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An Effective feature set in Quality Estimation of Natural Scene Statistics Images

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Abstract*:- Quality estimation in images is an area which demands high attention of researchers. Many recent algorithms in Image quality assessment relies on the computation of definite values from the image or comparison with the original pristine image. Here, we propose the extraction of a set of specific features from image and processing is done on these extracted features to obtain the objective quality score. The detailed inspection of behaviour of this set of highly specific image features extracted through less complex mathematical procedure from a collection good quality and low quality set of Natural Scene Statistics images available in LIVE dataset is elaborated in this work. Our studies and results are compared with the subjective opinion value and is proven to be accurate. The obtained results are demonstrated using statistical and graphical manner for promptness in understanding the nature of quality of the image. Thus the proposed feature set is proven to be complete in assessing the quantitative quality value of any Natural image.

***Keywords*: , Distortion, Generalized Gaussian Derivative, Natural Scene Statistics, Normalized Luminance Coefficients,**

I. INTRODUCTION

There has been always a study on the quality of images from the day users and researchers start working with images. Many methods currently exist in place to analyse the quality. Undoubtedly low quality images give negative visual experience to users and people demand good quality images and videos for a stimulating visual experience. Several studies have tested the effect of low-quality images on web sites. Poorly ranked images negatively impact the user retention ratio in websites which hosts them.

Some approaches of assessments come under subjective analysis and remaining comes under objective analysis. Subjective involves the presence of a group of people to carefully comment on the quality of the image in a range from low to high. The average of this individual responses is termed as MOS or mean opinion score.

Another means is to compute the score from the image using proper algorithm or computational method.

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This method doesn't need the assistance of subjects to help in assessing the quality, Also this is less time consuming and is efficient as it doesn't depend on the frame of mind fluctuation of subjects. Taking into consideration the different constraints of subjective assessment, objective analysis method is gaining acceptance and popularity. But the success of objective analysis depends on the correctness of the algorithm taken in to consideration. Out of the various procedures, some algorithms depend on comparing the image in hand with its original good quality version to analyse and tell the quality value. This procedure is called as Complete Reference Image Quality Assessment. Structural Similarity Index (SSIM) is one commonly used and greatly accepted method in this scenario. Another method of objective analysis depends on the availability of relevant and reliable information from the good quality image. It may be image edge information or some other extracted feature values. This category is called as Reduced reference quality assessment and the quality value is computed using this meta information. The third category is the one where no information about the pristine or good quality image is available. This is called as Blind or No Reference Quality Assessment . This method doesn't require a base image to evaluate image quality, and the only information that the algorithm receives is a distorted image whose quality is being assessed. This category is in high attraction as it is not basically possible to get pristine image or partial details of pristine image along with the image to be assessed.

II. REVIEW OF CURRENT STATE OF ART

Li Song and Chen in their paper "Blind Image Quality Assessment Based On a New Feature of Nature Scene Statistics " [1] explained the method of extraction of normalized luminance coefficient for computing image quality . There exist many blind image quality assessment algorithms and among them the most established and reputed methods are BRISQUE[3], BLIINDS - II[2] and DIVIINE[4]. These algorithms work exceptionally well in emulating human subjective response to image quality.

In the NSS based NR-IQA method DIVIINE, suggested by Anush Krishna, wavelet coefficient is extracted and is analysed in various orientations to extract parameters. BLIINDS- II is a method to analyse the quality by computing the Cosine transformation of the image. Another method, BRISQUE[3] has drawn a lot of attention for being simple and efficient. This algorithm works in spatial domain and features are extracted from the image by computing the Mean Subtracted Contrast Normalized coefficients.

These coefficients are then taken as a base to compute the correlation between adjacent pixels and hence the quality score of the image. Here the computational complexity of the algorithm is less and has proven in delivering optimal quality score.

Here, our research interest is also in Blind Image assessment, where in, the image is analysed and is concluded whether it is of poor, medium or good quality . Many researchers have worked in this area and are still working to estimate an accurate numerical quality score emulator. They have found that in Natural Scene Statistics (NSS) images, the transformations like wavelet and Discrete Cosine Transform (DCT) domain are powerful discriminators to assess the magnitude of distortion in an image.

No reference methods are mostly comprised of two steps. The first step calculates features that describe the image's structure and the second step converts this feature values to quality scores.

