Noise Estimation and Quality Assessment of Gaussian Noise Corrupted Images

V M Kamble and K Bhurchandi
Visvesvaraya National Institute of Technology, Nagpur, India
E-mail: vipinkamble97@gmail.com

Abstract. Evaluating the exact quantity of noise present in an image and quality of an image in the absence of reference image is a challenging task. We propose a near perfect noise estimation method and a no reference image quality assessment method for images corrupted by Gaussian noise. The proposed methods obtain initial estimate of noise standard deviation present in an image using the median of wavelet transform coefficients and then obtains a near to exact estimate using curve fitting. The proposed noise estimation method provides the estimate of noise within average error of +/-4%. For quality assessment, this noise estimate is mapped to fit the Differential Mean Opinion Score (DMOS) using a nonlinear function. The proposed methods require minimum training and yields the noise estimate and image quality score. Images from Laboratory for image and Video Processing (LIVE) database and Computational Perception and Image Quality (CSIQ) database are used for validation of the proposed quality assessment method. Experimental results show that the performance of proposed quality assessment method is at par with the existing no reference image quality assessment metric for Gaussian noise corrupted images.

1. Introduction
Digital images have become an important part of our lives. From CCTV camera to mobile phones, majority devices are equipped with imaging technology. The captured images are expected to be of high quality in accordance with the human perception. An ideal approach to estimate the noise and to evaluate the quality of an image is to score the image by different individuals and then pool the result. But this is a time consuming and subjective procedure and the quality score might not indicate the exact visual quality of an image as it is an average of individual scores. Thus, an algorithmic approach is required for real time quality assessment and noise estimation of images.

The image quality evaluation problem is broadly classified into 3 categories as,
- Full Reference Image Quality Assessment (FR-IQA)
- Reduced Reference Image Quality Assessment (RR-IQA)
- No Reference Image Quality Assessment (NR-IQA)

FR-IQA algorithms require a ground truth or reference image for quality evaluation of the distorted image. RR-IQA assesses quality of the distorted image by comparing only the features of distorted image with that of the reference image. In NR-IQA, the image quality is computed using information available in the distorted image only. This makes NR-IQA a challenging task. The NR-IQA problem is further classified into two sub categories-
- Distortion Specific (DS) NR-IQA
- Non-Distortion Specific (NDS) NR-IQA

Distortion Specific NR-IQA [1-3] refers to the algorithms that are designed only for specific type of distortions and their performance is highly dependent on the type of distortion present in an image. Non-Distortion Specific algorithms are generalized algorithms that can be used to evaluate the quality
of an image which is degraded by any type of distortion. Handling all types of distortions in a single algorithm is a challenging task. Few algorithms like BIQI [4] and DIIVINE [5] use a two-step framework to first identify the type of distortion present in an image and then analyze the quality accordingly. BLIINDS-II [6] uses Natural Scene Statistics (NSS) of Discrete Cosine Transform (DCT) coefficients to evaluate the quality of an image. Peng Ye and David Doermann [7] employed Gabor filter features to train a codebook for quality assessment.

The main parameter for distortion of image quality is noise. Estimating this noise can also assist in enhancing the performance of majority denoising algorithms which require a prior estimate of noise present in an image for effective noise removal. This noise estimate information is usually obtained from the user before denoising an image. This makes denoising a user dependent task whose performance is highly influenced by the noise estimate. Hence, an accurate estimate of noise is very important for effective denoising.

In this paper, we present a low complexity based DS NR-IQA algorithm which is optimized for quality evaluation of images corrupted by Gaussian noise. We also present a fairly accurate noise estimator of Gaussian noise present in an image. The proposed methods are based on initial noise estimation in distorted image using wavelet transform [8]. The initial noise estimate is mapped to Differential Mean Opinion Score (DMOS) using Velde’s non-linear mapping equation [9] for quality assessment. The same initial estimate is used to obtain the exact noise estimate of an image using curve fitting. A short description of wavelet transform and Velde’s non-linear equation is presented in section 2. In section 3, we describe our proposed approach for noise estimation based on initial estimate from wavelet transform. In section 4, we describe the proposed method for image quality assessment. We benchmark the proposed noise estimation method and the proposed image quality metric with existing state of the art algorithms in section 5 and conclude the paper in section 6.

