Noise Removed by Processing the Lightness and Chromatic Components Basic on YC_bC_r Color Space

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Abstract

In this research additive noise has been removed from color images by using a new method depends on processing the chromatic components (Hue and Saturation), and lightness component, basic YC_bC_r color space. Several algorithms are used as Weiner filter , the bilateral filter , anisotropic filter and Principal Component Analysis (PCA) algorithm with standard deviation of noise between (10-80). In order to know the best algorithm , PSNR values are calculated where he found that the best algorithm is the PCA algorithm, followed by Wiener filter.

Key words: noise, filters, color space.

الخلاصة

في هذا البحث تم إزالة الضوضاء الجمعية من الصورة الملونة باعتماد أسلوب معالجة جديد يعتمد على معالجة المركبات اللونية (التدرج اللوني والإشباع) إضافة الى معالجة مركبة الإضاءة، باستخدام فضاء YC_bC_r.

استخدمت عدة خوارزميات هي مرشح وينر والمرشح الثنائي و مرشح متباين الخواص ومرشح تحليل المركبة الرئيسة (PCA) بنسب ضوضاء تتراوح بين (10 – 80). من اجل معرفة افضل خوارزمية تم حساب قيم PSNR حيث وجد ان أفضل خوارزمية هي خوارزمية PCA يليها مرشح وينر.

الكلمات المفتاحية: الضوضاء، المرشحات، الفضاء اللوني.

1.Introduction

Many digital image processing applications require noise reduction and image restoration to produce more reliable results. To remove extraneous noise, These filters aim at smoothing the image to remove some form of noise. It is important in image restoration to remove noise while preserving meaningful detail such as blurred thin edges and low-contrast fine features [Bovik *et.al.*, 1987]. The proposed method can simultaneously preserve edges and fine details while filtering out noise in the diffusion process most applications of smoothing have evolved into three distinct types, according to the measurement data dependencies of the estimated state vector[Alexa, 2002].

There are many skin color spaces like RGB, HSV, YCbCr, YIQ, YUV, etc. that are used for skin color segmentation. The RGB color model represents the colors that are in the red, green, and blue planes and does not separate the luminance from the chrominance components, which makes it a poor choice for color analysis and color based recognition. The conversion from RGB color space to the HSV color model is time consuming due to the time which it takes to do a nonlinear transmission. To overcome the previous problems, we have proposed a new threshold [Tomasi and Manduchi, 1998].

the opponent color space would be orthogonal so that any processing performed on one channel does not affect the other channels. Historically, many opponent color spaces have been described such as YCbCr, YIQ, OPP, IPT, and DKL, each space is designed for specific applications YCbCr, color model is specified in terms of luminance(Y channel) and chrominance (Cb and Cr channels). It segments the image into a luminous component and chrominance components. In YCbCr color model, the distribution of the skin areas is consistent across different races in the Cb and Cr color spaces [Hamid Al-Tairi, *et al.*, 2014]. As RGB color model is light sensitive so to improve the performance of skin color clustering, YCbCr color model is used. Its chrominance components are almost independent of luminance and there is non-linear relationship between chrominance(Cb, Cr) and luminance(Y) of the skin color in the high and low luminance region. Range of Y lies between 16-235 where 16 for black and 235 for white whereas Cb & Cr are scaled in the range of 16-240 . The main advantage of YCCr color model is that influence of luminosity can be removed during processing of an image. Different plots for Y, Cb and Cr values for face and non-face pixels were plotted using the reference images and studied to find the range of Y, Cb and Cr values for the face pixels [Rewar and Saroj Kumar, 2013].

2.Weiner Filtering

It is a classic technology beginning to assess the signal to be applied to continuous signals of one dimension alongside with analyzing and approving it on basis of Fourier continuous theory [Pratt, 1972].

Weiner filter was used to remove the Gaussian noise from damaged image depending the estimating statistics for each neighbor per pixel [Siddeq and Sadar, 2009]. This filter relies on the strength of the noise (noise of contrast in damaged image). When there is large contrast, the filter with little smoothing. If the contrast is big, the filter will work on more smoothing. This filter produces better results than other filters used to enhancement the image [Sendur and Selesnick, 2002].

Also, it is applied in the frequency band where there is image deterioration *f (n, m)*. One takes Fourier continuous transformations for obtaining *f(i,j)* as assessed by the original image spectrum *S(i,j)* by multiplying *f(i,j)* by Weiner filter *G(i,j)* [Saeed V. Vaseghi, 2000].

$$S(i,j) = f(i,j)G(i,j) \qquad (1)$$

$$G(i,j) = \frac{P(i,j)}{P(i,j) + \sigma^2} \qquad (2)$$

$$\mu = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n} f(i,j) \qquad \sigma^2 = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n} f^2(i,j) - \mu^2 \qquad (3)$$

P(i,j): Power Spectrum of the noise process obtained by taking Fourier transform of the noise autocorrelation.

The Weiner filter coefficient are calculated to minimize the average square of the distance between the filter output and the required signal. In its basic form Weiner theory hypotheses that signals are constant processes. However, if the calculation of the filter coefficient is periodically repeated per mass for (N) of signal samples, the filter will adjust itself with the average of signal properties inside the masses to become adjustable mass [Saeed, 2000].