In this work, we are doing an analysis of the values of a set of carefully selected features extracted from a set of pristine image and low quality image. These features are carefully extracted after applying a set of computational methods. In order to state and prove the accuracy of method, it is important to have a dataset with sufficiently large number of varied quality images. TID 2008 and LIVE Release2 are two popularity used reference data bases. Our experiments and tests are done in LIVE Release2 Data set. LIVE contains a collection of 29 pristine images and around 1000 low quality images in the domain Natural Scene Statistics (NSS) which can be generously downloaded for research purpose.

III. DISTINCT NATURE OF NSS IMAGES

Natural Scene Statistics represents images which are captured in good sunlight in outdoor. Any natural visible-light image that is not subjected to artificial processing and is captured by an optical camera is regarded here as a natural image, including photographs of manmade objects. NSS models rely on the fact that good-quality real-world photographic images (*pristine* images) that have been suitably normalized follow statistical laws. Current Quality estimation models measure perturbations of these statistics to predict image distortions. ie NSS image domain possess some innate characteristics by itself which are shattered in the presence of noise or distortion and collecting together this variations from natural behavior gives the amount of unnaturalness[5].

A. Extraction and Analysis of Normalized luminance coefficients:-

i. Normalized coefficient are computed by subtracting local mean from all the pixels in an image patch of size MXN. Then the received result is divided by local variance. This set of values are able to strongly represent the characteristics of NSS images. This operation may be applied to a given intensity image I (i, j) to produce:

$$\bar{I}(i,j) = \left(I(i,j) - \mu(i,j)\right) * \left(\sigma(i,j) + C\right)^{-1} \quad (1)$$

Where μ represents the mean of the image and σ represents the variance of the image.

$$\mu(i,j) = \sum_{k=-K}^{K} \sum_{i=-L}^{L} w_{k,i}\, I_{k,i}(i,j) \quad (2)$$

Variance , σ(i ,j) is obtained as

$$\sigma(i,j) = \sqrt{\sum_{k=-K}^{K} \cdot \sum_{l=-L}^{L} w_{k,i}\, I_{k,i}(i,j) - \mu(i,j)2} \quad (3)$$

Where $w = \{w_{k,l} \mid k = -K, \ldots, K, l = -L, \ldots L\}$ is a 2D circularly-symmetric Gaussian weighting function. Here, K and L are taken as 3.

Consider the Fig 1 given below, Fig 1.1 shows the image in its original form , Fig 1.2 shows the computed mean , Fig 1.3 shows the variance and Fig 1.4 displays the normalized luminance coefficient value.

Fig 1.1 : Original Image

Fig 1.2 : Local mean value

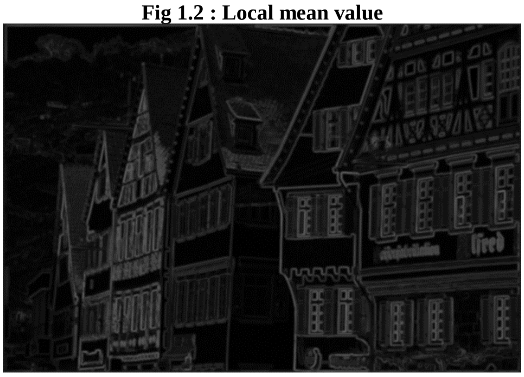


Fig 1.3 Variance value

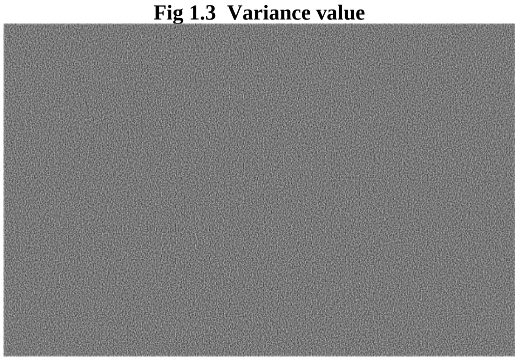


Fig 1.4: Computed Normalized Luminance value

The normalized coefficient values are also called as Mean Subtracted Contrast Normalized Coefficients (MSCN). This Coefficient is observed to exhibit a particular patter of behaviour. The histogram pattern of Normalized coefficient can give surprising information hidden in the image. In the absence of distortion and noise the histogram illustrates a Generalized Gaussian distribution curve pattern.

