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Data Content Weighing for Subjective versus Objective Picture Quality Assessment of Natural Pictures

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***Abstract*—**Estimating the visual quality of picture is a real challenge for various picture and video frame applications. The aim is to evaluate the quality of picture automatically in both subjective (human visual frame work) and objectively. The quality of picture is evaluated by comparing precision and closeness of a picture with reference or error free picture. The quality estimation can be done to achieve consistency in desired quality of picture with help of modeling remarkable physiological, psycho visual components framework and picture fidelity measure methods. In this article, the picture quality is evaluated by analyzing loss of picture information of the distortion system using differing noise models and examine the relationship between picture data, visual quality and error metric. The quality of picture & video frame assessment is really important that, every human can judge the visual quality of natural picture. The subjective quality of picture is assessed by using structural similarity metric, objective quality of picture is computed by root means squared error, mean squared error and peak signal to noise ratio and data content in picture is weighted through entropy.

***Index Terms*—**Gaussian, Local Variance, Poisson, Salt and Pepper, Speckle, Structural SIMilarity, Mean Squared Error, Root Mean Squared Error, Peak Signal to Noise Ratio, Entropy.

I. INTRODUCTION

In recent years, digital picture (DP) / video frame (VF) handling is a noteworthy field of examination in the region of computer science and communication engineering. It is subsequently increased in developing the interest of picture and video administrations. Be that as it may, advanced picture handling experience the ill effects of inherent noise from their phase of capturing [1], compressing[2], encoding[3], communication[4], decoding and processing stages[5]. This noise appearance will change the normal arrangement of original data in DP/VF signal.

Investigation of picture quality estimation is essentially done with various noise models. The digitized pictures are broadly utilized in the area of medicine for diagnosis of medical pictures like calcification in mammographic pictures[6], film/ video creation[7][8] and photography of natural pictures for psycho visual components of the human visual framework(HVF)[9], remote detecting satellites for recognition of components at far separation[10], military target distinguishing proof and their examination[11], and assembling mechanization and control of segments[12]. It is essential for the DP processing to distinguish and evaluate the quality debasements with an end goal to keep up the required quality of service. This offers the computation of ascend longing of exact & productive perceptual picture quality assessment (PQA), that can evaluate the subjective nature of the picture content under different sorts of distortions.

Hence the proposed work begin with noise models and the role of noise in picture deformation where noise is arbitrary signal utilized to decimate the part of picture data and picture distortion is pleasance issues in picture processing. Picture distorted because of different sorts[13] of noise, for example, Gaussian(Ga)[14][1], Local Variance(Lv), Poisson(Po)[15], Salt and Pepper (S&P)[16] and Speckle (Sp)[17] noise in case of DP. These noises in the picture might be originated from the improper catching gadgets [1] like cameras, misaligned lenses, improper focal length and dissipating. Then we attempt to co relate mutilated picture with "reference" or " flawless " picture subjectively by utilizing HVF very adapted for extracting structural data from a scene which is measured through structural similarity (SSIM)[18][9]. Then it attempted to co-relate objectively by using mean squared error (MSE)[9], root mean squared error (RMSE)[9] and peak signal to noise ratio(PSNR)[9]. Later the details of picture are weighed through statistical measure of haphazardness that can be utilized to portray the composition of the picture by means of entropy(EnT)[19][20].

The rest of this paper is organized as follows: The section 2 discusses the detailed literature survey, section 3 illuminates proposed architecture with different noise function and comparison of picture contents. The observations and performance analysis are discussed in section 4 with SSIM, Entropy, MSE, RMSE and PSNR finally we have summarized the article in the section 5.

II. Literature Review

Examination of picture quality is fundamental in several areas of digital picture processing. The picture quality calculations are broadly classified into two categories, first category uses a reference or clear picture for comparison with generated picture and second category calculates data content in generated picture.

