International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 2 Issue 1, January- 2013

A Novel Approach For Noise Estimation And Removal From An Image Through PCA

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Abstract:

Visual information transmitted in the form of digital images is becoming a major method of communication in the modern age, but the image obtained after transmission is often corrupted with noise. In this paper, we want to remove noise from a singly image. We divide the image into segment and estimate noise through Principal component analysis (PCA). We proposed a model for this effect, and use it to estimate noise standard deviation in noisy image. We want to remove noise through PCA. It is provide the efficiency for estimate and removal of noise.

Keywords: Image processing, principal component analysis, noise estimation, noise removal, contour based segmentation.

1. Introduction:

Noise estimation from a single image seems like an impossible task: we need to find out whether local image variations are due to color, texture, or brightness from an image itself, or due to noise. Many algorithms [1, 2, 3, 4] have been proposed for gray-level. Generally they are classifiable into segment-based and filter-based approaches, or some combination of them.

Many algorithms are proposed for noise removal like wavelet filters [5,6] and data mining [7]. The algorithm is used for changing the neighboring pixels values through filters. Many types of filters are used to remove noise form an image. There are many procedures for this, but all attempt to determine whether the actual differences in pixel values constitute noise or real photographic detail, and average out the former while attempting to preserve the latter. Image noise is random (not present in the object imaged) variation of brightness or color information in images. The filtering approach has been proved to be the best when the image is corrupted with salt and pepper noise. The wavelet based approach finds applications in denoising images corrupted with Gaussian noise. In the case where the noise characteristics are complex, the multifractal approach can be used.

Principal component analysis is a statistical procedure that uses an orthogonal property to transform to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables [8]. The denoising phenomenon goal is to remove the noise while retaining the maximum possible the important signal or image features. To achieve a good performance in this respect, a denoising algorithm has to adapt to image discontinuities. Generally the quality of image can be measured by the peak signal-to-noise ratio (PSNR). Many algorithm are based on the PCA based denoising like CFA- PCA [9], two stage denoising PCA through LPG[10] and so on. They consider the group of pixels through the filter based algorithm for finding the pixel values.

Digital images are often corrupted by impulse noise during the acquisition or transmission through communication channels. The original meaning of "noise" was and remains "unwanted signal"; unwanted electrical fluctuations in signals received by AM radios caused audible acoustic noise ("static"). In a variety of impulse noise models for images, corrupted pixels are often replaced with values equal to or near the maximum or minimum of the allowable range.

This paper presents a new and efficient scheme for estimation and removal of single image.

Estimating the noise level from a single image seems like an impossible task: we need to recognize whether local image variations are due to color, texture, or lighting variations from the image itself, or due to the noise.

In this paper, we propose a contour-based noise estimation algorithm using principal component analysis (PCA) and a novel texture strength metric to select the contour-based segmentation. There are number of goals we want to achieve by this noise estimation and removal algorithm.

(a) Noise should be complete removed from these regions.

(b) Texture detail should not be lost.

(c) No artifacts should appear in the denoised image.

We are using the RGB model for estimation the noise from a color image.

2. Proposed Algorithm

We propose an image noise estimation and removal method that exploits:

1. Contour based segmentation
2. Image noise estimation through PCA
3. Image noise removal through PCA

2.1 Contour Based Segmentation:

In image analysis, segmentation is the partitioning of a digital image into multiple regions (sets of pixels), according to some homogeneity criterion [11].

The basic building block of the P_b contour detector is the computation of an oriented gradient signal F(x; y, Θ) from an intensity image I. This computation proceeds by placing a circular disc at location (x; y) split into two half-discs by a diameter at angle Θ.

For each half-disc, we histogram the pixel values of the pixels of I covered by it. The gradient magnitude F at location (x; y) is defined by the X^2 distance between the two half-disc histograms g and h:

$$X^2(x,y) = \frac{1}{2}\sum_t \frac{(g(i)-h(i))^2}{g(i)+h(i)}$$

2.2 Noise estimation through PCA:

After decomposing the image into segments, we can write the image model as

$$Y_i = P_b + n_i$$

where P_b is the original image contour based block with the i^{th} pixel at its center written in a vectorized format and y_i is the observed vectorized block corrupted by i, zero-mean Gaussian noise vector n_i. The goal of noise level estimation is to calculate the unknown standard deviation n given only the observed noisy image.

The minimum variance direction is calculable using the PCA. The minimum variance direction is the eigenvector associated to the minimum eigenvalue of the covariance matrix defined as

$$\sum\nolimits_y = \frac{1}{N}\sum_{i=1}^{N}(y_i - \mu)(y_i - \mu)^T$$

Where N is the data number and μ is the average of the dataset $\{y_i\}$.