3.Bilateral Filter

It is Gaussian filter (non-linear technology) to keep the edge good. It can use the same technique with any type of simple filter (median or mean). The vectors of compensation for the weights w_1(spatial smoothing), it is known as local convolution and this weight is quantified from the second weight w_2(magnitude smoothing/ color) and it is known from the difference $f(x+a)-f(x)$ [C., P., and Tumblin J., 2003].

$$s(x) = \frac{1}{k(x)} \int_{\Omega} f(x+a).w_1(a).w_2\big(f(x+a)-f(x)\big)da \tag{4}$$

$$k(x) = \int_{\Omega} w_1(a).w_2\big(f(x+a)-f(x)\big)da \tag{5}$$

Where *S* is the function of smoothing and the function f(x) is used for calibration and the weights w_1, w_2 is known as Gaussian function with the standard deviation σ1 (color) and σ2 (spatial), respectively [C., P., and Tumblin, 2003].

This filter has many characters explaining its success, its formulation is simple, all pixel is replaced through the weighted median to its neighbors. This aspect is significant because it made it easy to identify its behavior, and its consistence with its applications and implementing that. In addition to two factors are only relied on: size and contrast of the properties. Also, this filter can be used infrequently. This makes it easy to identify the factors where their effects are not accumulative over several frequencies [Paris, *et. al.*, 2008].

Many approaches were suggested to reduce the noise across the years; such as Wiener filter, wavelet thresholding, anisotropic filtering, bilateral filtering, total variation and other techniques. Among such approaches which are considered wavelet thresholding as successful ultimately technique the problem lies behind smoothing the edges.

The bilateral filter was proposed as alternative for the wavelet thresholding and it is applied without smoothing the edges. That is achieved through collecting the two Gaussian filters. One of them operates in the spatial space and the other one operates in the intensity field. Therefore, it is not the spatial distance but also the intensity distance is important to identify the weights. Then, such types of filters can remove the noise in the image with maintaining their edges from the image and from the inability to remove the salt and pepper noise[Murali *et al.*, 2012].

4. Principal Component Analysis (PCA)

It is a method mostly used in the multiple variables statistical analysis. Its objective is to reduce the number of dimensions for the numerical measurements for several variables. However the dimensional minimization is, the method which searches simplification of the statistical problem with minimum loss of the information. This method is also used in processing the signals to separate the linear compiling from the signals generated from statistically independent sources. This is implemented by representing the data with the new coordinates system. This transformation is bi- directional and has no information loss [Chandrakar, 2013].

Preprocessing transformation technology creates new forms of inconsistent values of different images. That is achieved through linear transformation for

variables consistent with the circulation and move to the original coordinates system. PCA is used to find out the main components with the largest variables of the data matrix [Murali Mohan Babu, *et al.*,2012].
PCA is based on the covariance replicate or matrix convolution that can be calculated from the data matrix where the covariance matrix can be quantified from the total squares and vector multiplication. PCA solves the eigenvalues and eigenvectors to symmetrical square matrix with the total squares and vector multiplication. The eigenvector is correlated with the greater eigen value which is reflected on the same direction as being the first major element and accompanies eigenvector with second largest value identifying the second main component direction. Trace square matrix represents the total eigenvalues while the number of columns in the matrix represents the number in the matrix represents the number of the eigenvectors [Chaddad, 2014].

$$X = [x_1\, x_2 \dots\ x_m]^T \qquad (6)$$

m- component vector variable and denote by the sample matrix of X [Zhang et al., 2010]:

$$X = \begin{bmatrix} x_1^1 & x_1^2 & \dots & x_1^n \\ x_2^1 & x_2^2 & \dots & x_2^n \\ \vdots & \vdots & \vdots & \vdots \\ x_m^1 & x_m^2 & \dots & x_m^n \end{bmatrix} \qquad (7)$$

where $x_i^j,\ j = 1,2, \dots\dots, n\ \ and\ \ i = 1,2, \dots\dots, m$

The sample vector x_i is $X_i = [x_i^1\, x_i^2 \dots\dots x_i^n]$, the ith raw of sample matrix X.

$\mu_i = \frac{1}{n}\sum_{j=1}^{n} X_i(j)$ is the mean value of X_i

Then the sample vector of x_i is centralized as $\bar{X}_i = X_i - \mu_i = [\bar{x}_i^1\ \bar{x}_i^2 \dots . \bar{x}_i^n]$

Where $\bar{x}_i^j = x_i^j - \mu_i$

The centralized matrix of X is $\bar{X} = [\bar{X}_1^T\ \bar{X}_2^T \dots . \bar{X}_m^T]^T$, and the covariance matrix Ω of the centralized dataset is calculated as $\Omega = \frac{1}{n}\overline{XX}^T$

The goal of PCA is to find an orthogonal transformation matrix P to de-correlate $\bar{X}$ i.e. $\bar{Y} = P\bar{X}$, the co-variance matrix Ω of $\bar{Y}$ is diagonal:

$\Omega = \emptyset \wedge \emptyset^T$

Where $\emptyset = [\emptyset_1\, \emptyset_2 \dots\dots\dots \emptyset_m]$ is the (m x m) orthogonal eigenvector matrix

$\wedge = diag[\lambda_1\ \lambda_2 \dots\dots . \lambda_m]$ is the diagonal eigenvalue matrix with

$\lambda_1 \geq \lambda_2 \geq \cdots .. \geq \lambda_m$

$\emptyset_1\, \emptyset_2 \dots\dots\dots \emptyset_m$ and $\lambda_1\ \lambda_2 \dots\dots . \lambda_m$ are the eigenvector and eigenvalue of Ω.

