IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 7, Issue 5, May 2018

Additive White Gaussian Noise Estimation in SVD Domain for Single Images

M.Tejaswi[1], K.Suguna[2], P.Chandanakala[3], B.Lakshmi Devi[4]

M.Tech., Assistant Professor, Dept., of Electronics and Communication Engineering,
Narayanadri Institute of Science and Technology, Rajampet, Kadapa[1,2,3,4]

Abstract: Accurate estimation of Gaussian noise level is of fundamental interest in a wide variety of vision and image processing applications as it is critical to the processing techniques that follow. In this work, a new effective noise level estimation method is approaches on the basis of the study of singular values of noise-corrupted images. Two novel aspects of this project address the major challenges in noise estimation:1)how to infer the noise level according to image singular values out of SVD space .2)to add new noise to image to be estimated and analyses the change of singular values in order to determine the content related parameter in the model , so that the proposed scheme is adaptive to visual signals, thereby enabling a wider application scope of the proposed scheme. In this work example of algorithms noise estimates include motion estimation, denoising, super-resolution, shape-from-shading, and feature extraction. Noise level estimation is useful for many computer vision and other image processing algorithms that require knowing the noise level. It the fast noise estimation algorithm using a Gaussian filters in order to estimate the amount noise, images are spilt into a number of blocks and smooth blocks are selected. SVD is a basic tool for signal processing and analysis for long, but it is explored for noise estimation in images. The analysis and experiment results demonstrate that the proposed algorithm can reliably infer noise levels and show robust behavior over a wide range of visual content and noise conditions, and that is outperforms relevant existing methods.

Keywords: SVD, AWGN, MAD, ACF.

1 INTRODUCTION

Many computer vision algorithms can work well only if the parameters of the algorithm are hand-tweaked to account for characteristics of the particular images under study. One of the most common needs for algorithm parameter adjustment is to account for variations in noise level over input images. These variations can be caused by changes in the light level or acquisition modality, and the amount of variation can be severe. An essential step toward achieving reliable, automatic computer vision algorithms is the ability to accurately estimate the noise level of images. Estimating the noise level from a single image seems like an impossible task: we need to recognize whether local image variations are due to colour, texture, or lighting variations from the image itself, or due to the noise. It might seem that accurate estimation of the noise level would require a very sophisticated prior model for images. However, in this work we use a very simple image model–piecewise smooth over segmented regions–to derive a *bound* on the image noise comparison with the area of de noising). Apart from de noising, other algorithms that can benefit from noise level estimates include motion estimation, super-resolution, shape from- shading, and feature extraction.

There are two major challenges in noise estimation from a single image:
1) how to prepare a data basis for noise level estimation with minimum influence of the image signal itself (otherwise, we would estimate noise based upon signal data) and
2) how to allow the algorithm adaptive to visual content so that it is suitable for different images. Noise estimation algorithms developed so far can be classified into three different approaches: filter- (or smoothing-) based, block based and transform-based. To illustrate that estimating the noise can make vision algorithms more robust, we apply our noise inference to two algorithms: bilateral filtering for feature-preserving smoothing, and edge detection. The resulting algorithms, properly accounting for image noise, show robust behaviour over a wide range of noise conditions.

1.2 PROPOSED METHOD:

INTRODUCTION:

Noise is unavoidable during visual data acquisition, processing and transmission, and often exhibits as the random variation of brightness or colour in images. Possible sources of random noise include film grain, various sensors and circuits of digital equipment (e.g., a scanner, digital camera, or photon detector), signal quantization and communication channels. Denoising is therefore a very important step to improve the accuracy or performance of many image processing techniques, such as image segmentation and recognition . There has been a large body of

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 7, Issue 5, May 2018

literature on image denoising. Although very promising denoising results have been achieved using a variety of methods, such as wavelets, anisotropic diffusion and bilateral filtering, the noise level in the image is often assumed known or already estimated beforehand. Different attempts for noise and artefact estimation have been performed; the estimation of noise level is difficult in practice, and overall, noise estimation is a relatively less investigated issue in the literature (in comparison with the area of denoising). Apart from denoising, other algorithms that can benefit from noise level estimates include motion estimation, super-resolution, shape from- shading, and feature extraction.

