IDENTIFICATION OF SUITED QUALITY METRICS FOR NATURAL AND MEDICAL IMAGES

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ABSTRACT

To assess quality of the denoised image is one of the important task in image denoising application. Numerous quality metrics are proposed by researchers with their particular characteristics till today. In practice, image acquisition system is different for natural and medical images. Hence noise introduced in these images is also different in nature. Considering this fact, authors in this paper tried to identify the suited quality metrics for Gaussian, speckle and Poisson corrupted natural, ultrasound and X-ray images respectively. In this paper, sixteen different quality metrics from full reference category are evaluated with respect to noise variance and suited quality metric for particular type of noise is identified. Strong need to develop noise dependent quality metric is also identified in this work.

KEYWORDS

Quality Metrics, Image Denoising, SSIM.

1. INTRODUCTION

Determining image quality is one of the important objective for many image processing applications such as, image denoising, image compression and so on. Quality metrics in image denoising application gives idea about the quality of denoised image or in other way amount of noise removed from the image. There are many ways to classify image quality metrics. One of them is subjective and objective quality metrics. Subjective quality metrics depend upon human opinion about that image quality, that is, it varies from person to person. So, it requires mean opinion score (MOS) to get the actual quality of the image. Final judge of the image quality are human eyes. Considering this fact, subjective quality metrics seems to be advantageous but, it will be different for each viewer. Also, subjective quality metrics have some disadvantages such as slow processing, costly for practical use, etc. So, objective quality metrics which gives results comparable to the human visual system are considered to be state of art quality metrics.

Objective quality metrics make use of statistical parameters of the corresponding images to determine the quality of the image. These objective quality metrics can be further categorised based on the availability of reference image such as, full reference, partial reference and no reference. Full reference indicates that original image is available to compute the quality of degraded and reconstructed image while partial reference represents partial information

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availability about original image. Similarly, no reference category signifies quality metrics which can be evaluated without original image. This category is also known as blind reference type of quality metrics. In this paper, only full reference quality metrics are considered. Full reference quality metrics are also classified into different classes as, pixel difference based quality metrics, structural similarity based quality metrics, correlation based quality metrics, edge based quality metrics, spectral content based quality metrics and human visual system based quality metrics.

Quality assessment of medical images such as X-ray images, ultrasound images, MRI images, etc. is crucial job as compared to that of general/ natural photographic images. In case of X-ray images, high preference must be given to edge information while deciding quality of that images. Ultrasound images are mostly corrupted by speckle noise, which hides lesions and other important structural information in the image. Most of denoising algorithms removes speckle noise from ultrasound images at the cost of smoothing. Sometimes, doctors prefer noisy ultrasound image than over smoothed image. So, again determining quality of ultrasound images is itself a tough job. Hence objectives of this paper is to determine well suited quality metric for X-ray and ultrasound medical images along with natural images.

2. LITERATURE SURVEY

The field of image denoising is blessed with variety of objective quality metrics. Some popular basic quality metrics are Mean squared error (MSE), Peak signal to noise ratio (PSNR), Signal to noise ratio (SNR), etc. We may append this list with normalized absolute error (NAE), average difference (AD), maximum difference (MD), etc. All these basic quality metrics could be categorised into pixel difference based quality metrics. These are more popular due to their mathematical simplicity. MSE and PSNR are proportional to energy of the distortion/ noise. MSE and PSNR are based on the digital values of images than actual physical luminance [1]. Due to this reason, these quality metrics differ more from human perception.