$P = \emptyset^T$

$\bar{X}$ can be de-correlated then

$$\bar{Y} = P\bar{X} \ \text{ and }\ \wedge = \frac{1}{n}\overline{YY}^T \qquad (8)$$

5. Anstrobic Diffusion filter

It is nonlinear filter of different properties and it is based on the development of the nonlinear differential partial equations seeking to improve the quality of the images via removing the noise where it preserve the details as well as improvement of the edges. Practically, Perona and Malik [P. Perona and J. Malik, 1987], were suggested approximation of nonlinear diffusive to clarify the image.

$$\partial_t u = \nabla \cdot (g(|\nabla u|)\nabla u) \qquad u(0)=u_o \qquad (9)$$

Here, u_o: unfiltered image, t: diffusion time, u(t):the filtered image
The nonlinear diffusive g is a function in form of bell reducing the diffusion to zero when the diversion becomes greater than any time ago near the object edges. Some forms of the bell create front diffusion where | u∇ | is small and create back diffusion when | u∇ | is big sufficiently [Barbu, 2014].

Diffusion Pattern the Perona- Malik cannot perform well for large noise images based on point diversion. Cartte *et al* [Cartte, *et al.*,1992], was suggested contrasting properties diffusion model with Gaussian smoothing processes. This model estimates the diversion and can remove actively noisy points in the images. Also, they showed that Perona- Malik model has contrasting properties that is, resembling image can produce contrasting solutions [You, *et al.*,1996].

$$\left\{\begin{array}{l} \frac{\partial u}{\partial t} = div(C(x,y,t).\nabla u), (x,y) \in \Omega \subset R^2 \\ \quad u(0,x,y) = u_o \end{array}\right\} \qquad (10)$$

uo is the initial noised image, C is the diffusion tensor, $\Omega \subset R^2$ is the entire image domain.

$$div(C(x,y,t).\nabla u) = C(x,y,t).\Delta u + \nabla c.\nabla u$$
$$\frac{\partial u}{\partial t} = div(c.\nabla u) = c.\Delta u \qquad (11)$$

6. Noise removed by using Yc_bc_r color space

The proposed method is based on direct processing of the lightness (Y) component, and processing of indirect of the chromatic component (c_bc_r).Transform color image from basic RGB color space to Ycbcr color space by used [Perona and Malik, 1987]:

$$\begin{aligned} y &= 0.298r + 0.587g + 0.114b \\ cb &= -0.147r - 0.2880g + 0.436b \\ cr &= 0.6149r + 0.514g - 0.100b \end{aligned}$$

And the inverse transform is given by [Chandrakar, 2013]:

$$\begin{aligned} r &= y \quad + 1.401cr \\ g &= y \quad - 0.394cb \ - 0.580cr \\ b &= y \ \ 2.032cb \end{aligned}$$

The processing color components (RGB) directly cause deformation saturation and Hue components after the reverse conversion. But can handle processing color while maintaining a certain amount of saturation and Hue(c_b and r_b component). This is done by processing basic RGB color space and then convert this space into a space $YC_{bp}C_{rp}$ (we denoted p refers to processing)

We do this algorithm by the following steps:

1. Input color image C(x,y,i), i=1,2,3 (red ,green, blue) components.

2. Transform color image from RGB color space to Yc_bc_r *and estimation Y component.*

3. Apply any denoise algorithms as (Wiener,Biltral ,Anisotropic aiffusion and PCA) on the Y component to get Y_{p1} *component.*

4.Go to step 1 ,to apply any denoise algorithms on C(x,y,i) to get images with components $R_pG_pB_p$.

5. Transform color image from $R_pG_pB_p$ *to* Yc_bc_r *to getting* $Y_{p2}c_{bp}c_{rp}$.

6. Collection components Y_{p1} *and* $c_{bp}c_{rp}$ *, then applied inverse transformation to basic RGB color space to getting output image.*

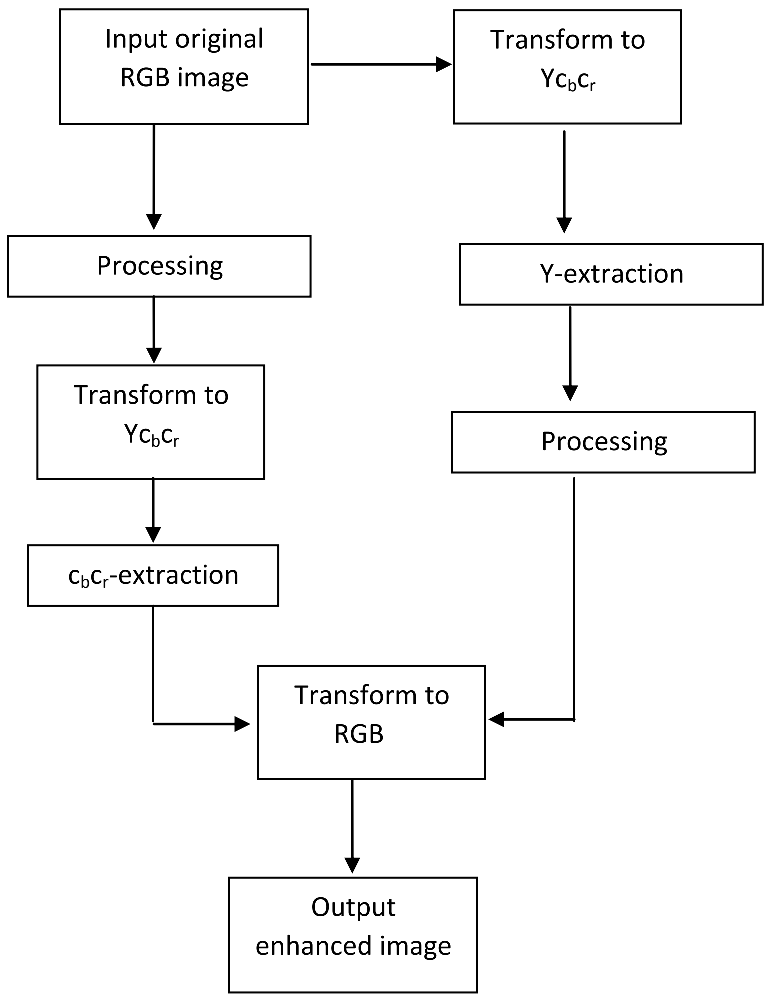

Figure 1: flowchart of adaptive algorithm for processing lightness and chromatic component in Yc_bc_r *color space.*

7.Results and discussion

In this research was used five groups of color images as illustrated in figure(2).