In most cases, noise can be modelled as Gaussian distribution, and such noise includes:
1) The amplifier noise of an image sensor;
2) The shot noise of a photon detector, which is a type of electronic noise that may be dominant when a finite number of particles that carry energy is sufficiently small; and
3) The grain noise of photographic film. Estimating the Gaussian noise level from a single image is a difficult task: we need to decide whether local image variations are due to colour, texture and lighting variations of the image itself, or due to the noise. In the image denoising literature, noise is often assumed to be zero-mean additive white Gaussian noise (AWGN).

In filter-based methods, a noisy image is first filtered by a low-pass filter to suppress the noise. Then the noise variance is computed from the difference between the noisy image and the filtered image. The main difficulty of filter-based methods in preparing the data basis is that the difference image is assumed to be the noise but this assumption is not held in general, because it is well known that a low pass filtered image is not the original image, especially for an image with strong structure or other visual details. In order to get a data basis for noise level estimation with minimum influence of the image signal itself, in, the vertical and horizontal information of an image is used for extracting vertical/horizontal detail components and histogram information for noise estimation, but it has a high computational load and a number of user-defined parameters to determine. In blocked-based methods, images are tessellated into a number of blocks. The noise variance is then computed from a set of homogeneous blocks. The main assumption here is that a homogeneous block in an image is a result of an absolutely smooth image block with added noise. In fact, homogeneity is a relative condition in real-world images, and a relatively homogeneous block has a big chance to contain some visual activities there. Another issue of block-based methods is how to identify the homogeneous blocks with model parameters suitable for images in general.

ADVANTAGES

1) Denoising is possible even in disturbed images regarding colour
2) Method is also applicable for texture images
3) Noise reduction is possible also in images with lightning variations
4) Noise estimation in high artefacts images is possible
5) Noise in Water marked images are also estimated using this method

OVERVIEW OF THE PROJECT

Initially we are giving an input image and then we are estimating the white Gaussian noise then we go for adding the noise and then noise is estimated using the SVD domain. Here the white Gaussian noise is estimated by using the Singular Value Decomposition method in which we can make use of the equations given in the next units.

PROPOSED APPROACH

Accurate estimation of Gaussian noise level is of fundamental interest in a wide variety of vision and image processing applications as it is critical to the processing techniques that follow. In this paper, a new effective noise level estimation method is proposed on the basis of the study of singular values of noise-corrupted images. Two novel aspects of this paper address the major challenges in noise estimation:

1) the use of the tail of singular values for noise estimation to alleviate the influence of the signal on the data basis for the noise estimation process and
2) the addition of known noise to estimate the content-dependent parameter, so that the proposed scheme is adaptive to visual signals, thereby enabling a wider application scope of the proposed scheme.

The analysis and experiment results demonstrate that the proposed algorithm can reliably infer noise levels and show robust behavior over a wide range of visual content and noise conditions, and that is outperforms relevant existing methods.

IJARCCE
ISSN (Online) 2278-1021
ISSN (Print) 2319 5940
International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 7, Issue 5, May 2018

Noise is unavoidable during visual data acquisition, processing and transmission, and often exhibits as the random variation of brightness or colour in images. Possible sources of random noise include film grain, various sensors and circuits of digital equipment (e.g., a scanner, digital camera, or photon detector), signal quantization and communication channels. Denoising is therefore a very important step to improve the accuracy or performance of many image processing techniques, such as image segmentation and recognition . There has been a large body of literature on image denoising . Although very promising denoising results have been achieved using a variety of methods, such as wavelets, anisotropic diffusion and bilateral filtering, the noise level in the image is often assumed known or already estimated beforehand. Different attempts for noise and artefact estimation have been performed; the estimation of noise level is difficult in practice, and overall, noise estimation is a relatively less investigated issue in the literature (in comparison with the area of denoising). Apart from denoising, other algorithms that can benefit from noise level estimates include motion estimation, super-resolution, shape from- shading, and feature extraction.

In most cases, noise can be modelled as Gaussian distribution, and such noise includes:
1) The amplifier noise of an image sensor;
2) The shot noise of a photon detector, which is a type of electronic noise that may be dominant when a finite number of particles that carry energy is sufficiently small; and
3) The grain noise of photographic film. Estimating the Gaussian noise level from a single image is a difficult task: we need to decide whether local image variations are due to colour, texture and lighting variations of the image itself, or due to the noise. In the image denoising literature, noise is often assumed to be zero-mean additive white Gaussian noise (AWGN).