To overcome the limitations of pixel difference based quality metrics, structural assessment based quality metrics were introduced such as structural similarity index (SSIM) [2], structural content (SC), complex wavelet structural similarity index (CWSSIM) [3], feature similarity index (FSIM) [4] and edge strength similarity index (ESSIM) [5], etc. Out of which structural similarity index became much popular because of its accuracy to determine quality of the image. It is based on amount of structural information degradation. Similarly, central idea behind CWSSIM quality metric is based on detecting consistent phase change in wavelet coefficients. Authors used complex wavelet transform in their work [3]. In reference paper [4], authors believe that human vision system interpret image according to low level images and they have used phase congruency as main feature in their work. ESSIM in [5] considers anisotropic regularity and irregularity of edge into proposed metric. This quality metric could be classified as edge based quality metric too. Such edge based metrics are primarily required in medical image assessment. Normalised cross correlation [6] comes under the correlation based quality metric category. It determines the correlation between the original and denoised image. There are some quality metrics which are designed to model the human visual system (HVS). This category includes image information and visual quality metric also known as visual information fidelity (VIF) [7] proposed by A. Bovik and H. Sheikh. Also, authors in [8] proved that universal image quality index (UIQI) is superior metric than MSE with simple mathematical model. Literatures [1-8] represent variety of quality metrics but the common consideration for their design is Gaussian noise or Gaussian distortion. As per our knowledge, we come across only one paper in which quality metric is specifically designed for speckle noise. Authors in [9] proposed speckle degradation index (SDI), which is used to compute the amount of speckle noise present in the ultrasound images.

As per literature survey, variety of objective quality metrics are proposed by many researchers for image processing applications. Applications may include image compression, image fusion and image denoising etc.

The organization of the rest of the paper is as follows.

Section 3 throw some light on selection of quality metrics along with explanation of adopted methodology. Section 4 is dedicated for experimentation and discussion and finally conclusions are mentioned.

3. PROPOSED METHOD

In this section, selection of quality metrics and procedure adopted for assessment of quality metrics is explained in detail.

3.1. Selection of Quality Metrics

It is observed from literature that most of the times evaluation of various quality metrics performance is done by considering image compression application. Very few papers consider image denoising application for performance assessment of quality metrics. Again from literature, it is observed that design of quality metric is based on Gaussian noise model. But, in practice, images may contain different type of noise other than Gaussian noise. For example, medical ultrasound images are mostly corrupted by speckle noise which is multiplicative in nature and X-ray images contain Poisson noise due to its formation process. Hence in this paper, we have considered image denoising application and tried to cover different categories of full reference type quality metrics. We have selected following sixteen quality metrics as given in following table 1.

Table 1: Broad classification of selected full reference quality metrics

Sr. No.	Category of Quality Metric	Example of Quality Metric
1.	Pixel Difference Based	MSE, SNR, PSNR, AD, MD, NAE
2.	Correlation Based	Normalized Cross Correlation
3.	Structural Similarity Based	SSIM, SC, UIQI, CWSSIM
4.	Visual Information Based	VIF
5.	Edge based	ESSIM, Beta (β)
6.	Human Visual System Based	FSIM
7.	Noise Dependent	SDI

Mathematical definition of above mentioned quality metrics are given below. Reference image is denoted by I_{ref} of dimension M * N and estimated image that is denoised image is referred as I_{est} in the following formulae.

1. **Mean Squared Error (MSE):**

$$MSE = \frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I_{est}(i,j) - I_{ref}(i,j)\right)^2 \tag{1}$$

2. **Signal to Noise Ratio (SNR) [13]:**

$$SNR = 10 * log_{10}\left[\frac{var\ (I_{ref})}{mean\ (I_{ref} - I_{est})}\right] \tag{2}$$

Here, var (I_{ref}) is variance of reference image.

3. **Peak Signal to Noise Ratio (PSNR):**

$$PSNR = 10 * log_{10}\left(\frac{I_{max}^2}{MSE}\right) \tag{3}$$

Here, I_{max} is maximum intensity value present in the reference image and MSE is mean squared error between reference and estimated image. SNR and PSNR are usually measured in decibels (dB).

4. **Average Difference (AD):**

$$AD = \frac{1}{M*N}\left(I_{ref} - I_{est}\right) \tag{4}$$

5. **Maximum Difference (MD):**

$$MD = \max(I_{ref} - I_{est}) \tag{5}$$

This quality metric is maximum difference between reference and estimated image.