These images with size (512×512) and type (Tif). They Processed by matlab (R 2013a) . All groups distorted by Gaussian noise(10-80) and denoised by used as Weiner filter, the bilateral filter, anisotropic filter and PCA algorithm. First groups denoised in the figures (3, 4, 5 and 6) ,we can see the best method is (PCA) compared with other methods. From figures (7, 8, 9,10 and 11) illustrated the relationship between the distortion factor (Sigma) and PSNR ,we can see that the PCA filter has best result from another filters in all noise density levels (low ,moderate ,high distortion) due to the preservation the contrast in the edge region. The Wiener filter has best result in the low density noise level and in the high density level the beavers of the denoise of this filter is similar the bilateral filter.

The bad result appears in the anisotropic diffusion filter because of the high smooth (blur) in the images. In all algorithm the new processing(hue and saturation), succeeded in preserving the details of color except anisotropic diffusion filter.

Conclusion

In this paper we suggested using method to devised Gaussian noise by using many algorithms depends on processing the chromatic components (Hue and Saturation) and lightness component basic YC_bC_r color space. From result we can concluded. This method succeeded in the Weiner filter , the bilateral filter ,and PCA algorithm. And best results appeared in the PCA algorithm. While the proposed method does not work with anisotropic diffusion filter.

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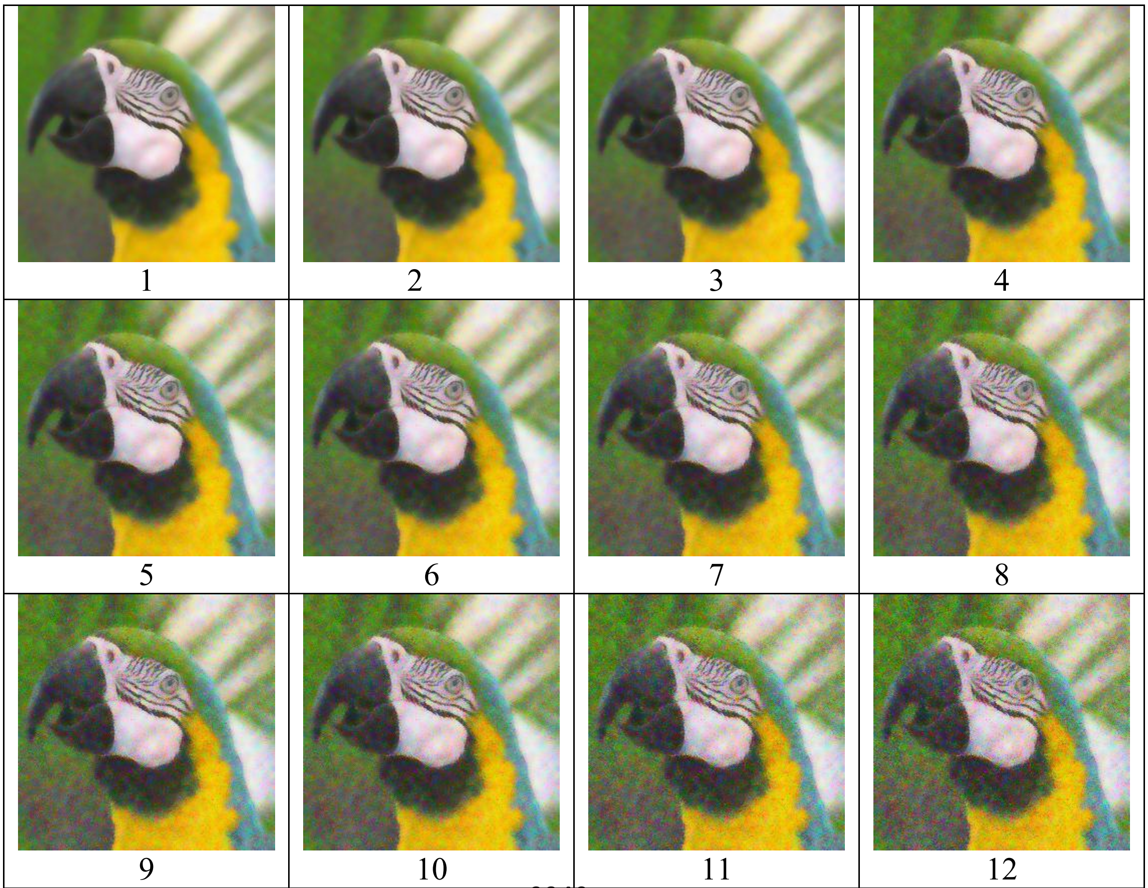
A B C D E