2. Noise Estimate and Mapping Function

We employ the signal noise estimator proposed by D. L. Donoho and I. M. Johnstone [8] to obtain an initial estimate of Gaussian noise using wavelet transform. Performance of this noise estimator is presented in figure 1 for four test images Lena, Barbara, Cameraman and Peppers. Ideally the performance should have been a straight line passing though origin. The important observation of figure 1 is that the performance curve closely matches for all the images. For low values of added noise standard deviation, the estimate is fairly correct.

The estimated noise is then mapped to correlate with human perception using Koen Velde’s non-linear equation [9] for image quality assessment. The same noise estimate is used to obtain exact noise present in an image using proposed curve fitting.

![Figure 1. Noise estimation using Wavelet Transform.](image-url)
2.1 Noise Estimate using Wavelet Transform

Discrete Wavelet Transform (DWT) decomposes a signal into high pass and low pass components. DWT is obtained by passing the signal through series of high pass and low pass filters. DWT for a signal \(x(n)\) is defined as in (1)

\[
y_{\text{high}}[k] = \sum_n x[n] \times g[2k - n]
\]

\[
y_{\text{low}}[k] = \sum_n x[n] \times h[2k - n]
\]

where \(g\) and \(h\) are high pass and low pass filters respectively. DWT of an image signal results in four sub-band components namely HP-HP, HP-LP, LP-HP and LP-LP (where, LP - low pass, HP – high pass). The noise estimator proposed by D. L. Donoho and I. M. Johnstone \[8\] uses the median of HP-HP component of wavelet transform to evaluate the noise present in an image. The noise estimate \(\sigma_{\text{est}}\) is defined as

\[
\sigma_{\text{est}} = \frac{\text{median}(\text{abs}(W))}{0.6745}
\]

where, \(W\) is the HP-HP component of the finest level of wavelet sub-band. The HP-HP sub-band contains the noise as well as diagonal edges present in an image. The coefficients corresponding to edges are the high vales present in sub-band. Noise is uniformly distributed throughout the sub-band, hence can be estimated using median of the sub-band coefficients.

\(\sigma_{\text{est}}\) is able to provides a rough approximation of standard deviation of Gaussian noise present in the image. Though \(\sigma_{\text{est}}\) is approximately equal to the noise present in the image, it does not linearly correlate with the human perception of visual quality. Hence, \(\sigma_{\text{est}}\) cannot be used independently as a visual quality indicator.

2.2 Mapping Function

Koen Velde \[9\] proposed a non-linear function to enhance the low value transform domain coefficients. It is observed from heuristic experimentation that the Gaussian noise present in an image and visual perception of human do not correlate linearly. Hence, we use this non-linear mapping function to correlate the noise estimate with the visual quality of an image. The mapping function \[9\] is defined as

\[
y(x) = \left(\frac{m}{x}\right)^p\]

where,

\(y\) - multiplying parameter for mapping \(x\)
\(m\) - cross-over parameter
\(x\) - input signal intensity
\(p\) - degree of non-linearity

‘\(y\)’ produces a value greater than 1 for all \(x\) below the cross-over parameter ‘\(m\)’ and vice versa. The values that are lower than \(m\) are boosted and the values greater than \(m\) are suppressed. \(y\) produces a nonlinear curve for boosting and suppressing the input values depending on the cross-over parameter \(m\).
3. Proposed Noise Estimation Method

The noise estimate obtained using (2) provides an approximate value of noise standard deviation of an image. But the error between estimated and actual noise content of the image goes on increasing as the amount of noise increases. To overcome this problem, we have proposed a novel noise estimator which is based on the wavelet domain estimator described in section 2.1.