6. **Normalized Absolute Error (NAE):**

$$NAE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} abs\left(I_{ref} - I_{est}\right)}{\sum_{i=1}^{M}\sum_{j=1}^{N} abs\left(I_{ref}\right)} \tag{6}$$

7. **Normalized Cross Correlation [6]:**

$$NC = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} I_{ref}(i,j) * I_{est}(i,j)}{\sum_{i=1}^{M}\sum_{j=1}^{N} I_{ref}(i,j) * I_{ref}(i,j)} \tag{7}$$

8. **Structural Similarity Index (SSIM) [2]:**

$$SSIM\left(I_{ref}, I_{est}\right) = f(l\left(I_{ref}, I_{est}\right), c\left(I_{ref}, I_{est}\right), s(I_{ref}, I_{est})) \tag{8}$$

This quality metric takes into consideration three different image parameters namely, luminance (l), contrast (c) and structural correlation (s).

$$l(I_{ref}, I_{est}) = \frac{2*\mu_x*\mu_y+C1}{\mu_x^2+\mu_y^2+C1} \tag{9}$$

$$c\left(I_{ref}, I_{est}\right) = \frac{2*\sigma_x*\sigma_y+C2}{\sigma_x^2+\sigma_y^2+C2} \tag{10}$$

$$s\left(I_{ref}, I_{est}\right) = \frac{\sigma_{xy}+C3}{\sigma_x\sigma_y+C3} \tag{11}$$

Where,
μ_x: Mean of reference image.
μ_y: Mean of estimated image.
σ_x: Standard deviation of reference image.
σ_y: Standard deviation of estimated image.
σ_{xy}: Cross correlation between reference and estimated image.

9. Structural Content (SC):

$$SC = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} I_{ref}(i,j)*I_{ref}(i,j)}{\sum_{i=1}^{M}\sum_{j=1}^{N} I_{est}(i,j)*I_{est}(i,j)} \tag{12}$$

10. Feature Similarity Index (FSIM) [4]:

$$FSIM = \frac{\sum_{x\in\Omega} S_L(x).PC_m(x)}{\sum_{x\in\Omega} PC_m(x)} \tag{13}$$

This quality metric gives score by considering Phase Congruency (PC) and Gradient Magnitude (GM). SL(x) gives similarity between reference and estimated image.

11. Complex Wavelet Structural Similarity (CWSSIM) [3]:

$$CWSSIM = \frac{2\left|\sum_{i=1}^{N} c_{x,i}c_{y,i}^*\right|+K}{\sum_{i=1}^{N}\left|c_{x,i}^2+\sum_{i=1}^{N} c_{y,i}\right|^2+K} \tag{14}$$

Basic idea behind CWSSIM is phase change in wavelet domain because of any distortions. This phase change is measured and score is obtained.

12. Edge Strength Similarity (ESSIM) [5]:

$$ESSIM = \frac{1}{N}\sum_{i=1}^{N}\frac{2E\left(I_{ref},i\right)E(I_{est},i)+C}{(E(I_{ref},i))^2+(E(I_{est},i))^2+C} \tag{15}$$

In this quality metric, similarity between edge strength of reference and estimated image is computed.

13. Visual Information Fidelity (VIF) [7]:

$$VIF = \frac{\sum_{j\in subbands} I(C^{N,j};F^{N,j}s^{N,j})}{\sum_{j\in subbands} I(C^{N,j};E^{N,j}s^{N,j})} \tag{16}$$

Here, numerator term denotes information present in all sub bands of estimated image and denominator represents information in reference image.

14. Universal Image Quality Index (UIQI) [8]:

$$UIQI = \frac{4\sigma_{xy}\bar{x}\bar{y}}{(\sigma_x^2+\sigma_y^2)[\bar{x}^2+\bar{y}^2]} \tag{17}$$

In this quality metric, x is reference image and y is estimated image.

15. Speckle Degradation Index (SDI) [9]:

$$SDI = C\left[\frac{\mu_u\sigma_v\sigma_v^2}{\mu_v\sigma_u\sigma_{uv}} - 1\right] \tag{18}$$

Here, u is considered as reference image and v is estimated image. μ_u, μ_v are mean of reference and estimated image respectively, σ_u, σ_v are standard deviation of reference and estimated image and σ_{uv} is joint standard deviation for these two images, C is a constant.

16. Beta (β) [14]:

$$\text{Beta} = \frac{\sum[(I_{refhpf}-m1)*(I_{esthpf}-m2)]}{\sqrt{\sum(I_{refhpf}-m1)^2*\sum(I_{esthpf}-m2)^2}} \tag{19}$$

Where, I_{refhpf} and I_{esthpf} are high pass filtered reference and estimated images, m1 and m2 are mean of I_{refhpf} and I_{esthpf} respectively.