Figure 2: Original Images used in this search.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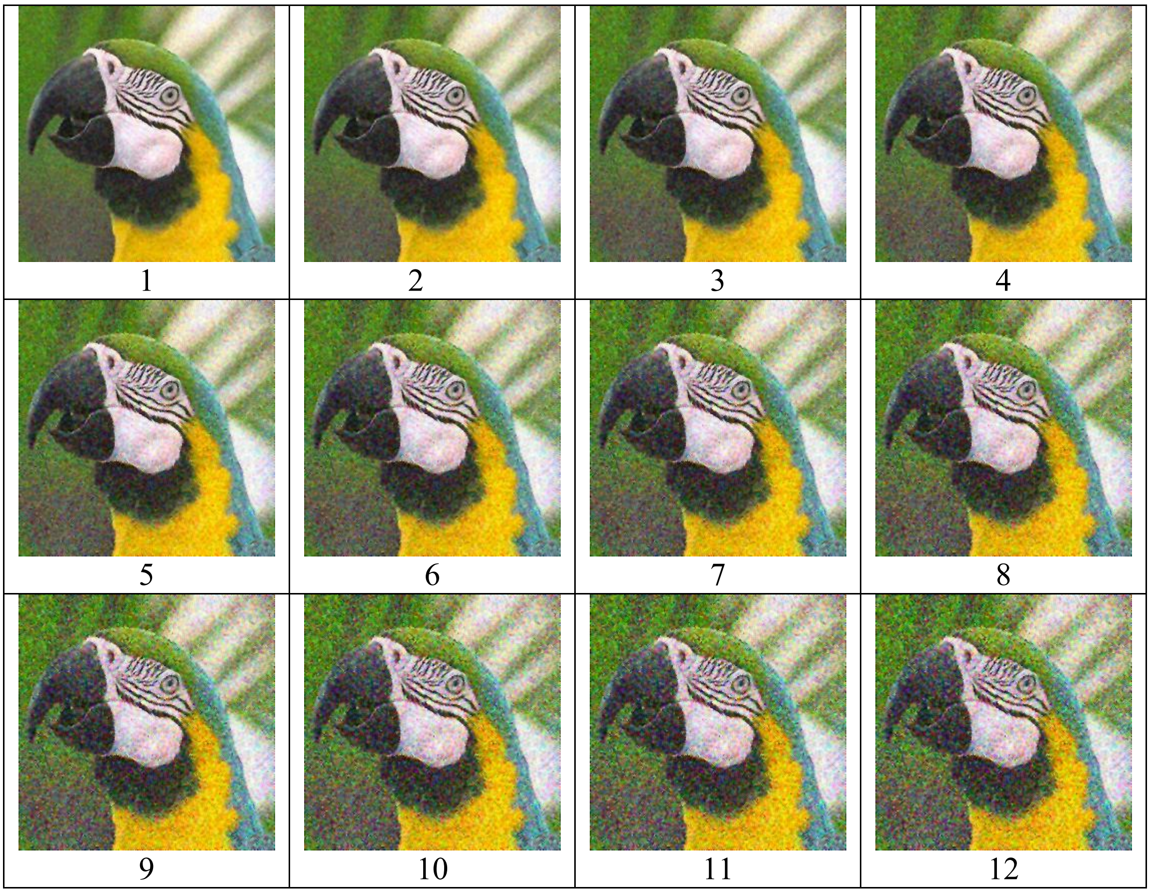
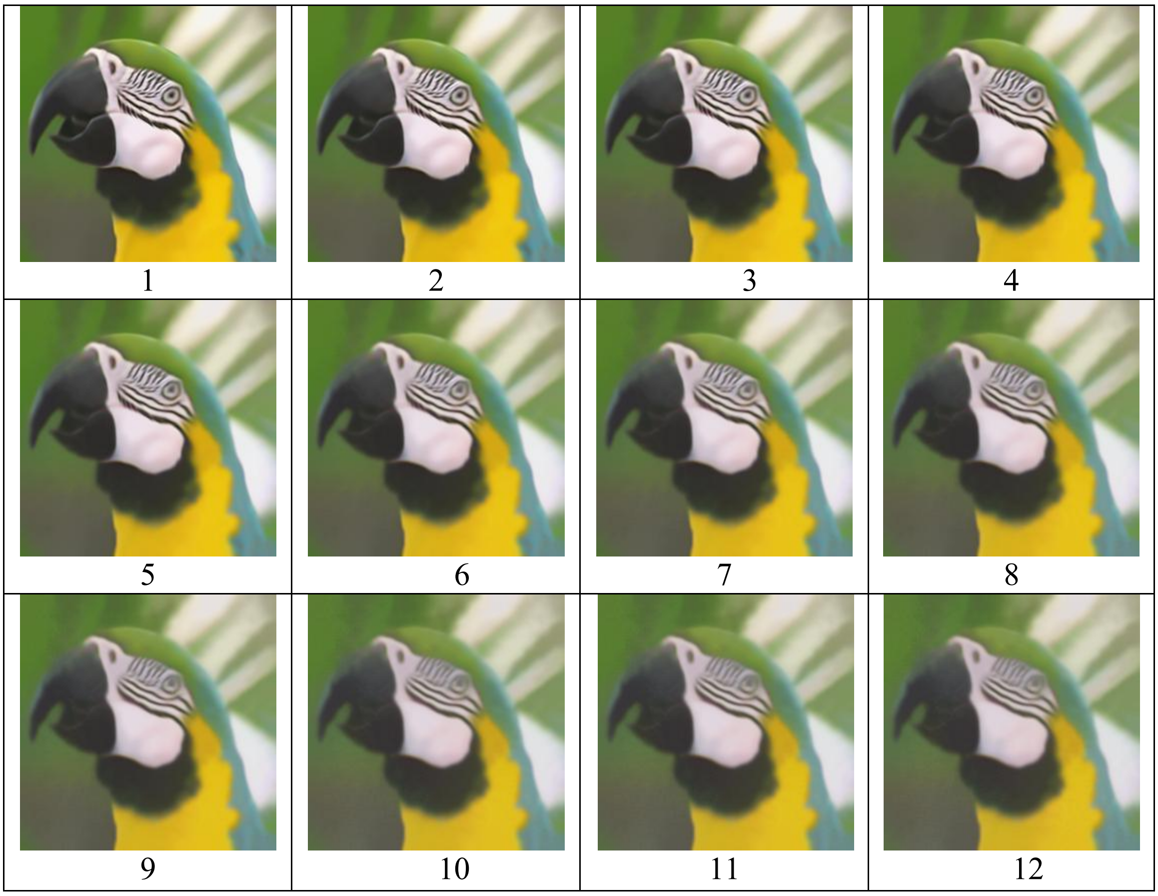