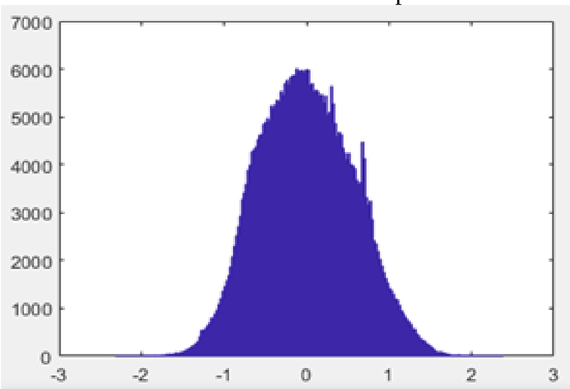


Fig 2.1 : Histogram of MSCN values of good quality Image.

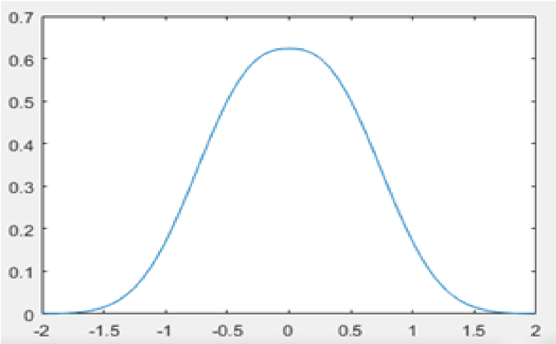


Fig 2.2 is the GGD plot for a good quality image shown in fig 1

By comparing this with Fig 3, the pdf of a Generalized Gaussian Distribution at mean =0, we have analyzed the behavioral pattern and have extracted the parameters shape and variance of the obtained curve. This parametric pair stands as a strong feature candidate exhibiting the nature of the image. For an ideal Bell Shaped Gaussian curve around mean 0, variance value will be around 0.5 (Refer Fig 3). The shape parameter α denotes the rate of decay: the smaller α, the more peaked is the distribution, and the larger α, the flatter is the distribution, so it is also called as the decay rate. The presence of noise and distortion increases variance value and thus the shape of the curve deviates from this its nature. This variation is clearly reflected in the extracted shape and variance parameters. Thus, these two parameters can act as strong candidates capable of representing the inherent naturalness in the NSS image.

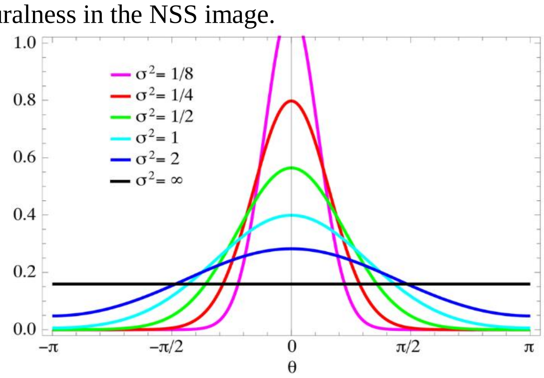


Fig 3.1PDF of Generalized Gaussian curve for various σ values

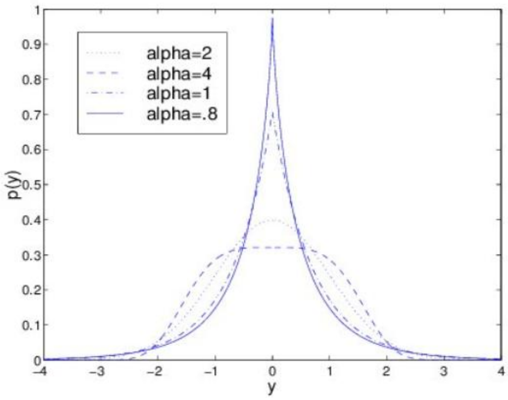


Fig 3.2 GGD for various ranges of α values.