3.2. Procedure to Assess Performance of Quality Metrics

In this paper, authors are concentrating on general (natural) images, ultrasound images and X-ray digital images for experimentation. Natural images are captured by camera and normally corrupted by Gaussian noise. The way of image acquisition in ultrasound and X-ray modalities are different. Both modalities are suffering from different kind of noise contamination. Hence to assess these two kind of medical images, we need different quality assessment metrics. This situation encourages us to identify suited quality metric for general (natural), ultrasound and X-ray images. To achieve this objective, experimentation is done by adding noise synthetically in the original images. This noisy image is then denoised by respective state of art algorithm and quality metric for noisy and denoised image is calculated. Following schematic diagram shows adopted method to test different quality metrics.

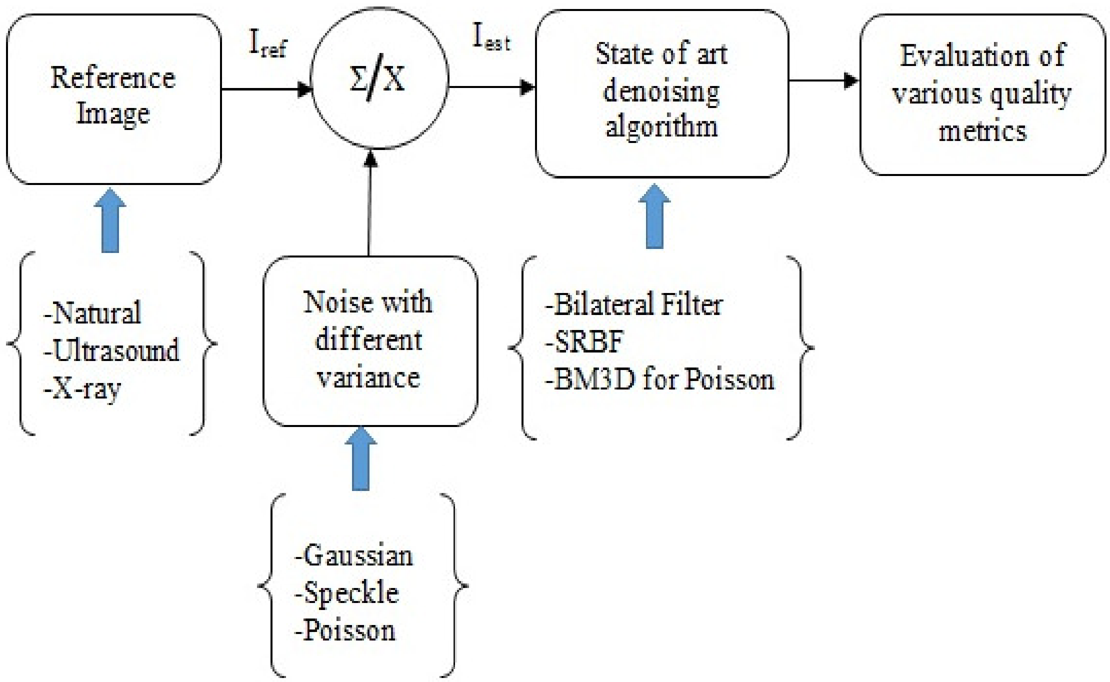


Figure 1: Procedural flow diagram for quality metric testing

Medical ultrasound images are formed by transmission and reception of ultrasound waves. At the time of image formation constructive and destructive scattering takes place. This phenomenon is responsible for introduction of speckle noise in ultrasound imaging. Hence ultrasound images are usually corrupted by speckle noise. Similarly, formation of X-ray images is based on photon counting statistics which follows Poisson process and thus X-ray images are mostly degraded by Poisson noise. Therefore, to determine the suited quality metric for natural, ultrasound images and X-ray images is prime objective of this work.