The superiority of generated picture in first category of PQA is decided by accuracy or differences generated by picture with reference picture. These computation metrics on quality of picture are divided into objective PQA computation and subjective PQA computation metric. The objective PQA computation will not consider HVF while designing metrics, instead they use pixel by pixel differences, square of their differences, absolute differences between pixels or maximum signal to noise ratio. The objective of these calculation is to have very low value for difference i.e. zero for perfect generated image and very high value for maximum signal to noise ratio i.e. infinity for perfect generated picture. The state of art calculations such as MSE, RMSE, mean absolute error (MAE) and PSNR generally used in measuring objective PQA. These category of calculation fit well for signal processing domain, but needs to be improved for picture processing classes where human can judge the visual quality of picture. The subjective PQA depends on human visual quality metric, which is hard to put into calculation[8][10] but these quality metric has been tried with structural similarity metric[18]. The subjective PQA use SSIM calculation and aim to achieve 1.0 for perfect construction image.

The quality of generated picture in second category of PQA is determined by equalizing data content in generated picture with reference picture. The calculations on these category measure statistical arbitrariness in picture surface which is calculated by EnT of a picture.

Many researchers have used the different quality metrics to prove their performance in achieving the high quality of picture. The author of [2] have discussed compression technique on DCT based picture compression in which PSNR is used to measure the performance of generated pictures over JPEG and JPEG2000. In designing mathematical model[3] for the noise in binary coding of multiplexed signals in imaging system signal to noise ratios are used in deciding performance. In designing post processing of JPEG-2000 low bit rate compression technique have been discussed in[5] to eliminate coding artifacts in which PSNR is used as a standard for deciding quality. The author of [6] have discussed the pre-processing of mammogram pictures for breast cancer detection in which picture quality is decided through MSE, PSNR, structural content(SC) and normalized absolute error(NAE). The quality of satellite pictures after their increase in resolution[10] are quantitatively compared through PSNR and picture visual content for demonstrating their superiority. The identification of enemy targets in synthetic aperture radar pictures are discussed in [11] which elaborates with more accuracy with binary image matching method for estimation of the clear target. The author of [19] increased the rate of identification of picture through unique identifier generation, which is the fusion of entropy with features of picture. For comparing the quality of super resolution picture with reference picture RMSE, MSE, PSNR are used in [21] and MSE,PSNR, EnT and Q-INDEX are used in [22]. The picture resolution up-sampling technique in [23] use PSNR with visual picture to decide the quality of generated up sampled picture.

The many researchers have used objective PQA calculation in presenting their quality results. But evaluating the quality of picture automatically in both subjective and objectively must be done to achieve the high quality of picture. The quality of picture should be assessed by objective PQA, subjective PQA and data content weighing. This paper focus on using various noise models on natural pictures and its implication on objective, subjective quality measures along with their data content.

III. Proposed Architecture of Experimentation

The proposed architectural design of data content weighing for subjective versus objective PQA is shown in Fig. 1. The experimentation setup receives reference natural picture (NaP) shown in Fig. 7 as an input to noise function (NoF) and results in noisy picture (NoP) as shown in (1). The data details of NaP and NoP are weighed by statistical measure of irregularity EnT, the HVF of NaP and NoP is measured by SSIM and objective quality by RMSE, MSE and PSNR.

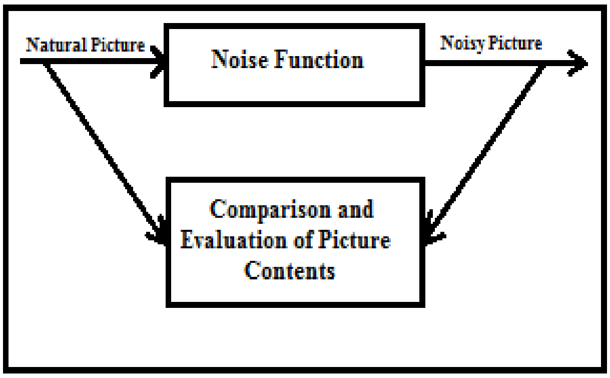

Fig.1. Proposed design of experimentation

NaP is subjected to NoF results in NoP as depicted in (1).

$$N_oP \quad = \quad N_oF(N_aP) \tag{1}$$

The *NoF* considered for experimentation are *Ga, Lv, Po, S&P* and *Sp* noise types discussed in section B.