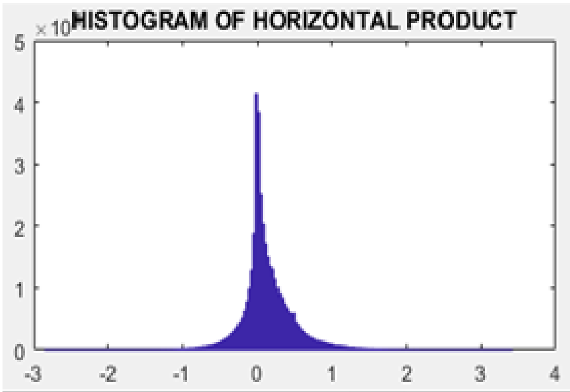
B. Product of Normalized Luminance Coefficients

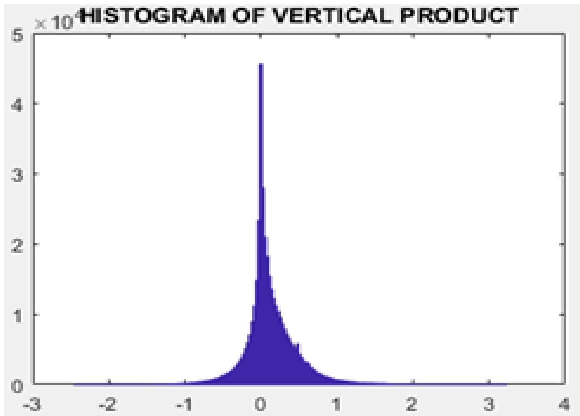
For NSS images, there exists a statistical relationship between neighboring pixels and these dependencies gets disturbed in the presence of distortion. We can model this by computing the pairwise products of neighboring normalized luminance coefficients along the four orientations – horizontal (H), vertical (V), main-diagonal (D1) and secondary diagonal (D2).

$$H(i,j) = \bar{I}(i,j)\ X\ \bar{I}(i,j+1)$$
$$V(i,j) = \bar{I}(i,j)\ X\ \bar{I}(i+1,j)$$
$$D1(i,j) = \bar{I}(i,j)\ X\ \bar{I}(i+1,j+1)$$
$$D2(i,j) = \bar{I}(i,j)\ X\ \bar{I}(i+1,j-1)$$

(4) - (7)

The histogram pattern of each of this can be plotted to extract further knowledge about the image.





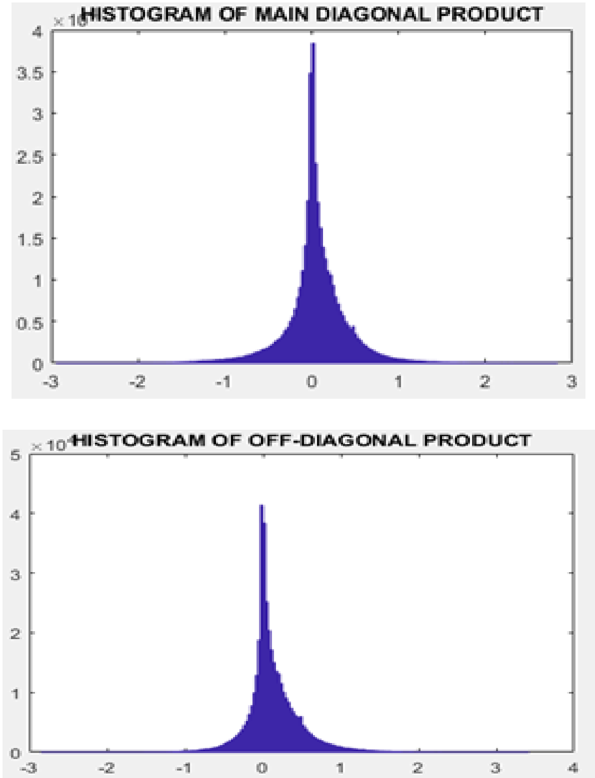


Figure 4 shows the histogram pattern of product of MSCN coefficients of adjacent pixels in all the four directions.