4. EXPERIMENTATIONS AND DISCUSSION

The main objective of work is to identify suited quality metric for natural, ultrasound and X-ray images. Hence, we used these three type of databases for analysis. Intention behind these three type of databases is to cover three different noise types in this work. For this work, experimentation environment used is MATLAB 2013a software. In case of natural images, Gaussian noise is added in reference images and bilateral filter [10] algorithm is used to denoise that images. For ultrasound images, speckle reducing bilateral filter (SRBF) [11] algorithm is used to remove speckle noise from noisy image and in X-ray images, BM3D algorithm dedicated to remove Poisson noise [12] is used to denoise Poisson corrupted X-ray images. Following tables 2 to 7 are sample results for above stated databases using state of art image denoising algorithms at noise variance varying from 0.01 to 0.1 level for natural and ultrasound images. For X-ray images, peak intensity is varied from 5 to 50.

Table 2. Quality metrics assessment for general (Barbara) image corrupted by Gaussian noise

Variance/ Quality Metric	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1
MSE	131.3	195.5	292.9	418.63	562	742.3	926.32	1105	1304	1516
AD	8.398	10.63	13.15	15.823	18.3	21.09	23.619	25.82	28.12	30.43
MD	82.69	77.66	97.21	119.47	128	126.1	135.39	159.3	159.2	161.4
PSNR	26.95	25.22	23.46	21.913	20.6	19.42	18.463	17.7	16.98	16.32
NAE	0.072	0.091	0.112	0.1348	0.16	0.18	0.2012	0.22	0.24	0.259
SSIM	0.766	0.661	0.555	0.4705	0.41	0.353	0.3101	0.276	0.255	0.226
SC	1.019	1.01	1.006	0.9947	0.99	0.983	0.9696	0.967	0.952	0.941
NC	0.987	0.989	0.988	0.99	0.99	0.986	0.9877	0.984	0.986	0.986
SDI	-0.84	-0.59	-0.20	0.3916	1.09	1.923	2.6818	3.703	4.697	5.932
VIF	0.324	0.259	0.216	0.1862	0.17	0.154	0.1405	0.127	0.119	0.107
FSIM	0.882	0.845	0.798	0.7548	0.72	0.681	0.65	0.627	0.599	0.578
ESSIM	0.988	0.986	0.982	0.978	0.974	0.969	0.964	0.960	0.955	0.951
UIQI	0.688	0.606	0.528	0.4653	0.42	0.373	0.3356	0.304	0.286	0.257
BETA	1399	1324	1193	1094.8	1037	939.3	838.24	812.2	833.5	744.7
CWSSIM	0.918	0.868	0.841	0.8043	0.77	0.764	0.7288	0.719	0.705	0.676
SNR	28.16	27.31	26.37	25.658	24.9	24.34	23.944	23.48	23.19	22.86

Table 3. Quality metrics assessment for general (House) image corrupted by Gaussian noise

Variance/ Quality Metric	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1
MSE	83.05	144.5	245.6	382.7	538.4	716.5	896.2	1107	1287	1497
AD	6.629	9.212	12.2	15.3	18.18	21.07	23.62	26.37	28.47	30.83
MD	84.27	82.58	116.8	111.8	124.3	143.9	148.3	155.1	158	164.6
PSNR	28.94	26.53	24.23	22.3	20.82	19.58	18.61	17.69	17.03	16.38
NAE	0.048	0.067	0.088	0.111	0.132	0.153	0.171	0.191	0.206	0.223
SSIM	0.748	0.58	0.446	0.35	0.286	0.244	0.21	0.186	0.168	0.153
SC	1.007	1.008	1	0.999	0.995	0.993	0.984	0.985	0.981	0.972
NC	0.994	0.992	0.994	0.992	0.99	0.987	0.987	0.981	0.98	0.979
SDI	-0.5	-0.16	0.485	1.507	2.564	3.753	4.979	6.679	8.177	10.13
VIF	0.291	0.238	0.206	0.176	0.158	0.147	0.135	0.124	0.119	0.112
FSIM	0.876	0.825	0.765	0.714	0.668	0.635	0.605	0.58	0.559	0.539
ESSIM	0.991	0.987	0.980	0.973	0.966	0.958	0.952	0.944	0.938	0.932
UIQI	0.396	0.334	0.289	0.252	0.221	0.203	0.181	0.168	0.155	0.146
BETA	842.5	856.9	853.8	832.2	816.1	762.6	724.6	706.8	666.1	650.9
CWSSIM	0.848	0.779	0.738	0.699	0.669	0.671	0.638	0.616	0.583	0.597
SNR	28.04	26.52	25.43	24.35	23.57	22.91	22.47	21.89	21.55	21.22