The mismatch between actual noise present in an image and the noise estimate using (2) for standard images (Lena, Barbara, Cameraman and Peppers) is shown in figure 1. It can be observed that the noise estimate is very consistent for different images. But, the difference between actual noise present in the image and estimated noise goes on increasing as the amount of noise increases. This non-linearity of the curve in figure 1 causes the error in estimation of exact noise present in an image.

To obtain the exact estimate of noise from a noisy image, we use curve fitting to the curves in figure 1. After heuristic experimentation, we found that the exact estimate of noise can be obtained by a fifth degree polynomial curve using data from figure 1. The final estimate of noise \( \sigma \) using curve fitting is presented in (4).

\[
\sigma = p_1 \sigma_{est}^5 + p_2 \sigma_{est}^4 + p_3 \sigma_{est}^3 + p_4 \sigma_{est}^2 + p_5 \sigma_{est} + p_6
\]

The values of polynomial coefficients in (4) are optimized to fit the curves in figure 1. Average of all four curves is taken to obtain a single curve; this curve is then fit using the curve fitting toolbox of MATLAB. Following are the values of coefficients:

\[
\begin{align*}
p_1 &= 5.404 \times 10^{-8} \\
p_2 &= -1.092 \times 10^{-5} \\
p_3 &= 8.695 \times 10^{-4} \\
p_4 &= -2.784 \times 10^{-2} \\
p_5 &= 1.383 \\
p_6 &= -1.707
\end{align*}
\]

The polynomial coefficients \( p_1 \) to \( p_6 \) are obtained using standard images of denoising experimentation. These images contain all major textures possible in natural images like smooth regions, sharp edges, curves and fine edges. Hence the polynomial coefficients \( p_1 \) to \( p_6 \) obtained using these images are robust to the changes in image textures.

4. Proposed Image Quality Assessment Method

The noise estimate and visual perception of humans are not linearly correlated. Hence, we map the noise estimate using a non-linear function to achieve high linear correlation. The noise estimate \( \sigma_{est} \) of an image is obtained using (2). The product of \( \sigma_{est} \) and mapping function gives the final quality metric \( Q \) as defined in (6).

\[
\text{QualityMetric}(Q) = \left( \frac{m}{\sigma_{est}} \right)^p \times \sigma_{est} = \frac{m^p}{\sigma_{est}^{p-1}}
\]

Values of the cross-over parameter \( m \) and the degree of non-linearity \( p \) are selected as 65 and 0.65 respectively. These values are obtained heuristically by comparing the values of \( Q \) with that of DMOS values from LIVE database [10] for varying \( m \) and \( p \). At \( m=65 \) and \( p=0.65 \), the values of \( Q \) and DMOS are observed to have a maximum linear correlation. The range of the proposed quality metric is from 0 to 100 where 0 indicates best image quality and 100 indicates poor image quality. A flowchart of proposed quality assessment method is presented in figure 2.
To establish the consistency of the proposed quality assessment method, we plot the proposed quality metric ($Q$) values for increasing magnitude of Gaussian noise standard deviation as shown in figure 3. Gaussian noise is added to standard Parrots.bmp image from LIVE database. Corresponding quality score obtained using the proposed method is plotted against the Gaussian noise standard deviation. It can be observed from figure 3 that the value of $Q$ is increasing non-linearly with the standard deviation of added noise. This non-linearity is required because the human perception of visual quality and the actual noise present in an image are not linearly related.

The proposed quality metric ($Q$) does not require any training and gives the quality score of an image based on an equation. Hence, it is computationally efficient and easy to calculate by simple coding. The proposed metric ($Q$) has same computation complexity as that of wavelet transform, i.e. $O(N)$. Average time taken for quality assessment of an image of size 512x512 using proposed metric ($Q$) is 20ms. The system on which the time computation is evaluated has the following configuration: i7-4770 CPU@3.4GHz, 32GB Ram, Windows 8.1 64 bit operating system.