In filter-based methods, a noisy image is first filtered by a low-pass filter to suppress the noise. Then the noise variance is computed from the difference between the noisy image and the filtered image. The main difficulty of filter-based methods in preparing the data basis is that the difference image is assumed to be the noise but this assumption is not held in general, because it is well known that a low pass filtered image is not the original image, especially for an image with strong structure or other visual details. In order to get a data basis for noise level estimation with minimum influence of the image signal itself, in, the vertical and horizontal information of an image is used for extracting vertical/horizontal detail components and histogram information for noise estimation, but it has a high computational load and a number of user-defined parameters to determine. In blocked-based methods, images are tessellated into a number of blocks. The noise variance is then computed from a set of homogeneous blocks. The main assumption here is that a homogeneous block in an image is a result of an absolutely smooth image block with added noise. In fact, homogeneity is a relative condition in real-world images, and a relatively homogeneous block has a big chance to contain some visual activities there. Another issue of block-based methods is how to identify the homogeneous blocks with model parameters suitable for images in general.

There have been modified filter-based and block based approaches for better noise estimation. Generally, block-based algorithms are simple, but their estimates may vary significantly depending on the input image and noise level. Filter-based algorithms yield good estimates for large noise cases, but they require a high computational load and a large amount of memory. There have some compromised methods as the combination of filter-based and block-based estimation algorithms. Among transform-based methods, a widely used estimation method is based on Mean Absolute Deviation (MAD). To address the two aforementioned major challenges and overcome the drawbacks in the existing work, we investigate into the possibility to estimate noise in singular value decomposition (SVD) domain. The SVD has been successfully applied to many image restoration and recognition problems. As to be analyzed in the next section, the remarkable property of the SVD is its statistical representations of image details in subspaces of decreasing importance, while the influence of noise maintains in all subspaces.

This fact is helpful since the tail of singular values (i.e., the later SVD subspaces) can be used as the proper data basis for noise estimation and image details do not have significant influence in that part of subspaces. In essence, the use of SVD enables separation of image details and noise in a single image and such separation is difficult otherwise.To be more specific in analysis, we divide "the singular" values S of a noise-corrupted image into two parts in SVD — Ss and Sn, where Ss denotes the part contributed by image structure and Sn denotes the part contributed by noise (we will explain how to calculate Ss and Sn in Section II). We did abundant experiments. Figure 1 shows experimental result of the Lena image of different sizes for Ss and Sn, with different noise injection. We can see that image details contribute very little to the later part of the singular values, as Ss; on the contrary, noise dominates the later part of the singular values, as Sn. When noise level (σ) become lower, the contribution of noise will be smaller either; however, the tail of the singular values is still dominated by noise. The figure shows the best dada basis (i.e., the range of singular values) for noise estimation is the later 80% of singular values, because this represents the data to which noise is the dominant factor. It is worthy of being noted that the influence of signal decreases rapidly in S, so the possible data basis for noise estimation can be as large as 80% of S – a bigger amount of data facilitates more reliable noise estimation.

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 7, Issue 5, May 2018

SVD FOR IMAGES AND THE INFLUENCE OF AWGN

A. Singular Values and Noise Levels

The SVD is based on the theory in linear algebra with which a rectangular matrix *A* can be decomposed into the product of three matrices - an orthogonal matrix *U*, a diagonal matrix *S*, and the transpose of another orthogonal matrix V. To be more specific, the SVD of an $m \times n$ image $\boldsymbol{A}$ (assume *r* is the rank of *A)* can be written as:

$$\mathbf{A} = \mathbf{U} \times \mathbf{S} \times \mathbf{V}^{\mathbf{T}}$$

where $U^TU = I_{mm}$; $V^T V = I_{nn}$ (I_{mm} and I_{nn} denote the m-square and n-square identity matrices); *m* and *n* represent the dimensions of *A*. The columns of *U* are orthonormal eigenvectors of AA^T, the columns of *V* are orthonormal eigenvectors of $A^T A$, and *S* is a diagonal matrix containing the square roots of eigenvalues of AA^T or $A^T A$ arranged in the descending order. Let the singular values be denoted by $s(i)(i = 0, 1, \ldots, r)$, and then $s(1) > s(2) > \cdots > \cdots > s(r)$.