Table 4. Quality metrics assessment for 'Ultrasound Image 1' corrupted by Speckle noise

Variance/ Quality Metric	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1
MSE	6.401	8.93	11.63	13.743	15.89	18.94	20.935	23.979	27.79	28.85
AD	1.147	1.305	1.468	1.5816	1.68	1.816	1.9257	2.0044	2.161	2.229
MD	30.52	49.45	44.73	53.359	65.45	59.05	57.805	68.599	67.83	85.92
PSNR	40.07	38.62	37.47	36.75	36.12	35.36	34.922	34.332	33.69	33.53
NAE	0.065	0.074	0.084	0.0901	0.096	0.103	0.1097	0.1141	0.123	0.127
SSIM	0.989	0.986	0.982	0.9796	0.978	0.974	0.9704	0.9692	0.964	0.962
SC	1.038	1.038	1.044	1.0401	1.028	1.039	1.0363	1.0421	1.044	1.038
NC	0.979	0.978	0.975	0.9758	0.981	0.974	0.975	0.9711	0.969	0.971
SDI	-0.35	-0.33	-0.35	-0.295	-0.19	-0.25	-0.181	-0.202	-0.18	-0.12
VIF	0.724	0.684	0.649	0.6324	0.606	0.588	0.5704	0.5654	0.539	0.536
FSIM	0.983	0.98	0.975	0.973	0.971	0.967	0.964	0.9631	0.959	0.957
ESSIM	0.992	0.990	0.988	0.987	0.986	0.984	0.982	0.982	0.979	0.978
UIQI	0.904	0.9	0.896	0.8929	0.89	0.886	0.8813	0.8784	0.872	0.868
BETA	1449	1406	1365	1317.2	1283	1208	1206.5	1120.6	1135	1101
CWSSIM	0.989	0.975	0.973	0.9667	0.96	0.954	0.9439	0.9412	0.929	0.938
SNR	32.48	31.89	31.3	31.01	30.91	30.44	30.132	29.888	29.55	29.46

Table 5. Quality metrics assessment for 'Ultrasound Image 2' corrupted by Speckle noise

Variance/ Quality Metric	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1
MSE	4.393	6.6458	9.0954	11.543	14.32	16.65	18.52	21.41	23.82	25.92
AD	1.034	1.2305	1.4181	1.5777	1.724	1.839	1.959	2.087	2.197	2.312
MD	40.35	45.811	39.801	45.175	50.74	57.55	66.22	49.75	63.47	71.3
PSNR	41.7	39.905	38.543	37.508	36.57	35.92	35.45	34.83	34.36	33.99
NAE	0.054	0.0645	0.0744	0.0827	0.09	0.096	0.103	0.109	0.115	0.121
SSIM	0.991	0.987	0.9832	0.9792	0.976	0.972	0.969	0.965	0.962	0.958
SC	1.024	1.0177	1.0166	1.0285	1.024	1.028	1.02	1.016	1.025	1.014
NC	0.986	0.9889	0.9885	0.9819	0.983	0.98	0.983	0.984	0.979	0.984
SDI	-0.24	-0.16	-0.133	-0.204	-0.14	-0.14	-0.07	0.03	-0.04	0.115
VIF	0.758	0.7046	0.6662	0.6342	0.609	0.591	0.576	0.559	0.546	0.54
FSIM	0.987	0.9814	0.9761	0.9726	0.969	0.965	0.961	0.958	0.956	0.952
ESSIM	0.994	0.992	0.990	0.988	0.986	0.984	0.984	0.981	0.980	0.979
UIQI	0.92	0.9163	0.911	0.9061	0.902	0.897	0.893	0.889	0.884	0.879
BETA	1613	1487.5	1364.7	1299.7	1201	1129	1089	1055	1007	952.6
CWSSIM	0.993	0.9902	0.9779	0.9784	0.971	0.963	0.966	0.96	0.959	0.957
SNR	32.68	32.003	31.379	30.696	30.35	30.01	29.83	29.52	29.23	29.02

