacts. Experimental results show that the proposed method provides a significant improvement in terms of PSNR and SSIM when compared with other existing filters.

MATERIALS AND METHODS

Types of filters

Wiener filter: Wiener works best when the noise is constant-power ("white") additive noise such as Gaussian noise. Wiener filter uses a local variance field of the distorted image that is based on statistical properties of the original image. If the variance is large, wiener performs little smoothing. If the variance is small, Wiener performs more smoothing. This approach often produces better results than linear filtering. In addition, wiener filter requires more computation time than linear filtering.

Median filter: A median filter is an example of a non-linear filter. This method is particularly effective when the noise pattern consists of strong, spike like components and the characteristic to be preserved is edge sharpness. In order to perform median filtering in a neighborhood of a pixel, sort the values of the pixel and its neighbors determine the median and assign this value to the pixel. The steps are followed as:

Step 1: Consider each pixel in the image

6	2	0
3	97	4
19	3	10

Step 2: Sort the neighboring pixels in order, based upon their intensities: 0, 2, 3, 3, 4, 6, 10, 19, 97.

Step 3: Replace the original value of the pixel with the median value from the list:

*	*	*
*	4	*
*	*	*

Median is very less sensitive than the mean of the extreme values (called outliers). Median filtering is used to remove these outliers better than the mean filtering without reducing the sharpness of the image.

Fuzzy filter: Fuzzy filter technique is developed for the enhancement of color image corrupted by additive Gaussian noise. Each pixel in the image is represented by a membership function and different types of fuzzy rules that consider the neighborhood information or other information to eliminate the noise with blur edge (Nejad *et al*., 2006). Image and fuzzy set can be modeled in a similar way.

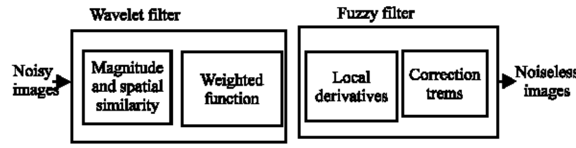

Fig. 1: Block diagram of wavelet based fuzzy filter

Wavelet based fuzzy filter: In this study, a wavelet based fuzzy filter is proposed to enhance the natural images. Wavelet filter is used to suppress the additive noise while retaining requiring features such as color, texture and so on. The fuzzy filter is used for enhancing wavelet coefficients' information. The combined wavelet based fuzzy denoising algorithm indicates that it produces a better performance in noise suppression and edge preservation as compared with the other filtering methods. The block diagram of wavelet based fuzzy filter is shown in Fig. 1.

A wavelet based fuzzy filter is used for the reduction of additive noise for digital color images. The filter consists of two stages namely wavelet filter and second fuzzy filter. In the first stage, wavelet is used to distinguish between local variations. The second stage, fuzzy filter is used to enhance the first method by reducing the noise in the color components differences without destroying the fine details of the image. This is realized by calculating the local differences in the red, green and blue environment separately. These differences are then combined to calculate the local estimation of the central pixel.

Gaussian noise removal: RGB color model is represented by a 3 dimensional vector. Red, Green and Blue are called as the primary components. Each element is quantized to the range $0\text{-}2^m\text{-}1$ where m is 8. A digital color image C is represented by a 2 dimensional array of vectors.

An additive Gaussian white noise is defined by a zero mean and a known σ^2 variance. The equation is expressed as:

$$N_{s,d}(i,j,1)\ N_{s,d}\ (i,j,2)\ N_{s,d}\ (i,j,3) = [(C_{s,d}\ (i,j,1)+\eta_1)\ (C_{s,d}\ (i,j,2)+\eta_2)\ (C_{s,d}\ (i,j,3)+\eta_3)] \quad (2)$$

Where:

$C_{s,d}\ (i,j,1)$ = Red component
$C_{s,d}\ (i,j,2)$ = Green component
$C_{s,d}\ (i,j,3)$ = Blue component
$C_{s,d}$ = Noise free wavelet coefficients of scale s and orientation d respectively
$N_{s,d}$ = Noisy wavelet coefficients of scale s and orientation d respectively
η_1, η_2, η_3 = Three separate randomly distributed Gaussian values with means (μ_1,μ_2 and μ_3) and standard deviations (σ_1,σ_2 and σ_3), respectively

Wavelet filter:

- Step 1: Choose window size of (2K+1)×(2K+1) for the current image pixel at position (i,j)
- Step 2: Obtain the feature using a non linear averaging filter in the wavelet sub bands of each single channel
- Step 3: Assign large weights to neighboring coefficients with similar magnitude and vice versa. The weights for the red, green and blue component at position (i+k,j+l) are w(i+k,j+l,1), w(i+k,j+l,2) and w(i+k,j+l,3), respectively
- Step 4: Calculate the fuzzy function of magnitude similarity and a fuzzy function of spatial similarity for the red, green and blue component which is defined in Eq. 3-8:

$$m(i+k,j+l,1)=\exp\left[-\left(\frac{N_{s,d}(i,j,1)-N_{s,d}(i+K,j+l,1)}{Thr}\right)^2\right] \quad (3)$$

$$m(i+k,j+l,2)=\exp\left[-\left(\frac{N_{s,d}(i,j,2)-N_{s,d}(i+K,j+l,2)}{Thr}\right)^2\right] \quad (4)$$

$$m(i+k,j+l,3)=\exp\left[-\left(\frac{N_{s,d}(i,j,3)-N_{s,d}(i+K,j+l,3)}{Thr}\right)^2\right] \quad (5)$$

$$s(i+k,j+l,1)=\exp\left[-\left[\frac{(i+k)^2+(j+l)^2}{N}\right]\right] \quad (6)$$

$$s(i+k,j+l,2)=\exp\left[-\left[\frac{(i+k)^2+(j+l)^2}{N}\right]\right] \quad (7)$$

$$s(i+k,j+l,3)=\exp\left[-\left[\frac{(i+k)^2+(j+l)^2}{N}\right]\right] \quad (8)$$

where, $Thr=K\times\sigma^c_n; 3\leq K\leq 4$; K ε[-k…k]; lε[-l…l], 2.55<Thr<7.65 σ^c_n is estimation noise variance of channel c using median estimator and N is the number of coefficients in the local window. According the three fuzzy functions, assign adaptive weight w(i+k,j+l,1) for each neighboring coefficient for red, green and blue component are expressed in Eq. 9-11:

$$w(i+k,j+l,1)=m(i+k,j+l,1)\times s(i+k,j+l,1) \quad (9)$$

$$w(i+k,j+l,2)=m(i+k,j+l,2)\times s(i+k,j+l,2) \quad (10)$$

$$w(i+k,j+l,3)=m(i+k,j+l,3)\times s(i+k,j+l,3) \quad (11)$$

Step 4: Find the output image of the wavelet filter for the red, green and blue component. It is shown in Eq. 12-14:

$$F(i,j,1)=\frac{\sum_{l=-k}^{+k}\sum_{l=-k}^{+k}w(i+k,j+l,1).N(i+k,j+l,1)}{\sum_{l=-k}^{+k}\sum_{l=-k}^{+k}w(i+k,j+l,1)} \quad (12)$$

$$F(i,j,2)=\frac{\sum_{l=-k}^{+k}\sum_{l=-k}^{+k}w(i+k,j+l,2).N(i+k,j+l,2)}{\sum_{l=-k}^{+k}\sum_{l=-k}^{+k}w(i+k,j+l,2)} \quad (13)$$

$$F(i,j,3)=\frac{\sum_{l=-k}^{+k}\sum_{l=-k}^{+k}w(i+k,j+l,3).N(i+k,j+l,3)}{\sum_{l=-k}^{+k}\sum_{l=-k}^{+k}w(i+k,j+l,3)} \quad (14)$$

Fuzzy filter: Step 1: Calculate the gradients or derivatives for the red (LD_R) green (LD_G) and blue (LD_B) for each element of the window. It is shown in Eq. 15-17:

$$LD_R(k,l) = F(i+K, j+l,1)-F(i,j,1) \quad (15)$$

$$LD_G(k,l) = F(i+K, j+l,2)-F(i,j,2) \quad (16)$$

$$LD_B(k,l) = F(i+K, j+l,3)-F(i,j,3) \quad (17)$$

where k, lε {-L,…,0,…,+L}. Step 2: calculate the correction terms ε(k,l) for a 3x3 window (L = 1). It is given by Eq. 18:

$$\varepsilon(k,l)=\frac{1}{3}\left(LD_R(k,l)+LD_G(k,l)+LD_B(k,l)\right) \quad (18)$$

Step 3: Finally find the output of the second sub filter for red, green and blue components. It is shown in Eq. 19-21:

$$Out(i,j,1)=\frac{\sum_{l=-k}^{+k}\sum_{l=-k}^{+k}\left(F(i+k,j+l,1)+\varepsilon(k,l)\right)}{(2L+1)^2} \quad (19)$$

$$Out(i,j,2)=\frac{\sum_{l=-k}^{+k}\sum_{l=-k}^{+k}\left(F(i+k,j+l,2)+\varepsilon(k,l)\right)}{(2L+1)^2} \quad (20)$$

$$Out(i,j,3)=\frac{\sum_{l=-k}^{+k}\sum_{l=-k}^{+k}\left(F(i+k,j+l,3)+\varepsilon(k,l)\right)}{(2L+1)^2} \quad (21)$$

The results of proposed and other filtering techniques are shown in Fig. 2.