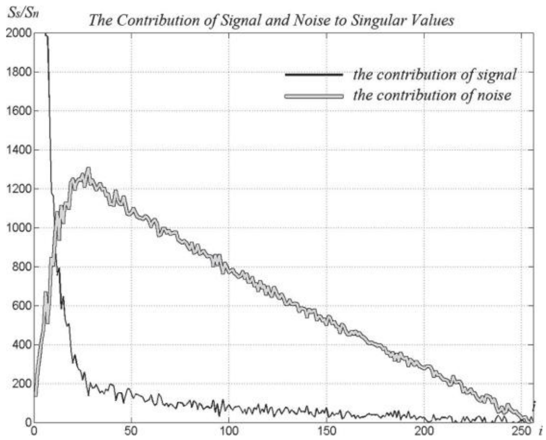

Fig (a) *Lena* 512×512, $\sigma = 50$

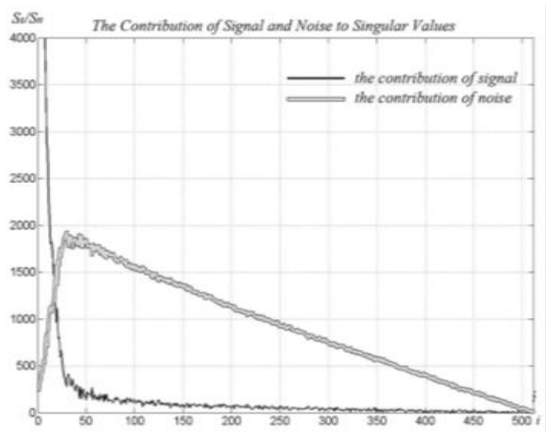

Fig (b) Lena 512×512, $\sigma = 10$

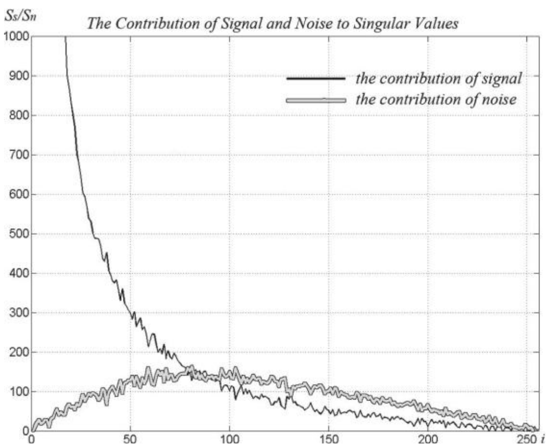

Fig (c) *Lena* 256×256, $\sigma = 50$

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 7, Issue 5, May 2018

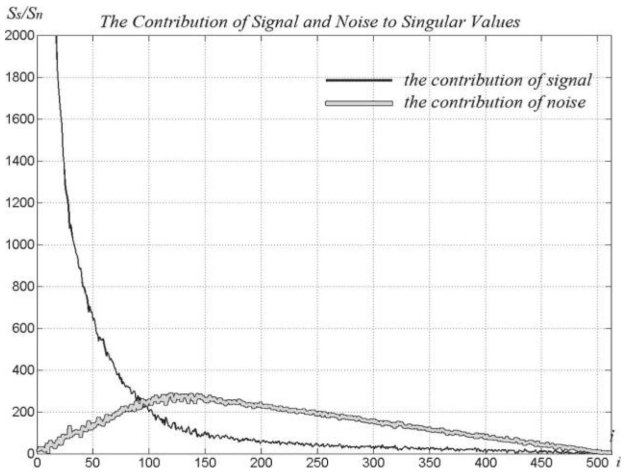

Fig. 1. Contribution of signal and noise to singular values. (a) *Lena* 512×512, $\sigma = 50$. (b) *Lena* 512×512, $\sigma = 10$. (c) *Lena* 256×256, $\sigma = 50$. (d) *Lena* 256 × 256, $\sigma = 10$.