From the studies and proper analysis of the figures, it is observed that the histogram pattern of product of neighbouring MSCN values follows Asymmetric Generalized Gaussian Distribution. Hence the parameters of AGGD Fitting is extracted. An AGGD is represented by a collection of four parameters , α, σl, σr and μ. α controls the "shape" of the distribution, and σl and σr control the degree of diffusion of the left and right sides and μ is the mean value . The estimation method of AGGD parameters refers to the paper 'Multiscale skewed heavy tailed model for texture analysis' (2009). For extracting the model parameters from the AGG Distribution, moment matching method which uses Gamma function is followed. In all the four directions, the four parameters ie the shape parameter, mean, left- variance and right variance parameters respectively are extracted from the AGGD distribution. It is then used to collect 16 features (4 parameters/ orientation × 4 orientations) from the image. Observing these parameters have given us an exact indication of the amount of distortion and noise content available in the image.

IV. RESULTS AND DISCUSSION

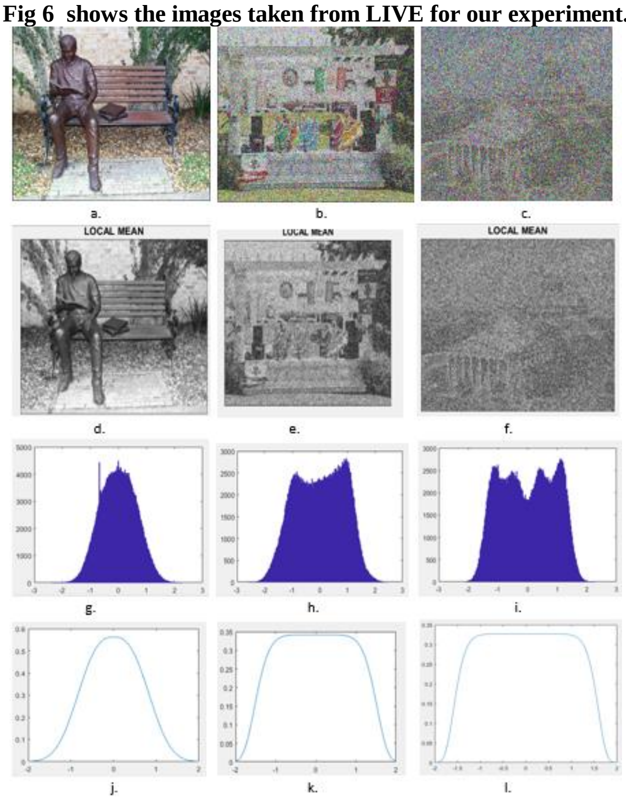
We have analysed the result in a collection of images taken from LIVE database. The following images represent three categories : a good quality, less than average quality and a very poor quality image.

Fig 5a, Fig 5b and Fig 5c represents the original image and Fig 5d, Fig 5e and Fig 5f gives its computed local mean. Figc5g, Fig 5h and Fig 5i gives the histogram pattern of MSCN coefficients of the images in Fig 5a, Fig 5b and Fig 5c. The pattern explains that, for pristine image, the histogram takes the shape of an ideal Gaussian curve or normal curve. As the amount of noise or distortion in the image increases, the pattern shifts from the ideal Gaussian nature. Fig 5j, Fig 5k and Fig 5l shows the approximate fitting of histogram with estimated GGD curve. Model curve parameters (α and µ) of GGD are extracted from this estimated curve fitting.

Fig 5m – Fig 5r shows the histogram of product of horizontal and product of main diagonal components. The histogram shows that values are centred around zero if the noise component is less (fig 5m and fig 5p). As the noise/ distortion increases, the values spread out thus deviating from zero. This nature of behaviour can be analysed to study the quality of the image.

More detailed analysis is done on a handful collection low and medium quality images (fig 6) from LIVE and is shown in the Table I. Here, as the noise increases, variation value tends to increase drastically and we have set 10 as its limiting value. The values in Table II shows the analysis of the same for a collection of a set of comparatively good quality image(with very less noisy) from LIVE. Here the shape and variance values in the range of Gaussian nature indicating a better image.

Fig 6 shows the images taken from LIVE for our experiment.