5. Benchmarking and Discussion
The proposed noise estimation method is benchmarked by comparing the actual (added) noise present in an image with the estimated noise. Noise estimation for standard images with added noise of standard deviation 20 is shown in figure 4.
The noise estimates and the percentage error in estimation for a wide range of added noise are presented in table 1.

| Added Noise | Estimated Noise / % Error |
|-------------|---------------------------|
|             | bikes | caps | House | lighthouse |
| 10          | 11.53/15.30 | 10.36/3.66 | 10.48/4.88 | 10.98/9.84 |
| 20          | 20.81/4.09 | 20.35/1.79 | 20.23/1.18 | 20.55/2.78 |
| 30          | 30.06/0.21 | 30.30/1.02 | 29.99/0.01 | 30.61/2.03 |
| 40          | 39.84/1.63 | 41.24/3.10 | 39.69/0.75 | 41.29/3.23 |
| 50          | 49.09/1.80 | 52.11/4.23 | 49.71/0.56 | 51.72/3.44 |
| 60          | 58.48/2.52 | 62.29/3.82 | 59.04/1.59 | 61.54/2.57 |
| 80          | 77.11/3.60 | 83.08/3.85 | 78.60/1.74 | 83.19/3.99 |
| 100         | 96.59/3.40 | 103.73/3.73 | 98.87/1.12 | 101.80/1.80 |
| 120         | 116.36/3.03 | 127.23/6.02 | 118.06/1.61 | 122.13/1.78 |
| 140         | 134.82/3.7 | 146.36/4.54 | 138.69/0.93 | 147.47/5.34 |
| 160         | 154.30/3.55 | 168.95/5.59 | 157.96/1.27 | 167.92/4.95 |
| 180         | 172.60/4.10 | 184.19/2.33 | 176.28/2.06 | 174.41/2.45 |
| 200         | 194.34/2.82 | 208.66/4.33 | 190.14/4.92 | 200.54/0.27 |
| Avg. % Error | 3.83 | 3.69 | 1.74 | 3.42 |

Graphical results for these images are presented in figure 5. The noise estimations are calculated for four popular images (Lena, Barbara, Cameraman and Peppers) which contain most major textures that might be possible in practical images. The average error in noise estimation over wide range of noise standard deviation is below 4%. Also, in figure 5, it can be observed that the noise estimates obtained using proposed estimator are very close to the ideal value of noise standard deviation which demonstrate the accuracy of the proposed noise estimation method.
Figure 5. Noise estimation using proposed method for four images

We also present the performance of the proposed noise estimation method on uniform patches of values 0, 128 and 255 in figure 6. The noise estimation for these patches using the proposed method is obtained for linearly increasing noise standard deviation. It can be observed from figure 6 that for the patch of uniform value 128, the estimated noise and the added noise are almost equal. The estimated noise for patches of values 0 and 255 is less than the added noise. This is because of the fact that the pixel values in an image are represented by 8 bits and have values from 0 to 255. So even if noise is added to an image, the deviation in pixel value would not be beyond 0 and 255. Hence effective estimated noise is less than the added noise which can be observed from figure 6.

Figure 6. Noise estimation using proposed method for uniform patches

The proposed quality metric (Q) is benchmarked with five state of the art published algorithms. Two databases are used for comparing the performance of proposed quality metric (Q) with these algorithms. Laboratory for Image & Video Engineering (LIVE) database [10] contain 29 reference images. For our experimentation, we have used only the Gaussian noise corrupted images of LIVE database. The 29 reference images are corrupted by five levels of additive Gaussian noise resulting in total 145 images. Categorical Subjective Image Quality (CSIQ) database [11] contain 30 reference images which are corrupted by five levels of Gaussian noise degradation resulting in total 150 images. Total 295 images from two databases are used for benchmarking.
Scatter plots of the proposed quality metric ($Q$) for LIVE and CSIQ databases are shown in figure 7(a) and figure 7(b) respectively. Scatter plot facilitate visual performance evaluation of an algorithm. A dispersed scatter plot indicates poor correlation and a concentrated scatter plot indicates high correlation between two variables. It can be observed from figure 7(a) and figure 7(b) that both the scatter plots can be approximated by a curve which indicates the consistency of proposed quality metric ($Q$). Also, there are no outliers in the scatter plot which demonstrate the robustness of proposed quality metric ($Q$). Few sample images from LIVE database are shown in figure 8.