To separate the contribution of image from that of noise, following the notations in the last section S_s and S_n are defined as the singular values due to the original image and the additive noise decomposed by singular vectors *U* and *V*

$$S_s = U^{-1} \times A_0 \times (V^T)^{-1} = U^T \times A_0 \times V$$

$$S_n = U^{-1} \times N \times (V^T)^{-1} = U^T \times N \times V$$

Figure 2 shows singular values *s(i)* of different test images with different noise levels. In Figure 2, (a), (b) and (c) are three standard 512 × 512 grayscale test images; (d) is a standard 256 × 256 grayscale test image; (e) is a 256 × 256 cartoon image; (f) is a 533 × 512 cartoon image. We can see that addition of noise to images increases the singular values in general (in line with what has been shown in Figure 1), and this is also agreeable with the results in [50]. In other words, the higher the noise level is, the larger the singular values become. More importantly, the early part of singular values (when *i* is small) are determined mainly by the image content (noise is there also but its influence is insignificant due to the strong presence from the signal itself), while the noise level can be distinguished much easily with the later part (i.e., the tail) of singular values (when *i* is large). This is the ground of the proposed technique in this paper for noise estimation.

B. AWGN Analysis

Let *N* be a zero-mean m×n AWGN image with standard deviation σ, and its SVD can be expressed as:

$$N = U \times S_n \times V^T$$

We use parameter *M* to represent the number of the last singular values (i.e., the tail) under consideration. Obviously, the average of the last *M* singular values is a function of σ, and can calculated as

$$P_M(\sigma) = \frac{1}{M} \sum_{i=r-M+1}^{r} sn(i)$$

Where $1 \le M \le r$. When M = 1, only the last singular value (i.e., sn(r)) is considered . When M = r , all singular values (i.e., sn(1) to sn(r)) are considered in the above equation

Singular value decomposition

In linear algebra, the Singular Value Decomposition (SVD) is a factorization of a real or complex matrix, with many useful applications in signal processing and statistics.

Formally, the singular value decomposition of an $m \times n$ real or complex matrix M is a factorization of the form $M = U\Sigma V^*$, where U is an $m \times m$ real or complex unitary matrix, Σ is an $m \times n$ rectangular diagonal matrix with non-negative real numbers on the diagonal, and V^* (the conjugate transpose of V, or simply the transpose of V if V is real) is an $n \times n$ real or complex unitary matrix. The diagonal entries $\Sigma_{i,i}$ of Σ are known as the singular values of M. The *m* columns of U and the *n* columns of V are called the left-singular vectors and right-singular vectors of M, respectively.

The singular value decomposition and the Eigen decomposition are closely related. Namely:

- The left-singular vectors of M are eigenvectors of MM^* .
- The right-singular vectors of M are eigenvectors of $M^* M$.
- The non-zero singular values of M (found on the diagonal entries of Σ) are the square roots of the non-zero eigenvalues of both $M^* M$ and MM^* .

IJARCCE
ISSN (Online) 2278-1021
ISSN (Print) 2319 5940
International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 7, Issue 5, May 2018

Signal & noise separation

In general, an observed (recorded) time series comprises of both the *signal* we wish to analyse and a *noise* component that we would like to remove. Noise or artifact removal often comprises of a data reduction step (altering) followed by a data reconstruction technique (such as interpolation). However, the success of the data reduction and reconstruction steps is highly dependent upon the nature of the noise and the signal. By definition, noise is the part of the observation that masks the underlying signal we wish and in itself adds no information to the analysis. However, for a noise signal to carry no information, it must be *white* with a _at spectrum and an autocorrelation function (ACF) equal to an impulse3. Most *real* noise is not really white, but colored in some respect. In fact, the term *noise* is often used rather loosely and is frequently used to describe signal contamination. For example, muscular activity recorded on the electrocardiogram (ECG) is usually thought of as noise or artifact. However, increased muscle artifact on the ECG actually tells us that the subject is more active than when little or no muscle noise is present. Muscle noise is therefore a source of information about activity, although it reduces the amount of information about the cardiac cycle. Signal and noise dentitions are therefore task-related and change depending on the nature of the information you wish to extract from your observations. We shall also examine the statistical qualities of these contaminants in terms of their probability distribution functions (PDFs) since the power spectrum of a signal is not always sufficient to characterize a signal. The shape of a PDF can be described in terms of its **Gaussianity**, or rather, departures from this idealized form (which are therefore called super- or sub-Gaussian).