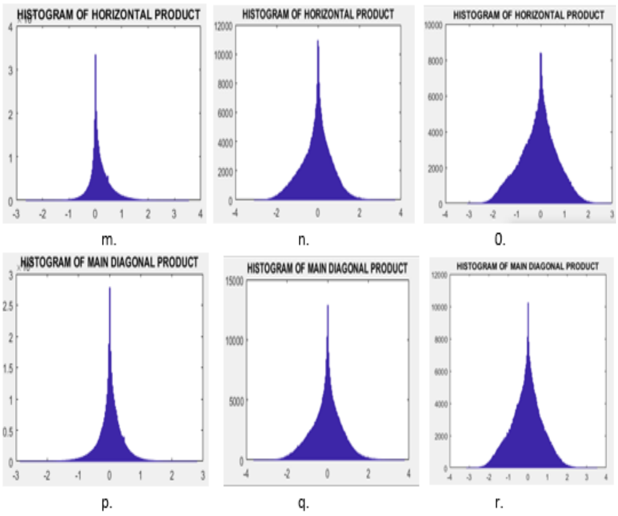


Fig 5a – Fig 5r showing the analysis of behavioral pattern of product of adjacent MSCN coefficients in all directions.

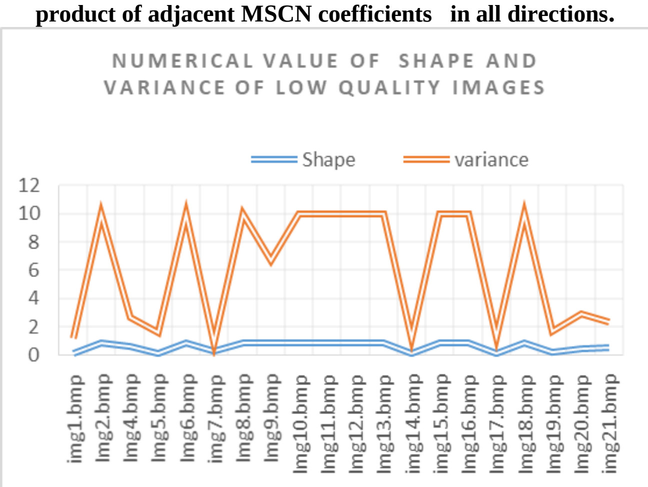


Chart1 : depicting the numerical values of shape and variance for the test set of low quality images.

Table I: Numerical Shape and variance values of a test set of low quality images.

Sl. No	image name	Value of Shape parameter	Value of variance parameter
1	img1.bmp	0.17145	1.208
2	Img2.bmp	0.903131	10
3	Img4.bmp	0.631114	2.656
4	Img5.bmp	0.150473	1.583
5	Img6.bmp	0.902906	10
6	img7.bmp	0.311597	0.852
7	Img8.bmp	0.899807	10
8	Img9.bmp	0.881853	6.725
9	Img10.bmp	0.898736	10
10	Img11.bmp	0.902739	10
11	Img12.bmp	0.902092	10
12	Img13.bmp	0.903069	10
13	img14.bmp	0.154351	1.205
14	img15.bmp	0.897834	10
15	Img16.bmp	0.902497	10
16	Img17.bmp	0.150304	1.307
17	Img18.bmp	0.888385	10
18	Img19.bmp	0.25752	1.722
19	Img20.bmp	0.515498	2.947
20	img21.bmp	0.55803	2.368

Table II: Numerical Shape and variance values of a test set of comparatively good quality images

Sl. No	image name	Shape	Standard Deviation
1	gblur plane.bmp	0.483576	1.137
2	img10.bmp	0.146496	1.399
3	img12.bmp	0.31227	1.616
4	img14.bmp	0.438238	2.272
5	img16.bmp	0.274946	2.145
6	img18.bmp	0.523058	2.711
7	img2.bmp	0.385756	2.095
8	img21.bmp	0.411149	2.313
9	img23.bmp	0.49988	2.148
10	img25.bmp	0.297331	1.917
11	img27.bmp	0.364043	1.658
12	img29.bmp	0.446137	2.608
13	img30.bmp	0.20928	0.824
14	img5.bmp	0.132782	0.784
15	img7.bmp	0.473435	3.009
16	img9.bmp	0.515067	2.632
17	img1.bmp	0.287546	1.75
18	img11.bmp	0.155695	1.628
19	img13.bmp	0.5173	2.693
20	img15.bmp	0.358765	1.837
21	img17.bmp	0.144678	1.588
22	img19.bmp	0.267342	1.897
23	img20.bmp	0.446793	2.742
24	img22.bmp	0.296211	1.985
25	img24.bmp	0.150473	1.583
26	img26.bmp	0.365765	2.664
27	img28.bmp	0.384956	1.788
28	img3.bmp	0.232283	1.782
29	img4.bmp	0.55803	2.368
30	img6.bmp	0.25752	1.722
31	img8.bmp	0.515498	2.947

In Table II, the variance values are within the numerical range 0 to 3 indicating the test set as a good quality image set. In the low quality image set(table 1), the variance values are up to the value 10 indicating the presence of more noise.