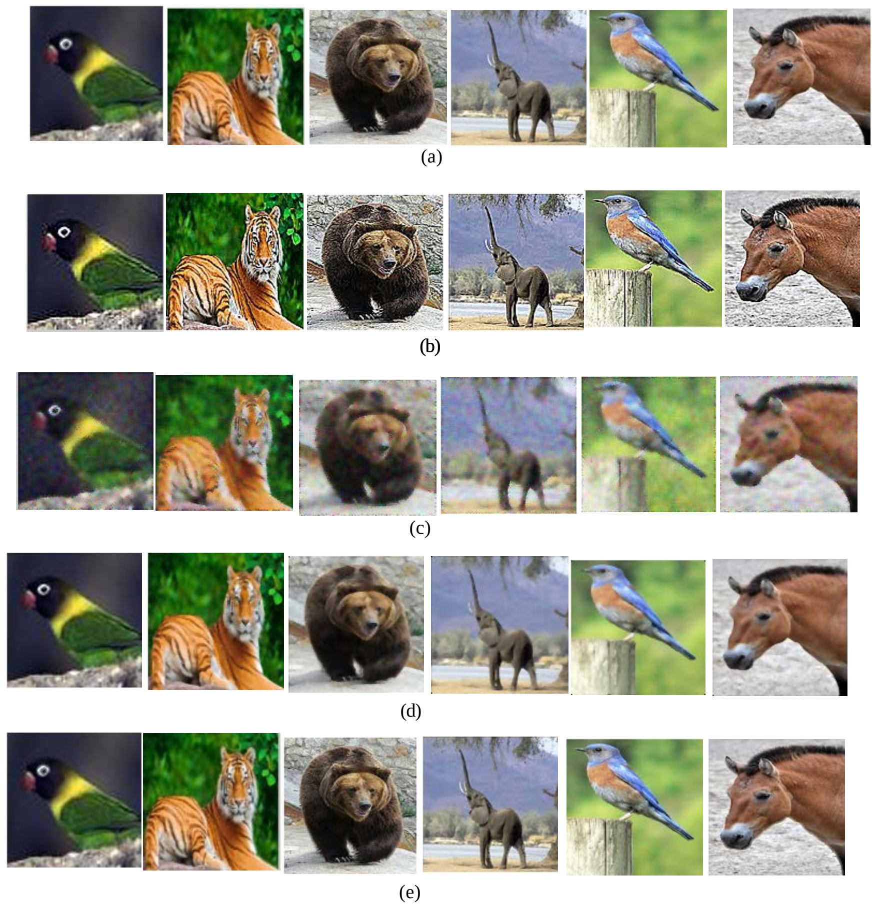

Fig. 2: Results of different filtering techniques: a) Sample images of ‘Bird 1’, ‘tiger’, ‘bear’ , ’elephant’, ’Bird 2’and ’donkey’; b) Using wiener filter; c) Using median filter; d) Using fuzzy filter; e) Using wavelet based fuzzy filter

RESULTS AND DISCUSSION

Performance evaluation: The proposed method has been used to remove the additive noise from the image using wavelet based fuzzy filter in color image processing. This filtering technique was applied to 1200 images and the output was compared with different filtering technique. Peak Signal to Noise Ratio (PSNR) and Structural SIMilarity (SSIM) are the two metrics used to compare the image quality.

Peak Signal to Noise Ratio (PSNR): It is used as a quality measurement between the noiseless and noisy image. The higher the PSNR, make the quality of the noiseless image better. It is calculated by using Eq. 22:

$$PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right) \tag{22}$$

where, R is the maximum fluctuation in the input image.