A. Notations Used

The notations used in this article are described in table 1 as follows.

Table 1. Notations used in the article

Notation	Explanation
NaP	Natural Picture
NoP	Noisy Picture
HVF	Human Visual Framework
PQA	Picture Quality Assessment
Ga	Gaussian
Lv	Local Variance
Po	Poisson
S&P	Salt and Pepper
Sp	Speckle
SSIM	Structural Similarity
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
PSNR	Peak Signal to Noise Ratio
EnT	Entropy
NAE	Normalized Absolute Error
SC	Structural Content
MAE	Mean Absolute Error

B. Noise Function

Noise function produces and describes undesirable data in digitized pictures, for example artifacts, farfetched edges, concealed lines, corners and obscured objects by disturbing background details. To minimize these undesirable impacts, prior learning of different noise function is fundamental for effective handling of NoP. Advanced noises might emerge from different sources through different sensors. The noise from sensors are modelled through probability density function (PDF)[14] or histogram. Hence the different noise models which are applied on NaP for experimental result as follows.

Gaussian(Ga) Noise:

It is a white electronic distortion during signal amplification or recognition. *Ga* is brought by normal sources like vibration of particles and radiation of objects. *Ga* aggravates the pixel values in computerized pictures. That is why *Ga* basically designed and characterized by normalizing histogram with pixel value.

Ga shown in (2)[14] includes mean μ and variance *Va* of NaP. For experimentation 0 μ noise with 0.02 and 0.03 times of *Va* is considered and its comparison is tabulated in table 3 & 4 respectively.

$$\mathrm{G_a} = \frac{1}{\sqrt{2\pi s_d}} \; e^{-(\mathrm{N_aP} - \mu)^2 / 2\mathrm{V_a}} \qquad (2)$$

Local variance(Lv) Noise:

It is a special *Ga* noise[13] to a NaP. *Lv* of the noise function is the function of normalized image intensity value of NaP.

Poisson(Po) Noise:

The presence of this noise in picture is because of statistical property[15] in electromagnetic waves. For example, visible light, x ray and gamma ray. The gamma and x rays source radiates the number of photons. These radiated photons are measured in unit time. The radiated rays are infused into patient body from their generation, in medical imaging frameworks. The patient body make irregular change to photons in the radiated rays. Results accumulated picture will have spatial with transient irregularity. This noise is additionally termed as quantum, photon or shot noise. These noise are created from picture as opposed to add fake noise to the picture. Probability distribution function(Podf) by poisson distribution is given by (3).

$$P_o df(\partial = n) = \frac{e^{-\lambda t}(\lambda t)^n}{n!} \quad k=0,1,2,... \qquad (3)$$

In (3) ∂ is a positive parameter measured as a count of photons given by sensors in time interval *n*. λ is the expecting count of photons in time interval *n*. ∂ is directly related to the incident location irradiance. The *Podf* with λt refers to the expecting incident photon measure.

Salt and pepper (S&P) Noise:

This is termed as information drop noise[16] due to its change in original values. However the picture is not completely corrupted by S&P noise rather than some pixel amplitudes are changed in the picture. In spite, the fact that noisy picture, there is a potential outcomes of a few unchanged neighbours. This category of noise is found during information transfer. Picture pixel amplitudes are supplanted by changed pixel amplitudes either most least or highest pixel which i.e., 0 or 255 if count of bits are 8 for transfer. This noise is embedded with dead pixels either dull or intense. S&P adds noise to the NaP, where probability1 is the likelihood of salt noise and probability2 is the likelihood of pepper noise. The total probability will be sum of probability1 and probability2 will be normalized with total count of the pixels. This influences the product of probability and number of components of NaP pixels as shown by (4).