![Figure 7(a). Scatter plot of proposed metric ($Q$) for LIVE database](image1)

![Figure 7(b). Scatter plot of proposed metric ($Q$) for CSIQ database](image2)

**Figure 7(a). Scatter plot of proposed metric ($Q$) for LIVE database**

**Figure 7(b). Scatter plot of proposed metric ($Q$) for CSIQ database**

![Few sample images from LIVE database](image3)

**Figure 8. DMOS and proposed quality metric ($Q$) values for images from LIVE database**

(a) DMOS = 48.86, $Q = 48.59$
(b) DMOS = 41.16, $Q = 40.46$
(c) DMOS = 28.32, $Q = 27.04$
(d) DMOS = 47.80, $Q = 47.22$
(e) DMOS = 65.53, $Q = 67.67$
(f) DMOS = 24.37, $Q = 22.35$
(g) DMOS = 20.30, $Q = 21.73$
(h) DMOS = 65.42, $Q = 64.12$
(i) DMOS = 35.15, $Q = 35.53$
Three correlation coefficients are used for quantitative performance comparison of the proposed quality metric ($Q$) with existing algorithms. The three correlation coefficients are Pearson’s Linear Correlation Coefficient (LCC), Spearman’s Rank Order Correlation Coefficient (SROCC) and Kendall’s Rank Order Correlation Coefficient (KROCC). The range of all three correlation coefficients is from -1 to +1 where -1 indicate perfect negative correlation and +1 indicate perfect positive correlation. Values close to -1 or +1 are indicator of better performance of algorithm.

The benchmarking results of the proposed quality metric ($Q$) with state of the art algorithms are presented in table 2. The performance of algorithms is validated on LIVE and CSIQ databases using LCC, SROCC and KROCC parameters. SROCC and KROCC are rank based correlation coefficients whereas LCC calculates correlation between two variables using their standard deviations and covariance resulting in a better indicator of their association.

For LIVE and CSIQ databases, the proposed image quality metric ($Q$) yields high correlation coefficient values which can be observed from table 2. For LIVE database, though the proposed image quality metric ($Q$) does not lead in terms of SROCC and KROCC, LCC value indicates that the performance of proposed quality metric ($Q$) is better than the state of the art algorithms. For CSIQ database, the proposed image quality metric ($Q$) leads in terms of LCC, SROCC and KROCC. The consistently high correlation values of the proposed image quality metric ($Q$) for LIVE and CSIQ databases demonstrate its robustness. Scatter plots in figure 7(a) and figure 7(b) can be approximated by curves which indirectly imply high correlation of the proposed image quality metric ($Q$) with subjective quality scores.

| Algorithm      | LIVE Database | CSIQ Database |
|----------------|---------------|---------------|
|                | LCC | SROCC | KROCC | LCC | SROCC | KROCC |
| BIQI [4]       | 0.9277 | 0.9600 | 0.8653 | 0.8949 | 0.8816 | 0.6843 |
| BLIINDS-II [6] | 0.9653 | 0.9596 | 0.8254 | 0.7939 | 0.8004 | 0.6044 |
| Visual Codebook [7] | 0.9435 | 0.9372 | 0.7818 | 0.8692 | 0.8733 | 0.6729 |
| DIIVINE [5]    | 0.9598 | 0.9769 | **0.8976** | 0.8724 | 0.8682 | 0.6800 |
| SSEQ [3]       | 0.9693 | **0.9801** | 0.8762 | 0.8706 | 0.8713 | 0.6795 |
| Proposed($Q$) | **0.9789** | 0.9787 | 0.8728 | **0.9133** | **0.9027** | **0.7179** |

DMOS and proposed image quality metric ($Q$) score for few sample images from LIVE database are presented in figure 8. The images are chosen randomly and corresponding quality scores are obtained using the proposed image quality metric ($Q$). It can be observed that the proposed image quality metric value ($Q$) is nearly equal to the DMOS of the image.