Structural SI Milarity (SSIM): It is a method for measuring the similarity between two images. It is calculated on window size of 3x3 in an image. The measurement between two windows x and y of common size N×N is in Eq. 23:

$$SSIM_{x,y} = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{23}$$

Where:

μ_x = The average of x
μ_y = The average of y
σ^2_x = The variance of x
σ^2_y = The variance of y
σ_{xy} = The covariance of x and y
C_1 = k_1L^2
C_2 = k_2L^2 two variables to stabilize the division with weak denominator
L = The dynamic range of the pixel ($2^{\#bits\ per\ pixel}$) k_1 = 0.01 and k_2 = 0.03 by default

Table 1: Performance evaluation of an image based on PSNR values

	PSNR (Peak Signal to Noise Ratio) values			
Sample images	Wiener filter	Median filter	Fuzzy filter	Waveletbased fuzzy filter
Bird 1	25.66	35.87	39.45	42.53
Tiger	21.59	25.28	27.34	35.47
Bear	22.13	25.42	29.46	41.25
Elephant	23.70	30.01	32.93	38.28
Bird 2	23.84	28.53	32.86	41.10
Donkey	23.21	29.08	36.74	42.58

Table 2 : Performance evaluation of an image based on SSIM values

	SSIM values			
Sample images	Wiener filter	Median filter	Fuzzy filter	Waveletbased fuzzy filter
Bird 1	0.886	0.894	0.994	0.999
Tiger	0.875	0.884	0.988	0.999
Bear	0.932	0.955	0.963	0.975
Elephant	0.845	0.888	0.960	0.967
Bird 2	0.824	0.863	0.958	0.989
Donkey	0.853	0.878	0.959	0.969

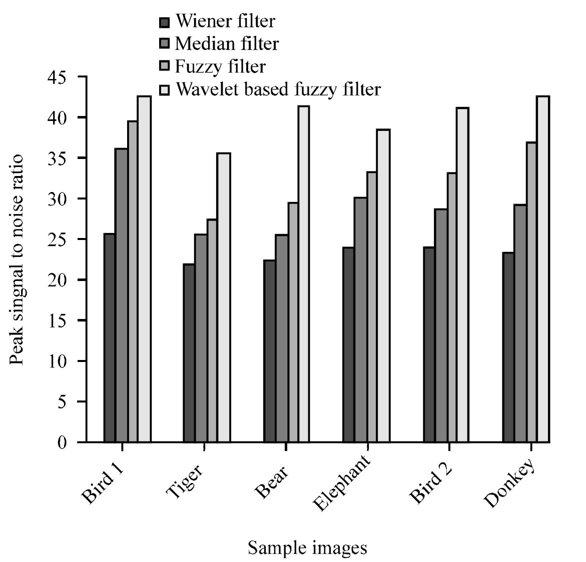

Fig. 3: Graphical representation of PSNR for different filtering techniques

Whereas PSNR measure estimates only the perceived errors and SSIM consider image degradation as perceived change in structural information. The evaluation of this method is given in Table 1 and 2.

Graphical representation of PSNR and SSIM for wavelet based fuzzy filter is shown in Fig. 3 and 4. The results obtained using wavelet based fuzzy filter technique ensures noise free and increase in quality of the image. Hence, this method is suitable than other filters available at present to remove noises and to enhance the image quality.

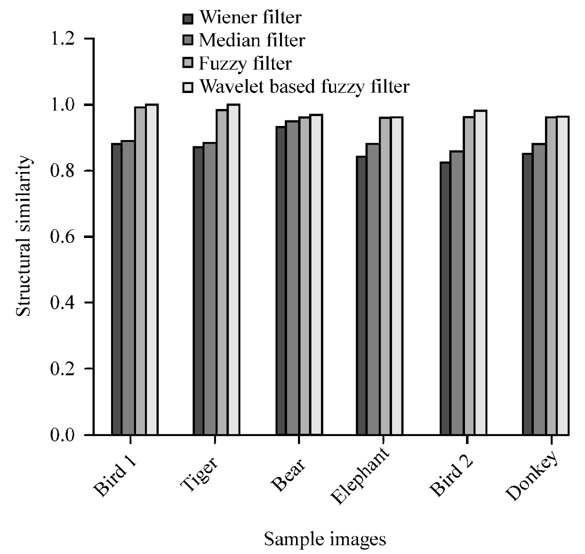

Fig. 4: Graphical representation of SSIM for different filtering techniques

CONCLUSION

In this study, wavelet based fuzzy filtering technique for removing additive noise in color image is discussed. The result for the wavelet based fuzzy filter is compared with other filtering techniques such as wiener filter and median filter and fuzzy filter. The performance results are obtained using wavelet based fuzzy filtering technique has proven better results in terms of PSNR and SSIM values.

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