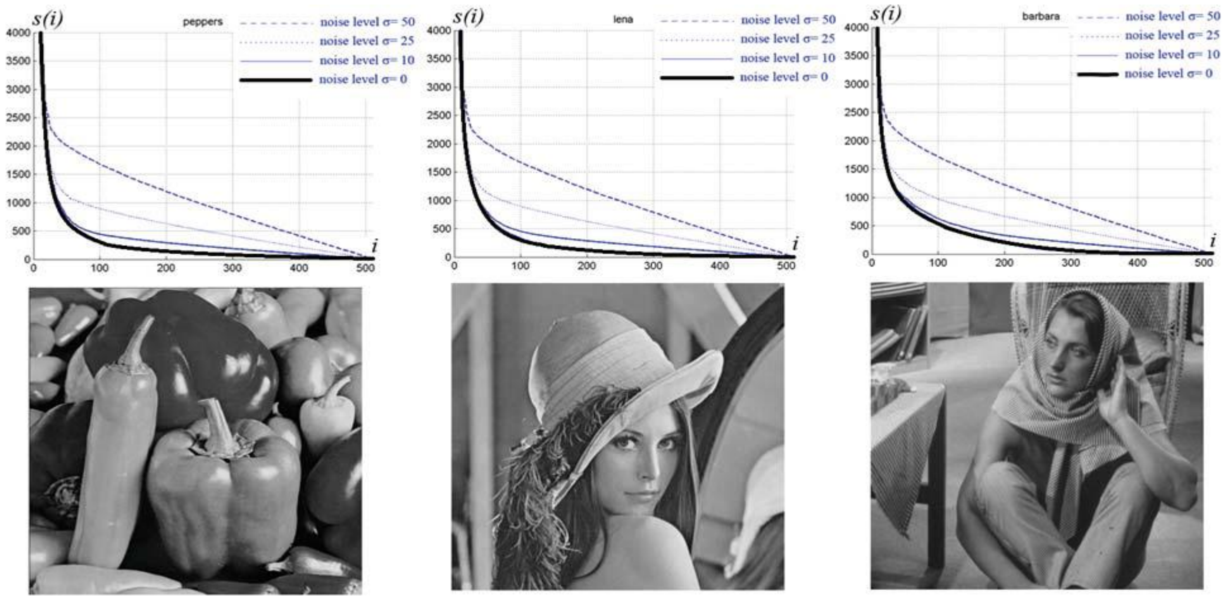

Fig (a) fig (b) fig (c)

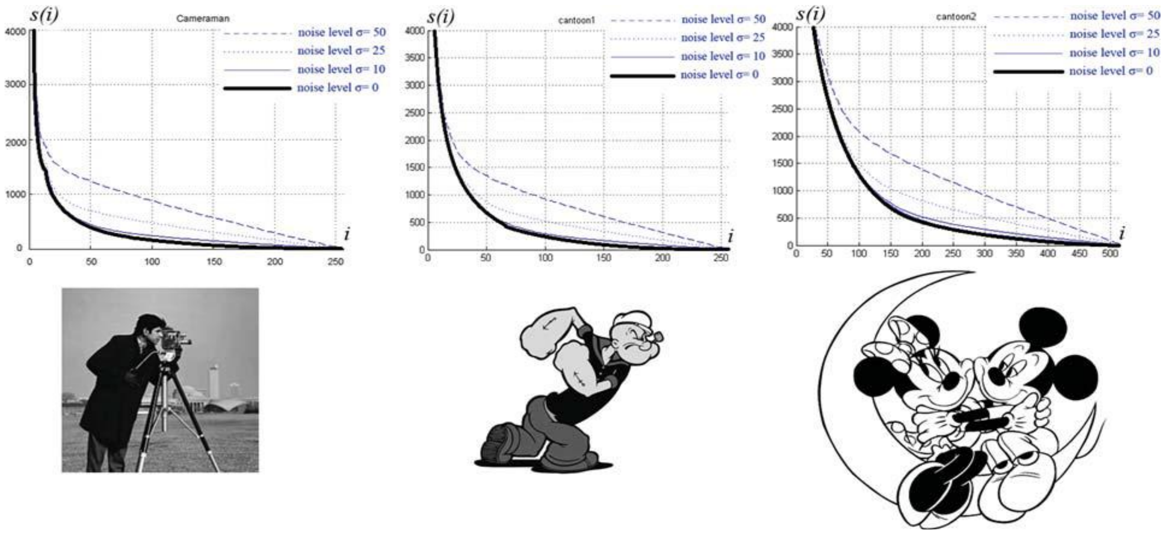

Fig (d) fig (e) fig (f)

Fig. 2. Singular values of different test images with different noise levels. (a) Singular values of *Peppers* (512×512). (b) Singular values of *Lena* (512×512). (c) Singular values of *Barbara* (512 ×512). (d) Singular values of *Cameraman* (256 ×256). (e) Singular values of image (256 ×256). (f) Singular values of image (533 × 512).