$$S\&P = \begin{cases} 255 & probability1 \\ 0 & probability2 \\ NaP & 1 - Total\ probability \end{cases} \qquad (4)$$

Speckle (Sp) Noise:

This is a multiplicative noise[17] to the picture NaP. The *Sp* is observed in imaging framework like laser, radar and acoustics and so forth. Speckle noise can exist comparative in an picture as *Ga* noise. Its likelihood follows gamma distribution, Noise function of Sp is portrayed by (5).

$$Sp= \eta_{mul}*NaP+ \eta_{add} \tag{5}$$

Where *NaP* is Natural Picture and η will be uniformly distributed random noise where η_{mul} is multiplicative and η_{add} is additive constant. For experimentation, 0 mean noise with 0.02 and 0.03 times of variance is considered.

C. Measurement metric of Picture

PQA tries to measure a visual quality of picture, a measure of distortion in a given picture. These distortions are inescapable part of any digital picture handling phase of acquiring, compressing, encoding, transmission, deciphering and processing stages.

Objective PQA

The objective PQA measures a contrast between two pictures and the outcome can be comprehended with level of errors between pictures. Their measure is public, effectively computable by legitimate distance metric and gives consistent understanding of picture similarity. As all result of this MSE, RMSE and PSNR turned into a convention[21][22][23] in objective PQA.

The mathematical formulation for MSE, RMSE and PSNR[9] are represented by (6), (7) and (8) respectively.

$$MSE = \frac{1}{S_z} \sum_{z=1}^{3}\sum_{y=0}^{n-1}\sum_{x=0}^{m-1}(NaP(x,y,z) - NoP(x,y,z))^2 \tag{6}$$

$$Where\ S_z = mXnX3$$
$$m: number\ of\ rows$$
$$n: number\ of\ columns$$

$$\text{RMSE} = \sqrt{\text{MSE}} \tag{7}$$

$$PSNR = 10log_{10} \frac{M_x{}^2}{MSE} \tag{8}$$

Mx: Maximum value of gray level of pixel(255)

Based on various experimental observation, the objective PQA doesn't give much information to human perceived quality of picture. This prompted endeavours to make measures, whose performance would be firmly identified with the human perception of visual appearance.

Modelling Human Visual Framework

The contrast between pictures does not quantify the distortion. It attempts to characterize the model of human visual framework (HVF)[18][9]. The main correct technique for assessing the human perceived visual quality of pictures is the assessment by people. Unfortunately, such method is not usable in progressive applications. Hence, there is a requirement for an automated technique, that would predict the human-perceived visual quality as close as expected under the above circumstances.

In this framework all parts of HVF were absolutely modeled and exact prediction of subjective picture visual quality of picture which would be most likely accomplished. Exact modeling of HVF is difficult to achieve, because HVF is very complicated framework with a lot of nonlinearities. SSIM is a measure in view of the assumption that HVF is adjusted to extract structural information from the field of perspective. With these, the change of basic structural information amongst distorted and original picture could be a good estimation of observed picture distortion. SSIM works well if it utilized locally and contrasts the pixel-to-pixel like objective PQA. SSIM is scientifically figured according to the (9) is collected by a comparison of luminance, contrast and structure of NaP and NoP in grey level. First, the luminance is compared by a function $l(NaP, NoP)$ of mean intensities μ_{NaP} and μ_{NoP}, Contrast comparison is a function $\mathrm{c(NaP, NoP)}$ of standard deviations $\mathrm{S_{d_{NaP}}, S_{d_{NoP}}}$ and variances $\mathrm{V_{a_{NaP}}, V_{a_{NoP}}}$, Finally, structure comparison is a function $\mathrm{s(NaP, NoP)}$of correlation between the NaP and NoP of standard deviations $\mathrm{S_{d_{NaP}}, S_{d_{NoP}}}$ with $\mathrm{S_{d_{NaP,NoP}}}$.

