# Enhancement of Human Visual System (HVS) using different multi resolution based filter banks

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*Abstract*— **Gaussian noise level estimation is of fundamental interest in vision and image processing applications. A new effective noise level estimation method is proposed by study of singular values of noise corrupted images. Tail of singular values is used for noise estimation and also known noise is added to the noisy image for the noise estimation by singular value decomposition. For the simple implementation and low computation costs and for visual quality improvements, to have higher PSNR values compared to previous methods different multi resolution Directional Filter Banks (DFB) is used.**

***Index Terms***— Additive white Gaussian noise, Singular values, Directional Filter Banks (DFB) .Singular Value Decomposition(SVD).

## I. INTRODUCTION

Noise is unavoidable during visual data acquisition, processing and transmission, and often exhibits as the random variation of brightness or color in images. Possible sources of random noise include film grain [1]–[3], various sensors and circuits [4]–[6] of digital equipment (e.g., a scanner, digital camera, [7], [8] or photon detector [9]–[11]), signal quantization and communication channels. De-noising is therefore a very important step to improve the accuracy or performance of many image processing techniques, such as image segmentation [12], [13] and recognition [14], [15].

In most cases, noise can be modeled as Gaussian distrib- ution, and such noise includes: 1) the amplifier noise of an image sensor [29]; 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 [9]–[11]; and 3) the grain noise of photographic film [1]–[3].

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.

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Noise estimation algorithms developed so far can be classified into three different approaches: filter- (or smoothing-) based, block- based and transform-based. In filter-based methods [21], [31], 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. In order to get a data basis for noise level estimation with minimum influence of the image signal itself, in [31], 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. In blocked-based methods [22], [32], 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.

There have been modified filter-based [31], [33] and block- based approaches [34], [35] for better noise estimation. There have some compromised methods as the combination of filter -based and block-based estimation algorithms [36]–[38]. Among transform-based methods, a widely used estimation method is based on mean absolute deviation (MAD) [23], [39]. The estimation of noise standard deviation σ is formulated as follows:

$$\hat{\sigma} = \frac{median(|\, y_i \,|)}{0.6745}, y_i \in subbandHH$$

where HH denotes the diagonal band in wavelet decompo- sition, $y_i$ denotes the coefficients in the diagonal band, and median(·) represents the median operation. The approach is based on the assumption that wavelet coefficients in the HH sub band are dominated by noise. In practice, the outcome achieved by this approach is usually higher than the truth value; the reason is that coefficients in HH sub band are dominated not only by noise, but also by image details. To overcome the drawbacks in the existing work, the SVD has been successfully applied to many image restoration [41]–[46] and recognition [47]–[49] problems.

## II. 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.

### *B. AWGN Analysis*

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

$$N = U * S_n * V^T$$

$$\sigma^2 = \sum_{i=1}^{r} S_n^2$$

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

$$P_M = \frac{1}{M} \sum_{i=r-M+1}^{r} S_n$$

where 1≤ M ≤r. WhenM = 1, only the last singular value (i.e., $S_n$ (r)) is considered in (8); when M = r, all singular values (i.e., sn(1) to s(r)) are considered.

## III. PROPOSED NOISE ESTIMATION ALGORITHM IN THE SVD DOMAIN

The experimental results and analysis we described in Section II show the relation of the average of the last M singular values (i.e., $p_M$ ) and the AWGN level (i.e., σ) is of approximate linearity.

we can calculate the standard deviation $\sigma_2$ as:

$$\sigma_2 = \sqrt{\sigma^2 + \sigma_1^2}$$

we can figure out the value of σ

$$\hat{\sigma} = \frac{\alpha\sigma_1^2}{2(P_{1M} - P_M)} - \frac{P_{1M} - P_M}{2\alpha}$$

The proposed noise level estimation procedure for image A is therefore composed of 7 stages as follows:

1) Choose a proper M (the suggested M value is r×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 PM;
4) Add AWGN of σ1 = 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 $p_{1M}$
7) Figure out the estimated noise level by above Formula.