Figure 3 : Images A) denoised by using wiener filter from σ=10 to σ=80 .

Figure 4 : Images (A) denoised by using bilateral filter from σ=10 to σ=80 .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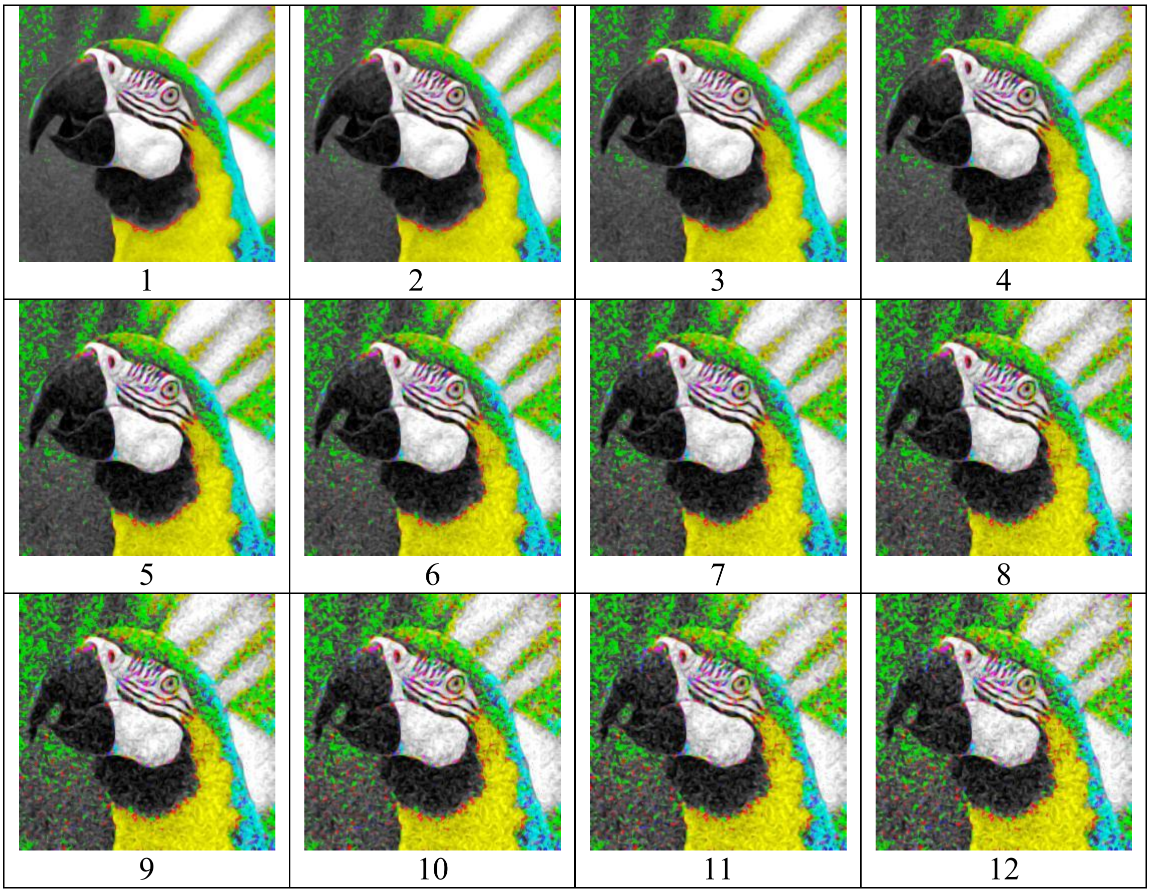
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Figure 6: Images (A) denoised by using diffusion filter from σ=10 to σ=80 .