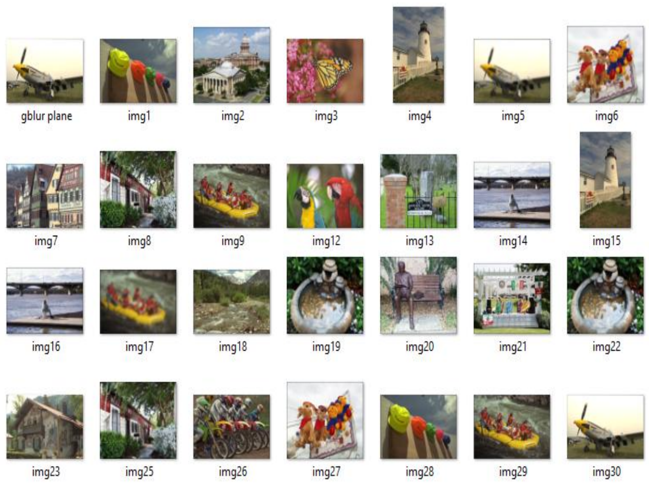


Table III shows the parameters (mean, shape, left variance and right variance) extracted from AGGD fit of product of MSCN coefficients' in all four directions on a sample set of good quality images. Shape value is approximately 0.5 , mean is centered around 0 ,left and right variance values are around 0.1.

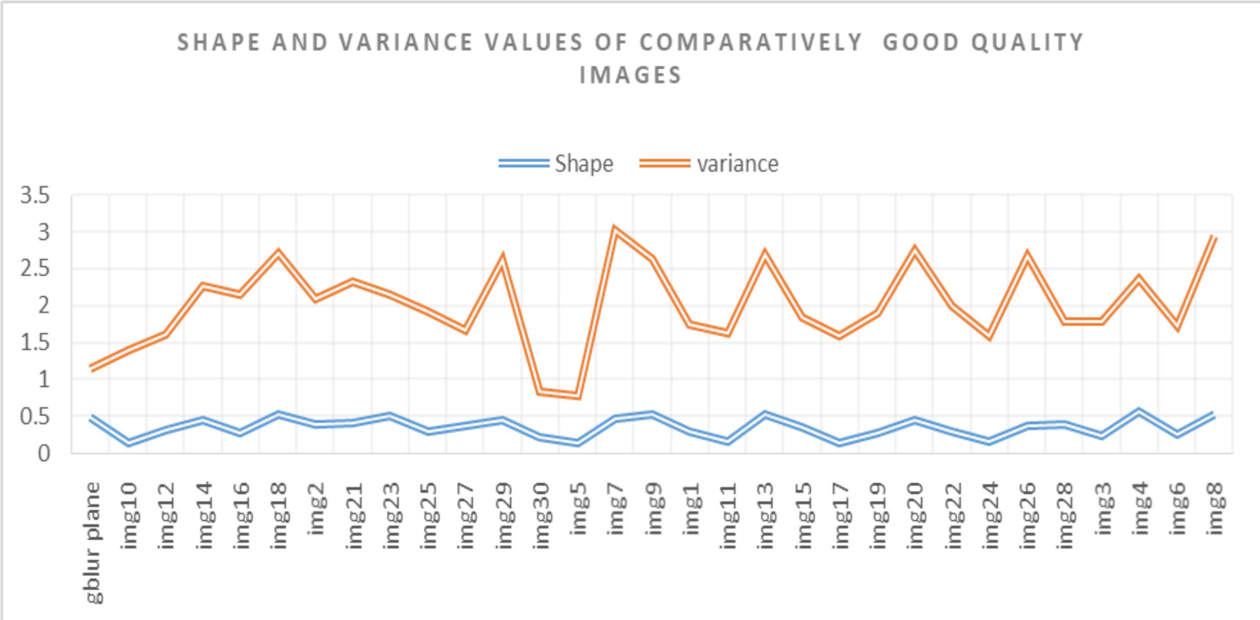


Chart 2 showing the numerical values of shape and variance for a test set of good quality images.