## IV. 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 select some test images shown in Fig 1, the test images (a), (b), (c) are 512×512 standard grayscale 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 grayscale 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

| Noise | σ=10 | σ=15 | σ=20 | σ=25 | σ=30 | σ= 35 | σ= 40 | σ=45 | σ=50 |
|---|---|---|---|---|---|---|---|---|---|
| Lena | 0.17 | 0.18 | 0.30 | 0.34 | 0.41 | 0.47 | 0.52 | 0.60 | o.64 |
| Pepper | 0.15 | 0.21 | 0.29 | 0.30 | 0.44 | 0.46 | 0.58 | 0.57 | 0.67 |
| cameramen | 0.19 | 0.23 | 0.26 | 0.34 | 0.36 | 0.51 | 0.67 | 0.69 | 0.81 |

Table I . Standard deviation of noise estimation for 100 test images

We test each image 100 times under a certain noise level in order to check if the proposed method can work stably. The experimental results proved that the proposed method is effective for both real-world and cartoon images, and the noise level of AWGN can be estimated reasonably well in the SVD domain. Comparing the estimate results of each image, we can also see the efficiency of our technique has little to do with the content of images. Our abundant tests show that from "flattest" image to ordinary images with details and flat areas, and to images that are rich of edges, the estimate results are of about the same accurate.


Fig 1. Input image with different noise levels.


Fig 2. Output image by applying SVD process

### *B. Performance Comparisons*

We have compared proposed method with 3 existing meth- ods. The X axis denotes the noise level σ, and they denotes the noise estimation error.