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

IJARCCE

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 7, Issue 5, May 2018

If P_M is linearly dependent on σ, two sufficient and necessary conditions must be satisfied:

$$P_M(k\sigma) = k \times P_M(\sigma)$$
$$P_M(\sigma + \sigma 1) = P_M(\sigma) + P_M(\sigma 1)$$

where σ represents the standard deviation of an additional noise $N1$.

Let us look at the first condition in (9) first. Assume $N_k = k \times N$ to be an $m \times n$ AWGN image from the same process of N : N_k is a modified version (i.e., an amplified or reduced version, depending on k) of N; that is, N and N_k are formed by a same AWGN process. The resultant standard deviation will be $k \times \sigma$, and we have

$$\begin{aligned} N_k &= k \times N \\ &= k \times U \times S_n \times V^T \\ &= U \times kS_n \times V \\ &= U \times S_{kn} \times V^T \end{aligned}$$

Where $S_{kn} = k \times S_n$

Therefore,

$$P_M(k\sigma) = \frac{1}{M} \sum_{i=r-M+1}^{r} k s_n(i) = k \times P_M(\sigma)$$

Let $N1 = (\sigma 1/\sigma) \times N$ be an $m \times n$ AWGN image of the same process of N with standard deviation $\sigma 1$, *and* $N2 = N1 + N$ be an $m \times n$ AWGN image of the same process of N with standard deviation $(\sigma + \sigma_1)$. We have

$$N_1 = U \times S_{1n} \times V^T$$
$$S_{1n} = \frac{\sigma 1}{\sigma} S_n$$

Figures 3 and 4 take 512×512 noise-corrupted Lena image as an example and show the experimental results. In Figure 3, M = 384. We can see that the line of P_{Mn} is almost the same as that of pure AWGN. The line of PMs is almost horizontal, i.e., PMs is a constant. This is agreeable with (19), where PM is the sum of $\alpha\sigma$ and β, $\alpha\sigma$ is the contribution from noise and constant β is the contribution from image structure. The more complex an image is, the greater the value of β is. Figure 4 shows the relationship of PMn and M at different noise levels. We can also see from Figure 1, the tail of Sn changes according to noise level. When noise level is low, the tail where noise is dominant is short; when noise level is high, the tail is long.

Algorithm:

1) Choose a proper M (the suggested M value is $r \times 3/4$), and calculate corresponding α;
2) Perform singular value decomposition to the noised image A;
3) calculate the average of the last M singular values P_M;
4) Add AWGN of $\sigma 1 = 50$ to noised image A to yield a new image $A1$;
5) Perform singular value decomposition to the acquired image $A1$;
6) calculate the average of the last M singular values $P1M$;
7) Figure out the estimated noise level.

Simulation results:

A. Performance of the Proposed Method

The proposed method was tested on various types of images. In our experiments on both cartoon and real-world gray images, we calculate PM and P1M as the average of the tail of singular values (the last 75% of singular values, i.e., $M = (3r)/4$).

$$S_{1n} = \frac{\sigma 1}{\sigma} S_n$$
$$N_2 = U \times S_{2n} \times V^T$$

Where $PM(\sigma + \sigma 1) = PM(\sigma) + PM(\sigma 1)$.