$$l(NaP, NoP) = \frac{2\mu_{\mathrm{NaP}}\mu_{\mathrm{NoP}} + c_1}{\mu_{\mathrm{NaP}}^2 + \mu_{\mathrm{NoP}}^2 + c_1}$$

$$c(NaP, NoP) = \frac{2S_{d_{\mathrm{NaP}}}S_{d_{\mathrm{NoP}}} + c_2}{V_{a_{\mathrm{NaP}}} + V_{a_{\mathrm{NoP}}} + c_2}$$

$$s(NaP, NoP) = \frac{S_{d_{\mathrm{NaP,NoP}}} + c_3}{S_{d_{\mathrm{NaP}}}S_{d_{\mathrm{NoP}}} + c_3}$$

$$SSIM = l(NaP, NoP)^{\alpha}c(NaP, NoP)^{\beta}s(NaP, NoP)^{\gamma} \tag{9}$$

Where

$\alpha>0$, $\beta>0$ and $\gamma>0$

For simplification $\alpha=\beta=\gamma=1$ & $c_3 = \frac{c_2}{2}$ [18]

$$\mathrm{SSIM} = \frac{(2\mu_{\mathrm{NaP}}\mu_{\mathrm{NoP}} + c_1)\ (2S_{d_{\mathrm{NaP,NoP}}} + c_2)}{(\mu_{\mathrm{NaP}}^2 + \mu_{\mathrm{NoP}}^2 + c_1)\ (V_{a_{\mathrm{NaP}}} + V_{a_{\mathrm{NoP}}} + c_2)}$$

μ_{NaP} : Mean of NaP

μ_{NoP} : Mean of NoP

$V_{a_{NaP}}$: Variance of NaP

$V_{a_{NoP}}$: Variance of NoP

$S_{d_{NaP}}$: Standard deviation of NaP

$S_{d_{NoP}}$: Standard deviation of NoP

$S_{d_{NaP,NoP}}$: Standard deviation of NaP and NoP

c_1, c_2 and c_3 : The stabilizing variables for division with weak denominator

D. Evaluation of Picture Contents

Entropy(EnT) is a statistical calculation for arbitrariness[19][20] in characterizing input picture surface. EnT is characterized by (10) as

$$EnT= -sum(p.*log2(p)) \tag{10}$$

where p contains the histogram counts

IV. Experimental Observations and Discussion

The NaP pictures for experimentation shown in Fig.7. The experimentation is led on dataset[24] for estimation of PQA. Table 2 is the tabulation of EnT of the input NaP pictures shown in Fig. 7 calculated as per (10).

Table 2. Statistics of EnT for NaP

NaP	EnT
1.tiff	6.8981
2.tiff	6.2945
3.tiff	7.7502
4.tiff	7.4858

The input NaP pictures shown in Fig. 7 are subjected to Ga noise as per (2) with 0 mean, 0.02 variance, and resultant noisy pictures displayed in Fig. 8. Ga noise with 0 mean, 0.03 variance displayed in Fig. 9. The pictures of Fig. 7 are contrasted with noisy pictures Fig. 8 and Fig. 9 as per (6)-(10) and tabulated in table 3 & 4 respectively.

Table 3. Statistics of Ga noise with 0 mean and 0.02 times of variance

Picture	SSIM	MSE	RMSE	PSNR	EnT
1.tiff	0.8923	17.1797	4.1448	35.7806	7.1934
2.tiff	0.9299	9.0492	3.0082	38.5647	6.4818
3.tiff	0.8148	31.3242	5.5968	33.1720	7.8022
4.tiff	0.8605	27.9207	5.2840	33.6715	7.5766

Table 4. Statistics of Ga noise with 0 mean and 0.03 times of variance

Picture	SSIM	MSE	RMSE	PSNR	EnT
1.tiff	0.8521	24.5115	4.9509	34.2371	7.1885
2.tiff	0.9029	13.0878	3.6177	36.9622	6.4672
3.tiff	0.7544	41.7774	6.4635	31.9214	7.8135
4.tiff	0.8113	37.9993	6.1644	32.3330	7.5989

The analysis of table 3 & 4 on SSIM and PSNR reveals that even though the subjective SSIM is high but its objective PQA PSNR is low for picture 4.tiff of table 3 when compared to picture 1.tiff of table 4 of subjective SSIM and objective PSNR.