The variance of the data projected onto the minimum variance direction equals the minimum eigenvalue of the covariance matrix. Then we can derive the equation

$$\lambda_{min}\left(\sum\nolimits_y\right) = \lambda_{min}\left(\sum\nolimits_p\right) + \sigma_n^2$$

2.3 Noise Removal through PCA:

The total variability in the observed data can be described by the following three components:

(Total variance)= (common variance) + (specific variance) + (error variance).

In matrix form, this can be represented as

$$\frac{1}{N}Kb = \lambda b \quad where\ b = K\alpha$$

Hence, *b* represents the Eigen vector of K with Eigen value λ. Normalizing the solutions V_k, i.e. $(V_k.\ V_k) = 1$ translates to $\lambda_k\ (b_k.b_k) = 1$. To extract non-linear principal components of a point, we compute projections onto the eigenvectors by

$$\beta_K = \left(V^K, \varphi(x)\right) = \sum_{i=1}^{N}\alpha_i^K\ K\ (x_i, x)$$

This algorithm presents several advantages over other color image noise estimation and removal algorithms. This method is very helpful for the removal of noise from an image that has a complex and irregular nature.

3. Experimental Results

We compare the proposed method with results obtained using existing methods by different scenes with different noise levels.

Level	Red pixel	Green pixel	Blue pixel	Calculation Time
σ = 5	4.98	5.08	5.10	2.28 sec
σ = 10	9.78	9.82	10.02	2.09 sec
σ = 20	19.58	19.85	19.90	2.22 sec
σ = 40	39.05	39.11	39.47	2.32 sec

Table 1 Dependence of the PSNR value on the noise variance of the Gaussian noise (Berkeley data set)

Fig.1 Experimental image (lena.png)

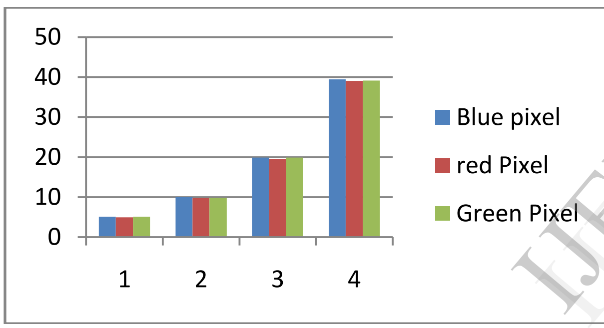

Fig.2 Experimental result

Noise level estimation results of lena.png image, where we are using the RGB model for noise estimation.

Method	MMID[10]	Wavelet denoising [8]	K-SVD Denoising [11]	Proposed
Lena	25.7(0.7315	26.0(0.7466)	26.2(0.7504)	26.0(0.7578)
Camera man	25.3(0.7310)	26.0(0.7806)	26.5(0.8048)	26.2(0.8211)
House	28.1(0.7409)	28.9(0.7708)	29.1(0.7771)	28.9(0.7891)
Paint	25.6(0.7408)	26.0(0.7616)	26.0(0.7599)	25.6(0.7569)
Tower (color)	27.3(0.7277)	27.9(0.7505)	27.9(0.7583)	27.8(0.7695)
Parrot (color)	26.7(0.7642)	27.2(0.7925)	27.4(0.7994)	27.5(0.8097)

Table.2 the PSNR (dB) and SSIM results of the denoised images at different noise levels and by different schemes

We then compare the different methods on denoising. Table 2 list the PSNR and SSIM results by different methods on the 6 test images. We evaluate and compare the different methods by using two measures: PSNR and SSIM.

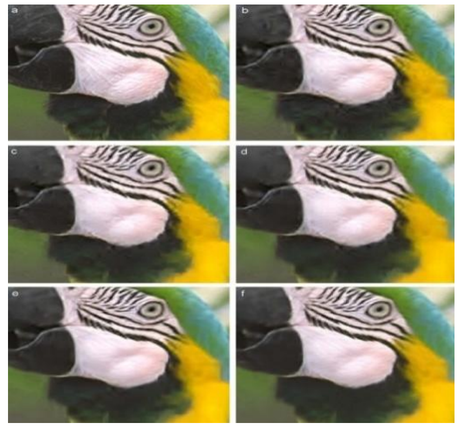

Fig. 3 The denoising results of color Parrot by different schemes.(a)Noiseless Parrot; denoised images by methods(b) [13], (c) [14]; (d) [15]; and(f)the proposed PCA method.

Conclusion:

As described in this paper, we proposed an algorithm to select contour based segmentation from the images corrupted by the Gaussian noise. We applied the PCA technique to estimate and removal the noise level based on the contour based segmented dataset. We use the maximum eigenvalue of the image gradient covariance matrix as the metric for texture strength and discuss how it changes with different noise levels. In contrast to state-of-the-art methods, the proposed method is more scene-independent and presents significant improvement for both accuracy and stability for a range of noise levels in various scenes.

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