In the case of different processes of AWGN (e.g., we use the randn( ) function in Matlab to generate an AWGN sequence N of standard deviation σ, and then randn( ) is used again to generate another AWGN sequence $N1$ of standard deviation $\sigma 1$, i.e., $N1$ is not an amplified or reduced version of N), PM is no longer linearly dependent on σ for any M value. The extensive experimental results confirm that PM of a noise from a different process behaves almost the same as the case of noise

IJARCCE
ISSN (Online) 2278-1021
ISSN (Print) 2319 5940
International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 7, Issue 5, May 2018

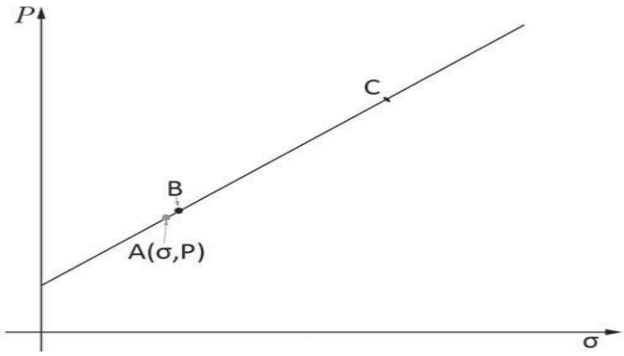

Fig. 7. Influence of $\sigma 1$

We select some test images shown in Figure 1, the test images (a), (b), (c) are 512 × 512 standard gray scale images; among them (a) is an image with simple structure and less visual details, while (c) is a complicated image with lots of details; image (d) is a 256 × 256 standard gray scale image; images (e) and (f) are cartoons of size 256 × 256 and 533 × 512 respectively. A 256 × 256 blank image with gray levels equal to 127 was also included in our experiment as the "flattest" image. When drawings of cartoonists are scanned into computers, noise is inevitable, so we take cartoons into consideration in this research. All these images are selected for test in this work due to their meaningful span and variations in visual content and resolution and show the statistical results from the.

CONCLUSION

Singular Value Decomposition (SVD) has been a basic tool for signal processing and analysis for long, but has been less explored for noise estimation in images. In this paper, we have firstly shown how to infer the noise level according to image singular values out of SVD, due to the fact that the influence of signal and noise can be separated well in the SVD space. In addition, we have proposed to\ add new noise (and therefore, known noise) to images to be estimated, and analyze the change of singular values in order to determine the content related parameter in the model (so that the proposed method can be applied to any kind of images). Our simulation results show that the proposed approach outperforms the relevant existing estimation methods over a wide range of visual content and noise conditions. Experiments results demonstrated that the proposed algorithm can determine noise levels better. Noise level estimation is useful for many computer vision and other image processing algorithms that require knowing the noise level beforehand. Examples of algorithms requiring noise level estimates include motion estimation, denoising, super-resolution, shape-from-shading, and feature extraction. Automatically inferring the image noise level and taking it into account in the algorithms that follow are important and meaningful in such algorithms and systems. The proposed and image processing algorithms better-grounded and more reliable.

REFERENCES

[1] C. Boncelet, Image Noise Models. New York: Academic, 2005.
[2] T. S. Huang, Advances in Computer Vision and Image Processing, Greenwich, CT: JAI Press, 1986.
[3] B. W. Keelan and R. E. Cookingham, Handbook of Image Quality. Boca Raton, FL: CRC Press, 2002.
[4] M. A. Covington, Digital SLR Astrophotography. Cambridge, U.K.:Cambridge Univ. Press, 2007.
[5] J. Ohta, Smart CMOS Image Sensors and Applications. Boca Raton, FL:CRC Press, 2008.
[6] R. C. Gonzalez and R. E. Woods, Digital Image Processing. Englewood Cliffs, NJ: Prentice-Hall, 2007.
[7] L. G. Shapiro and G. C. Stockman, Computer Vision. Englewood Cliffs, NJ: Prentice-Hall, 2001.
[8] J. G. Pellegrino, J. Zeibel, R. G. Driggers, and P. Perconti, Infrared Camera Characterization. Boca Raton, FL: CRC Press, 2006.
[9] L. MacDonald, Digital Heritage. London, U.K.: Butterworth, 2006.
[10] J. R. Janesick, Scientific Charge-Coupled Devices. Bellingham, WA: SPIE, 2001.
[11] R. E. Jacobson, S. F. Ray, G. G. Attridge, and N. R. Axford, The Manual of Photography. Waltham, MA: Focal Press, 2000.
[12] M. Droske and M. Rumpf, "Multiscale joint segmentation and registration of image morphology," IEEE Trans. Pattern Anal. Mach. Intell.,vol. 29, no. 12, pp. 2181–2194, Dec. 2007.
[13] X. Shen and C. R. Dietlein, "Detection and segmentation of conceal