The NaP pictures shown in Fig. 7 are subjected to Lv noise with 0.01 random noise, resultant noisy pictures are displayed in Fig. 10. The pictures of Fig. 7 are contrasted with noisy pictures Fig. 10 as per (6)-(10) and tabulated in table 5.

Table 5. Statistics of Lv noise with 0.01 random noise

Picture	SSIM	MSE	RMSE	PSNR	EnT
1.tiff	0.5672	56.9777	7.5484	30.5738	7.1406
2.tiff	0.5732	47.5187	6.8934	31.3622	6.3194
3.tiff	0.5450	64.1639	8.0102	30.0579	7.8379
4.tiff	0.6108	64.1656	8.0103	30.0578	7.6949

The analysis table 5 on SSIM and PSNR reveals that even though the subjective SSIM is high but its objective PSNR is low for picture 4.tiff when compared to picture 3.tiff of subjective SSIM and objective PSNR.

The NaP pictures shown in Fig. 7 are subjected to Po noise as per (3) resultant noisy pictures are displayed in Fig. 11. The pictures of Fig. 7 are contrasted with noisy pictures Fig. 11 as per (6)-(10) and tabulated in table 6.

Table 6. Statistics of Po noise

Picture	SSIM	MSE	RMSE	PSNR	EnT
1.tiff	0.8686	24.1362	4.9129	34.3041	7.2207
2.tiff	0.9316	14.6803	3.8315	36.4634	6.5031
3.tiff	0.7400	44.5790	6.6768	31.6395	7.8017
4.tiff	0.7158	50.3413	7.0952	31.1116	7.6605

The analysis of table 6 on SSIM and PSNR reveals that the subjective SSIM is in-line with objective PSNR.

The NaP pictures shown in Fig. 7 are subjected to S&P noise as per (4) with 0.01 density resultant noisy pictures are displayed in Fig. 12. The pictures of Fig. 7 are contrasted with noisy pictures Fig. 12 as per (6)-(10) and tabulated in table 7.

Table 7. Statistics of S&P noise with 0.01 density

Picture	SSIM	MSE	RMSE	PSNR	EnT
1.tiff	0.7789	1.1612	1.0776	47.4815	6.9200
2.tiff	0.7796	0.9008	0.9491	48.5847	6.3224
3.tiff	0.7743	1.2777	1.1304	47.0665	7.7626
4.tiff	0.8127	1.2608	1.1228	47.1244	7.4956

The analysis of table 7 on SSIM and PSNR reveals that even though the subjective SSIM is high but its objective PSNR is low for picture 4.tiff when compared to picture 1.tiff of subjective SSIM and objective PSNR.

The input NaP pictures shown in Fig. 7 are subjected to Sp noise as per (5) with 0.02 density resultant noisy pictures are displayed in Fig. 13 and Sp noise with 0.03 density displayed in Fig. 14. The pictures of Fig. 7 are contrasted with noisy pictures Fig. 13 and Fig. 14 as per (6)-(10) and tabulated in table 8 & 9 respectively.

Table 8. Statistics of Sp noise with 0.02 density

Picture	SSIM	MSE	RMSE	PSNR	EnT
1.tiff	0.8373	33.9324	5.8252	32.8247	7.2059
2.tiff	0.9398	16.7352	4.0909	35.8945	6.4381
3.tiff	0.5744	74.6813	8.6418	29.3987	7.7500
4.tiff	0.5153	84.6488	9.2005	28.8546	7.7567

Table 9. Statistics of Sp noise with 0.03 density

Picture	SSIM	MSE	RMSE	PSNR	EnT
1.tiff	0.7848	41.7593	6.4621	31.9233	7.2142
2.tiff	0.9174	21.6677	4.6549	34.7727	6.4375
3.tiff	0.5073	82.9405	9.1072	28.9431	7.7192
4.tiff	0.4558	91.4773	9.5644	28.5177	7.7286

The analysis table 8 & 9 on SSIM and PSNR reveals that even though the subjective SSIM is high but its objective PQA PSNR is low for picture 4.tiff of table 8 when compared to picture 3.tiff of table 9 of subjective SSIM and objective PSNR.