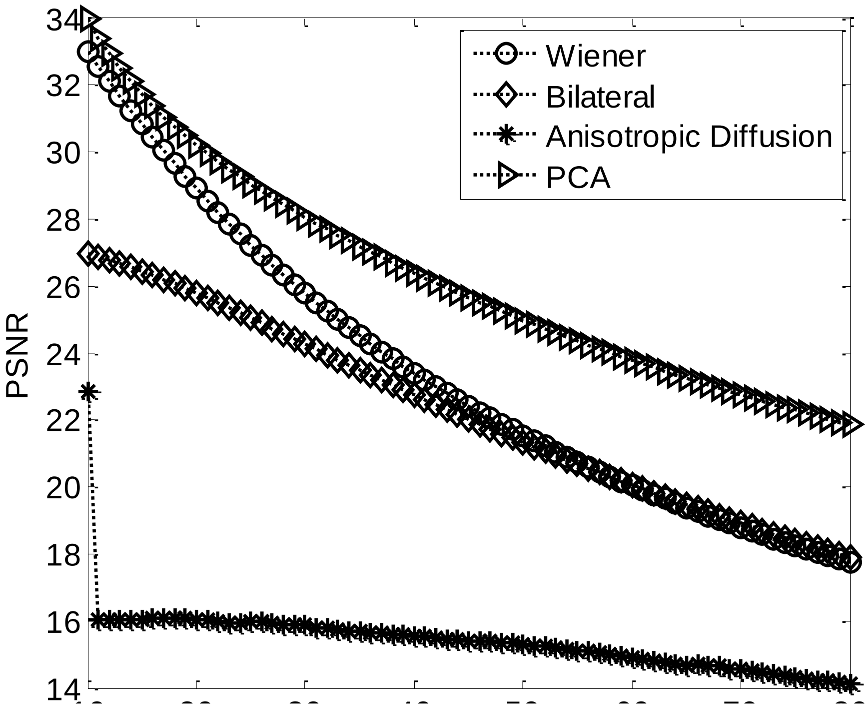


Figure 4: Images (A) denoised by using bilateral filter from σ=10 to σ=80 .

Figure 7: the relationship between the distortion factor (Sigma) and PSNR for image A for all filters with σ=10 to σ=80 .

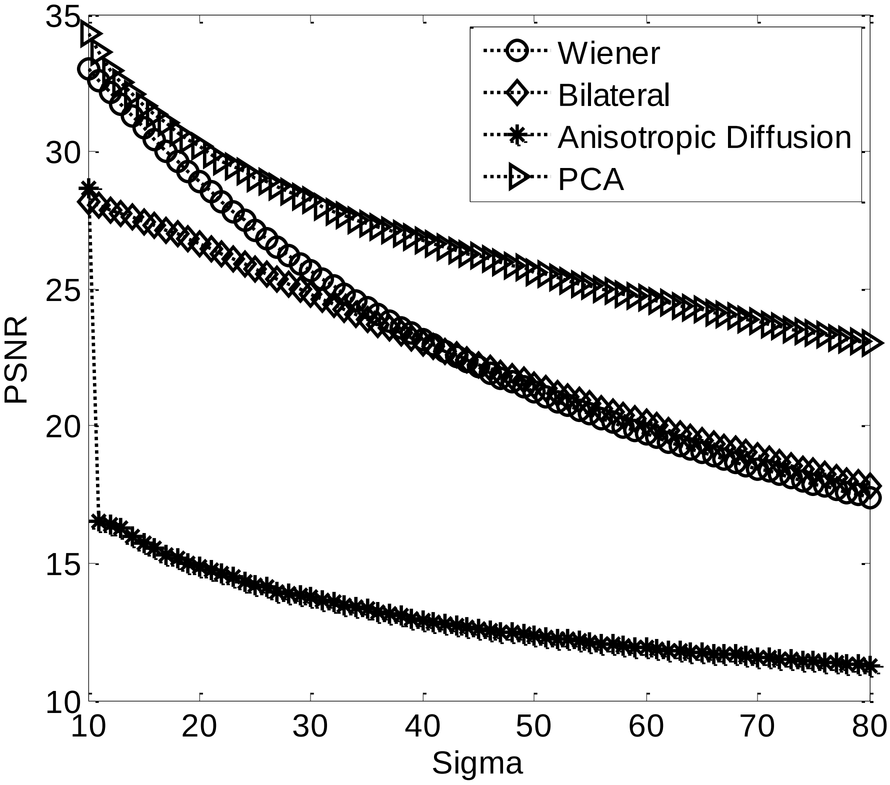
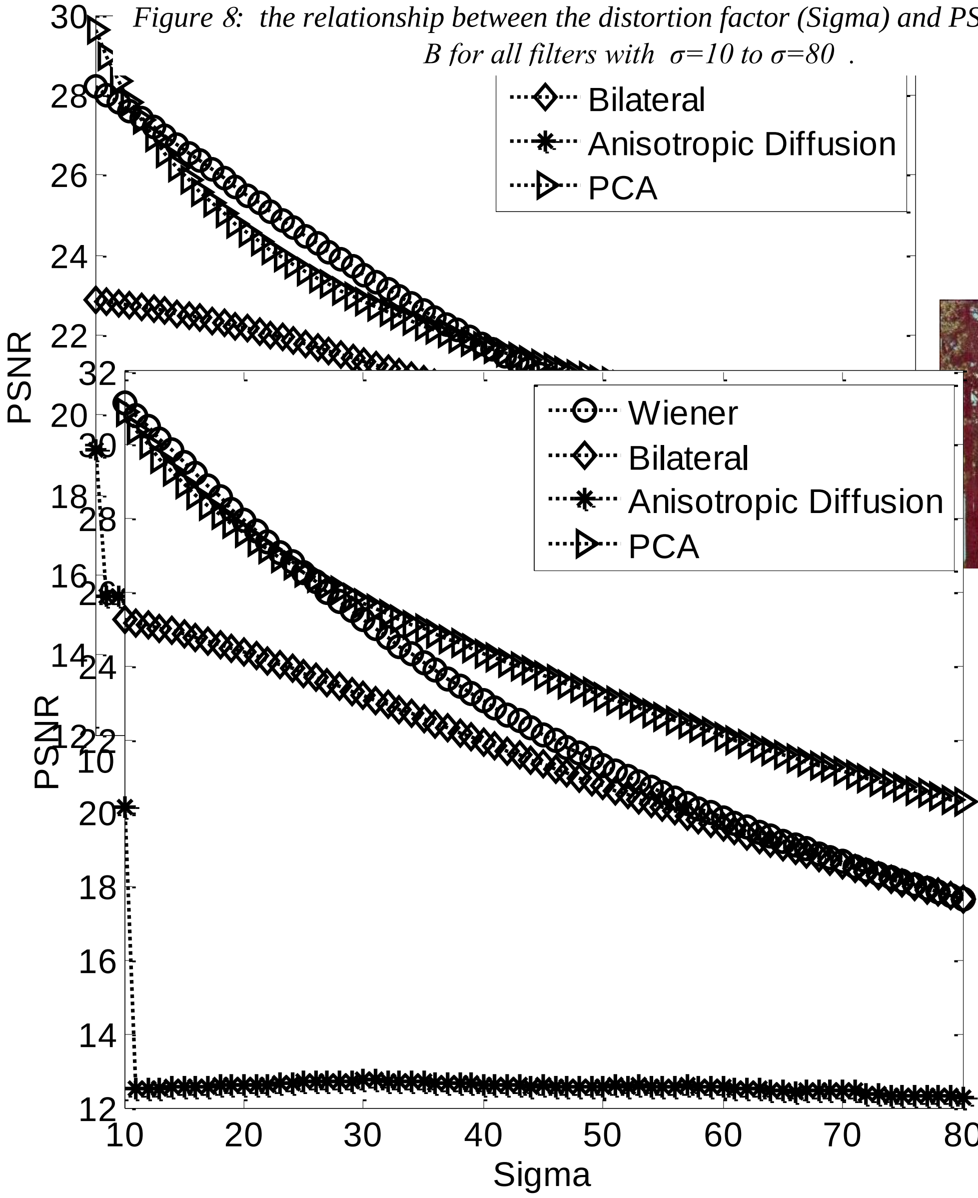