The proposed metric ($Q$) is specifically optimized for quality evaluation of images corrupted by Gaussian noise only. This limitation is because of the fact that the estimator is able to gauge the noise present in an image using the median of wavelet domain coefficients. Addition of Gaussian noise raises the median value of HP-HP wavelet sub-band coefficients which is used for noise estimation. Other types of distortions cause different effects on the wavelet coefficients and hence these distortions cannot be handled using the discussed wavelet domain estimator. The methodology used in the proposed quality metric ($Q$) can be extended for quality evaluation of images corrupted by other distortions using a different estimator which has higher sensitivity for those distortions.
6. Conclusion
In this paper, we propose a wavelet transform based noise estimation and image quality assessment method for images corrupted by Gaussian noise. The proposed method for noise estimation obtains the initial estimate of noise standard deviation using wavelet domain high pass sub-band coefficients of the image. This estimate is modified using curve fitting to obtain a near perfect noise estimate of an image. The average noise estimation error using the proposed method is below 4% over a wide range of noise. The proposed method for image quality assessment also uses the same high pass wavelet coefficients for initial noise estimation. The noise estimate is mapped to correlate with human perception using a nonlinear equation. The combined use of noise estimate and a nonlinear mapping yields a robust method to evaluate quality of images corrupted by Gaussian noise. It is a minimum training approach hence it is fast and the performance is consistent on different image databases. The proposed quality metric \( Q \) is benchmarked on Gaussian noise corrupted images from LIVE and CSIQ databases using three correlation coefficients. The performance of the proposed quality metric \( Q \) is comparable with existing state of the art algorithms in terms of Spearman’s and Kendall’s correlation coefficients. It outperforms the existing algorithms in terms of Pearson’s correlation coefficient. We plan to extend the concept to tackle distortions other than the Gaussian noise in future work.

7. References

[1] Mittal A, Moorothy A K and Bovik A C 2012 No-reference image quality assessment in the spatial domain IEEE Transactions on Image Processing 21 4695-708
[2] Mittal A, Soundararajan R and Bovik A 2013 Making a completely blind image quality analyzer IEEE Signal Processing Letters 22 209-12
[3] Liu L, Liu B, Huang H and Bovik A C 2014 No-reference image quality assessment based on spatial and spectral entropies Signal Processing: Image Communication 29 856-63
[4] Moorothy A K and Bovik A C 2010 A two-step framework for constructing blind image quality indices IEEE Signal Processing Letters 17 513-6
[5] Moorothy A K and Bovik A C 2011 Blind image quality assessment: From natural scene statistics to perceptual quality IEEE Transactions on Image Processing 20 3350-64
[6] Saad M A, Bovik A C and Charrier C 2012 Blind image quality assessment: A natural scene statistics approach in the DCT domain IEEE Transactions on Image Processing 21 3339-52
[7] Ye P and Doermann D 2012 No-reference image quality assessment using visual codebooks IEEE Transactions on Image Processing 21 3129-38
[8] Donoho D L and Johnstone I M 1994 Ideal spatial adaptation by wavelet shrinkage Biometrika 81 425-55
[9] Velde K V 1999 Multi-scale color image enhancement. In: International Conference on Image Processing (ICIP): IEEE pp 584-7
[10] Sheikh H R, Wang Z, Cormack L and Bovik A C LIVE image quality assessment database release 2.
[11] Larson E C and Chandler D M Categorical Subjective Image Quality (CSIQ) database.