Table III: shows the parameters (mean, shape, left variance and right variance) extracted from AGGD fit of product of MSCN coefficients

Image Name	HORIZONTAL				VERTICAL				MAIN DIAGONAL				OFF DIAGONAL			
	Mean	Shape	Left varian ce	Right Varian ce	Mean	Shape	Left varian ce	Right Varian ce	Mean	Shape	Left varian ce	Right Varian ce	Mean	Shape	Left varian ce	Right Varian ce
gblur pla	0.015	0.507	0.274	0.302	0.010	0.508	0.276	0.293	-0.044	0.517	0.327	0.249	-0.051	0.517	0.334	0.243
img1 □□	0.063	0.553	0.036	0.145	0.047	0.611	0.051	0.128	0.047	0.591	0.051	0.130	0.026	0.623	0.070	0.112
img10 □□	0.006	0.413	0.027	0.040	0.007	0.390	0.027	0.041	0.007	0.414	0.024	0.038	0.007	0.417	0.025	0.038
img11 □□	0.008	0.425	0.027	0.043	0.008	0.437	0.027	0.042	0.007	0.456	0.026	0.040	0.007	0.459	0.026	0.040
img12 □□	0.058	0.541	0.058	0.160	0.061	0.543	0.056	0.163	0.038	0.551	0.080	0.146	0.029	0.559	0.086	0.137
img13 □□	0.124	0.840	0.166	0.349	0.140	0.824	0.152	0.362	0.033	0.852	0.237	0.286	0.040	0.854	0.230	0.290
Average Value			0.098	0.173			0.098	0.172			0.124	0.148			0.128	0.143

Table 4 shows the parameters (mean, shape, left variance and right variance) extracted from AGGD fit of product of MSCN coefficients

Image Name	HORIZONTAL				VERTICAL				MAIN DIAGONAL				OFF DIAGONAL			
	Mean	Shape	Left varian	Right Varian	Mean	Shape	Left varian	Right Varia	Mean	Shape	Left varian	Right Varian	Mean	Shape	Left varian	Right Varian
img1	0.017	0.341	0.028	0.067	0.02	0.307	0.027	0.077	0.017	0.347	0.026	0.064	0.016	0.349	0.026	0.064
img2	0.015	0.321	0.023	0.058	0.016	0.315	0.021	0.06	0.014	0.335	0.021	0.055	0.014	0.335	0.021	0.055
img4	-0.11	1.573	0.842	0.694	-0.12	1.581	0.842	0.691	-0.07	1.501	0.829	0.734	-0.07	1.508	0.83	0.734
img5	-0.12	1.605	0.85	0.698	-0.12	1.605	0.851	0.699	-0.07	1.54	0.835	0.739	-0.08	1.534	0.838	0.739
img6	-0.12	1.462	0.839	0.685	-0.11	1.467	0.836	0.688	-0.07	1.404	0.822	0.729	-0.07	1.402	0.822	0.73
img7	-0.11	1.32	0.804	0.659	-0.11	1.315	0.805	0.658	-0.07	1.265	0.796	0.697	-0.07	1.264	0.795	0.697
Avrage Value			0.564	0.477			0.564	0.479			0.555	0.503			0.555	0.503

Table IV shows the parameters (mean, shape, left variance and right variance) extracted from AGGD fit of product of MSCN coefficients' in all four directions on a sample set of low quality images. Shape value is random, mean is centered around 0 and left and right variance values are also showing a random characteristics indicating the presence of distortions and noise.

V. CONCLUSION

Through this paper, we have made an attempt to predict the nature of quality of NSS image by extracting a set of 18 features. Images are taken from a collection of good quality and low quality images from LIVE Dataset Release2. Detailed analysis of this parameters are done and have observed that for good quality NSS images, the parametric values fall in a defined ideal range and as the disorder or noises increases, these 18 model parameters deviate from the ideal nature. Thus we have proven and concluded that this set of wisely selected features can be used as strong candidates in estimating the quality value of images. Here, we extract the parameters using efficient , less time consuming mathematical operations in MATLAB thus delivering the result rapidly.

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