Figure 8: the relationship between the distortion factor (Sigma) and PSNR for image B for all filters with σ=10 to σ=80 .



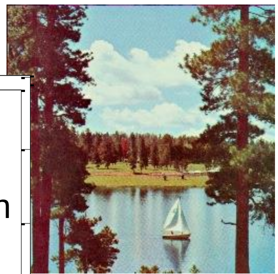


Figure 9: the relationship
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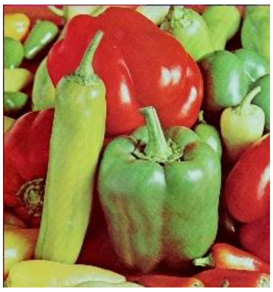

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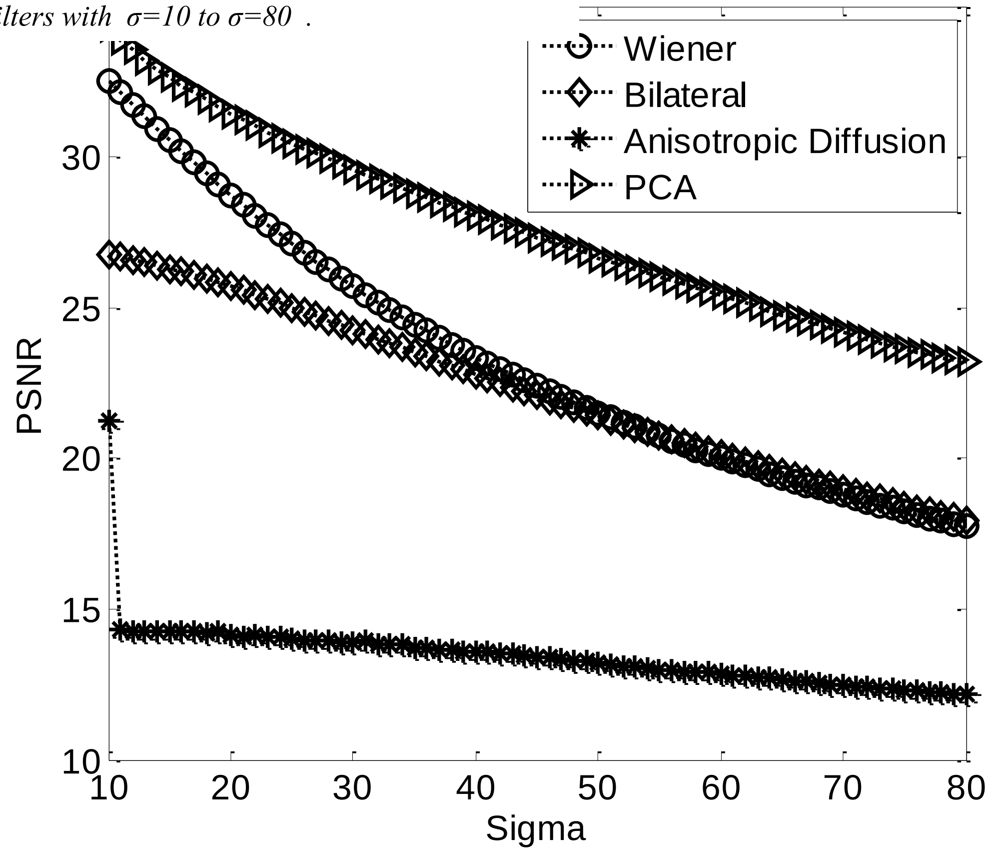

Figure 11: the relationship between the distortion factor (Sigma) and PSNR for image E for all filters with σ=10 to σ=80 .