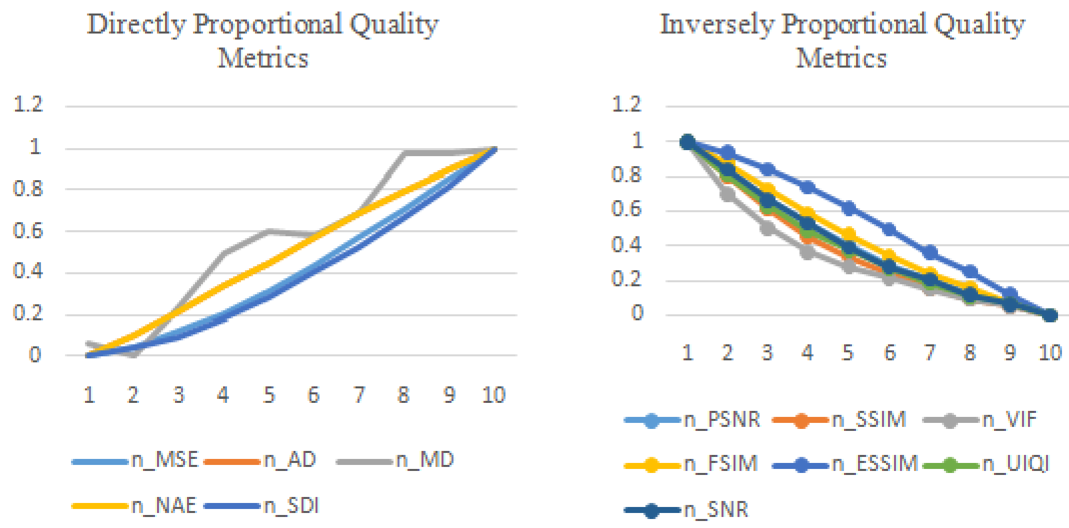
Table 6. Quality metrics assessment for 'X-ray Image 1' corrupted by Poisson noise

Peak Intensity/ Quality Metric	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
MSE	0.05	0.119	0.225	0.344	0.442	0.598	0.741	0.876	1.0327	1.193
AD	0.159	0.248	0.339	0.419	0.478	0.549	0.603	0.665	0.7229	0.776
MD	2.61	3.942	5.666	7.458	8.648	9.763	13.25	9.426	15.416	9.753
PSNR	27.25	29.48	30.21	30.87	31.72	32	32.4	32.83	33.143	33.43
NAE	0.057	0.045	0.041	0.038	0.034	0.033	0.031	0.03	0.0289	0.028
SSIM	0.999	0.998	0.997	0.996	0.995	0.994	0.993	0.992	0.991	0.99
SC	0.987	1.001	1.004	1.002	1.001	1	1	1.001	0.9999	1.002
NC	1.004	0.998	0.997	0.998	0.999	0.999	0.999	0.999	0.9995	0.999
SDI	0.369	0.034	-0	0.044	0.068	0.015	0.026	0.005	-0.012	0.002
VIF	0.724	0.704	0.671	0.667	0.685	0.673	0.667	0.677	0.6684	0.67
FSIM	0.976	0.981	0.983	0.984	0.984	0.985	0.985	0.985	0.9847	0.985
ESSIM	0.998	0.997	0.996	0.995	0.994	0.993	0.992	0.992	0.991	0.991
UIQI	0.543	0.601	0.637	0.663	0.684	0.693	0.719	0.728	0.734	0.75
BETA	561.3	579	582	590.2	578.3	584.4	582.5	585.4	592.17	589.4
CWSSIM	0.683	0.778	0.786	0.803	0.837	0.849	0.875	0.88	0.8904	0.893
SNR	15.12	19.15	21.18	22.71	24.3	25.33	26.27	27.04	27.703	28.17

Table 7. Quality metrics assessment for 'X-ray Image 2' corrupted by Poisson noise