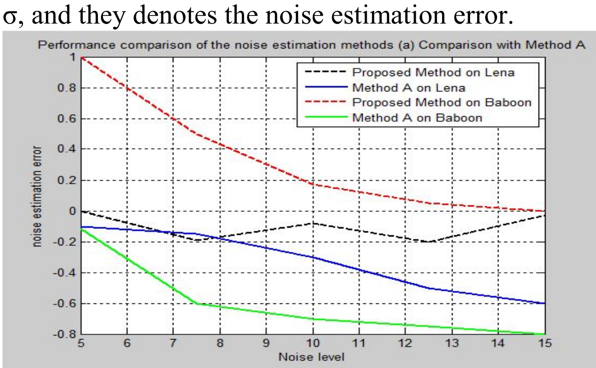


Fig a. Comparison with method A

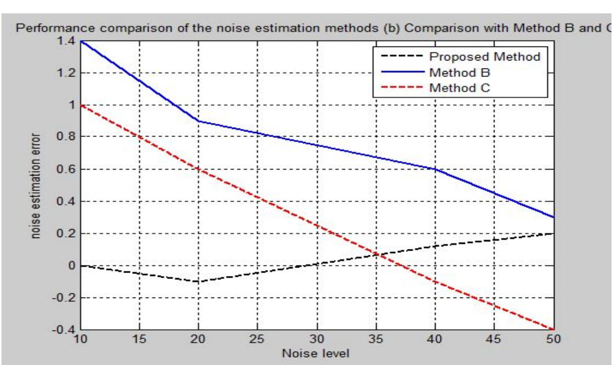


Fig b. Comparison with method B and C

Fig 3.performance comparison of the noise estimation methods

### *C. Three Criteria for Noise Estimators*

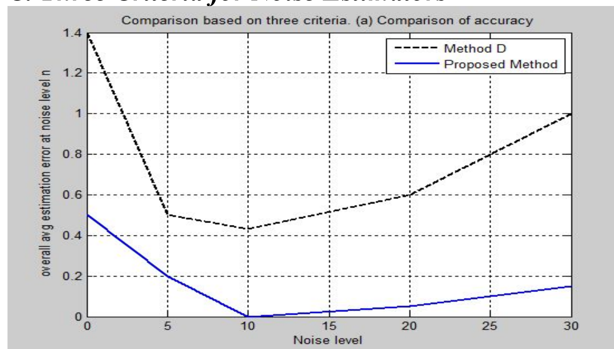


Fig a. Comparison of accuracy

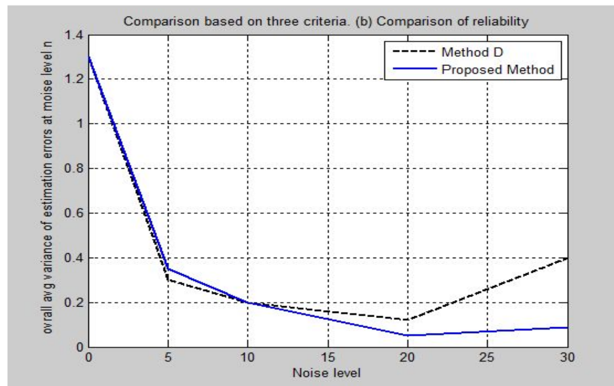


Fig b.Comparison of reliability

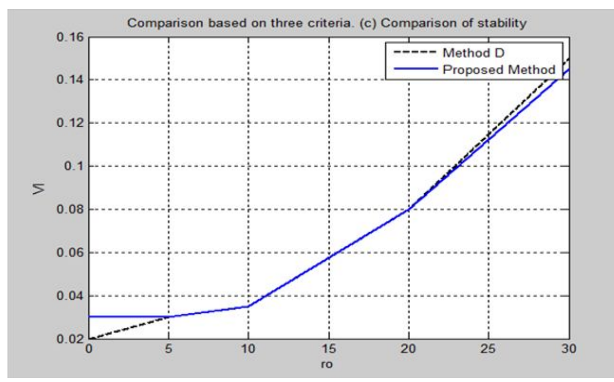


Fig C: Comparison of stability

Fig 4:Comparison based on three criteria

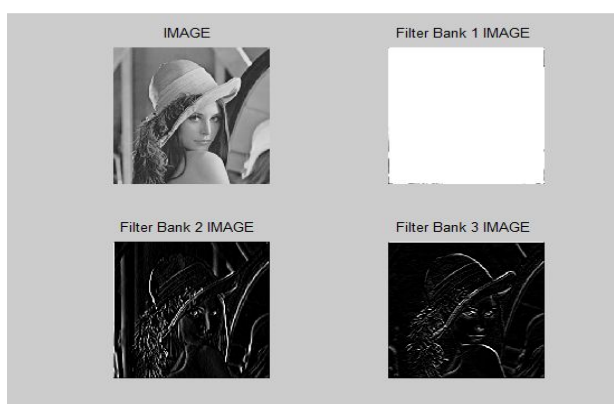


Fig 5:Simulation result by using different multi resolution directional filter banks

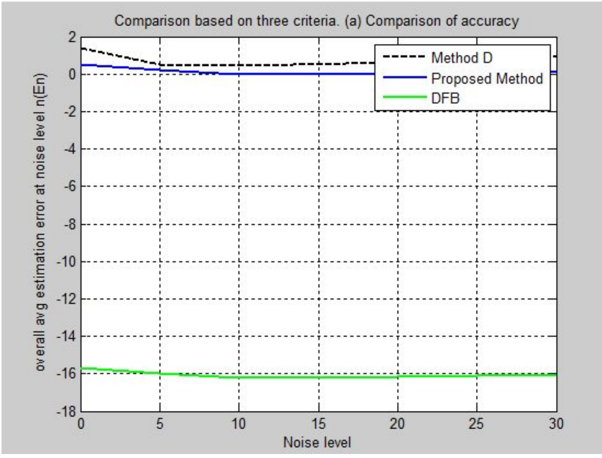


Fig a: Comparison of accuracy

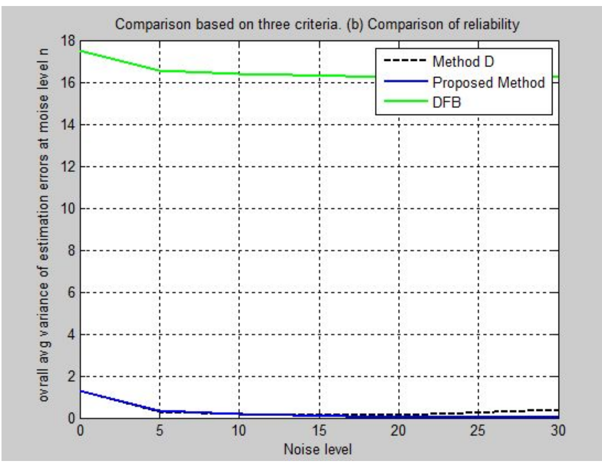


Fig b:Comaparison of reliability

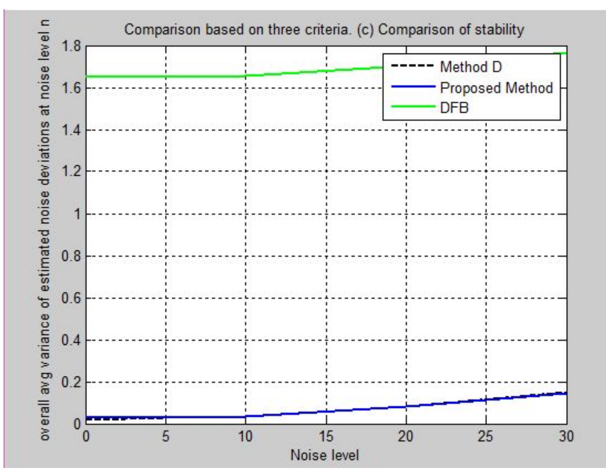


Fig c: Comparison of stability

Figure 6:Performance comparision of existing method and Directional filter banks

## 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, 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 better. The implementation of the proposed approach has resulted in low computation costs and for visual quality improvements and to have higher PSNR values.

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