Each parameter comparisons from all the tables are represented in-terms of graph in which the result of parameter of one tables with same parameter of other table as shown in the Fig 2 - 6.

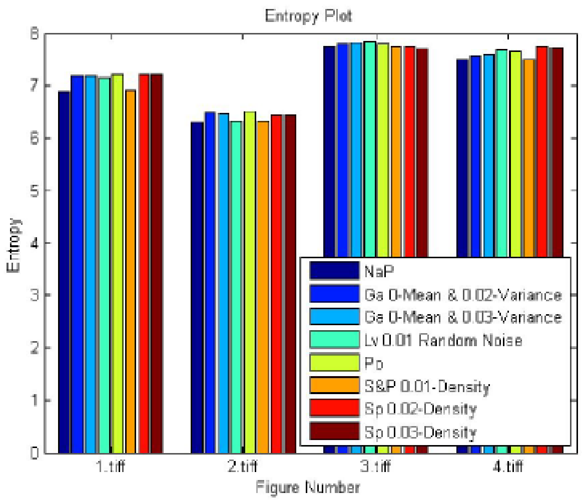

Fig.2. Entropy comparison plot of table 2 - 9

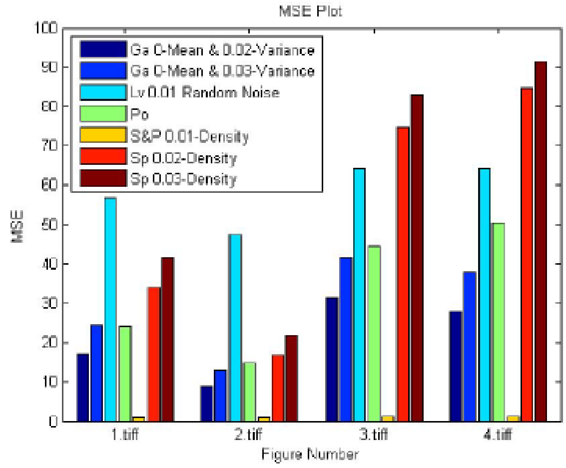

Fig.3. MSE comparison plot of table 3 - 9

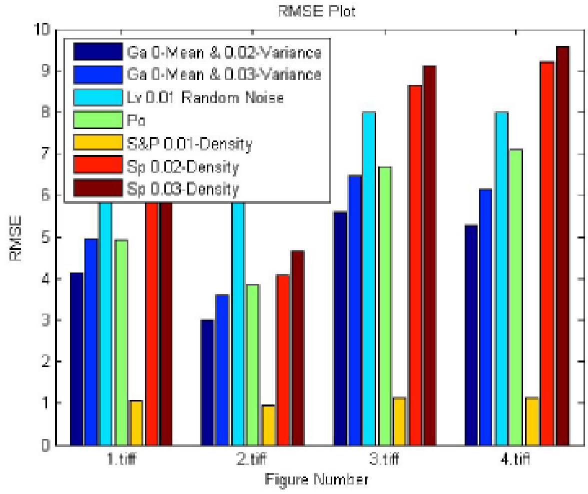

Fig.4. RMSE comparison plot of table 3 - 9

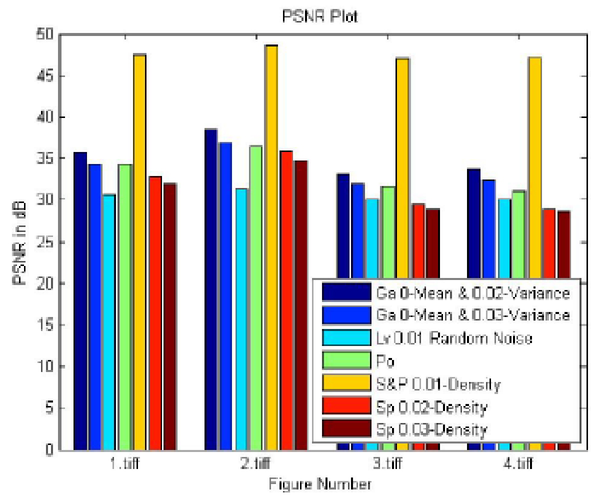

Fig.5. PSNR comparison plot of table 3 - 9

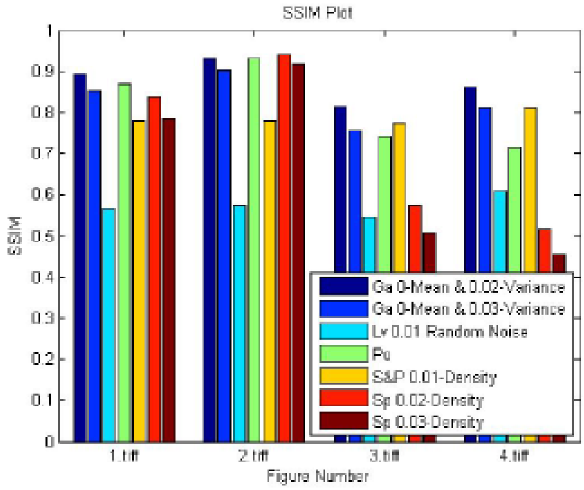

Fig.6. SSIM comparison plot of table 3 - 9

The analysis of data content weighing through EnT plotted in Fig.2 and table 2 - 9 gives a measure of randomness for a picture. The comparison plot reveals that addition of noise increase the details by increasing EnT of picture. The subjective analysis of SSIM versus objective picture quality assessment of MSE, RMSE and PSNR of natural pictures plotted in Fig.3 - 6 and tabulated in table 3 to 9 which reveals that subjective analysis results are independent of objective assessment results. Even though objectively results are high but their counterpart subjective results are not good at every time. So, to have high quality pictures both objective and subjective measures must be good. The MSE & RMSE must be lower and PSNR & SSIM must be higher for objective & subjective PQA respectively.

1.tiff 2.tiff 3.tiff 4.tiff

Fig.7. NaP

1.tiff 2.tiff 3.tiff 4.tiff

Fig.8. Noisy pictures of Ga noise with 0 mean and 0.02 times of variance

1.tiff 2.tiff 3.tiff 4.tiff

Fig.9. Noisy pictures of Ga noise with 0 mean and 0.03 times of variance

1.tiff 2.tiff 3.tiff 4.tiff

Fig.10. Noisy pictures of Lv noise with 0.01 times of random noise

1.tiff 2.tiff 3.tiff 4.tiff

Fig.11. Noisy pictures of Po noise

1.tiff 2.tiff 3.tiff 4.tiff

Fig.12. Noisy pictures of S&P noise with 0.01 density

1.tiff 2.tiff 3.tiff 4.tiff

Fig.13. Noisy pictures of Sp noise with 0.02 density

1.tiff 2.tiff 3.tiff 4.tiff

Fig.14. Noisy pictures of Sp noise with 0.03 density

V. Conclusion

PQA is a vital issue in the field of DP /VF processing. It is still not satisfyingly comprehended and new methodologies are yet showing up. Our research work focuses on data content weighing with subjective versus objective PQA on NaP. The most utilized measures for PQA in objective and subjective domain are depicted and tested on NaP. The tests in objective domain RMSE, MSE and PSNR with subjective domain SSIM along with content weighing through EnT is demonstrated in which none of the tried strategies can be used alone for PQA functions admirably. The PQA decision should be based on combination of higher SSIM and PSNR with lower MSE and RMSE along with measurable EnT for better PQA.

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