Peak Intensity/ Quality Metric	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
MSE	0.06	0.14	0.231	0.377	0.522	0.645	0.838	0.993	1.153	1.365
AD	0.17	0.28	0.346	0.444	0.512	0.577	0.65	0.706	0.766	0.832
MD	2.69	6.27	5.119	8.842	15.78	11.06	13.67	12.19	24.59	11.6
PSNR	27.1	29	30.44	30.82	31.34	32.01	32.21	32.63	33.01	33.19
NAE	0.05	0.04	0.036	0.034	0.032	0.03	0.029	0.027	0.026	0.026
SSIM	1	1	0.997	0.996	0.995	0.994	0.992	0.991	0.99	0.989
SC	0.99	1	1	1.002	1	0.998	0.999	1.001	0.999	1.002
NC	1	1	0.999	0.998	0.999	1	1	0.999	1	0.998
SDI	0.28	0.06	0.032	0.114	0.006	0.044	-0.02	-0.01	0.043	-0.04
VIF	0.73	0.71	0.684	0.667	0.668	0.673	0.639	0.654	0.666	0.65
FSIM	0.98	0.98	0.984	0.982	0.984	0.984	0.982	0.984	0.983	0.982
ESSIM	0.998	0.996	0.995	0.994	0.993	0.992	0.991	0.991	0.990	0.989
UIQI	0.52	0.56	0.611	0.617	0.648	0.664	0.672	0.687	0.692	0.7
BETA	621	621	622.1	618.1	619.5	625	623.3	616	611.6	628.9
CWSSIM	0.71	0.77	0.813	0.805	0.848	0.866	0.87	0.883	0.881	0.891
SNR	14.7	18.9	21.55	22.22	23.98	25.15	26.06	26.69	27.41	27.98

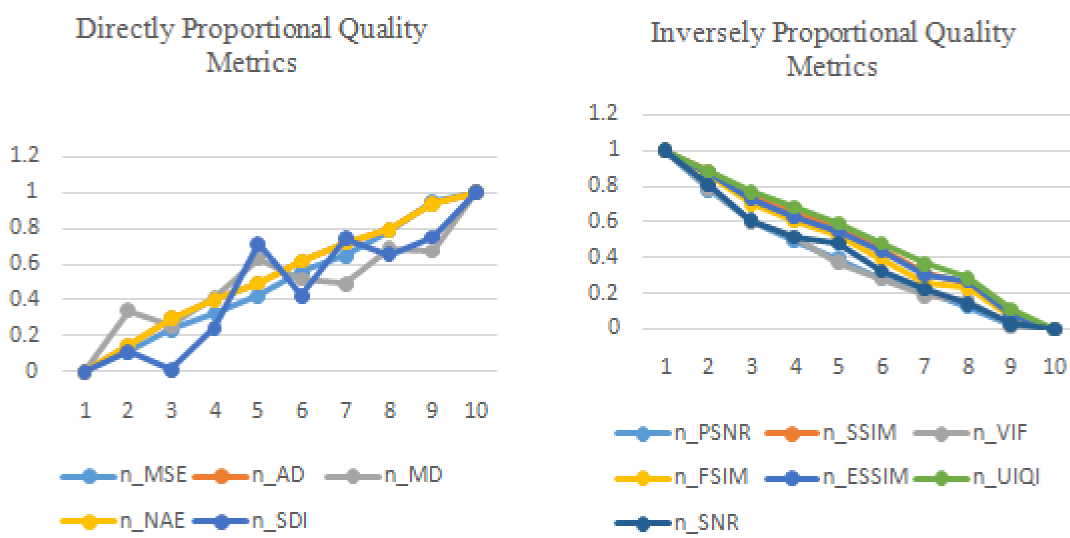
Following figure 2 shows graph of values of different quality metrics for general image Barbara



(a) (b)

Figure 2. (a) Shows comparison of different normalized quality metrics which are directly proportional to noise variance and (b) gives comparison of different normalized quality metrics which are inversely proportional to noise variance for general image.

Similar to above, figure 3 gives graphs for ultrasound image and figure 4 for X-ray images.



(a) (b)

Figure 3. (a) Shows comparison of different normalized quality metrics which are directly proportional to noise variance and (b) gives comparison of different normalized quality metrics which are inversely proportional to noise variance for ultrasound image.

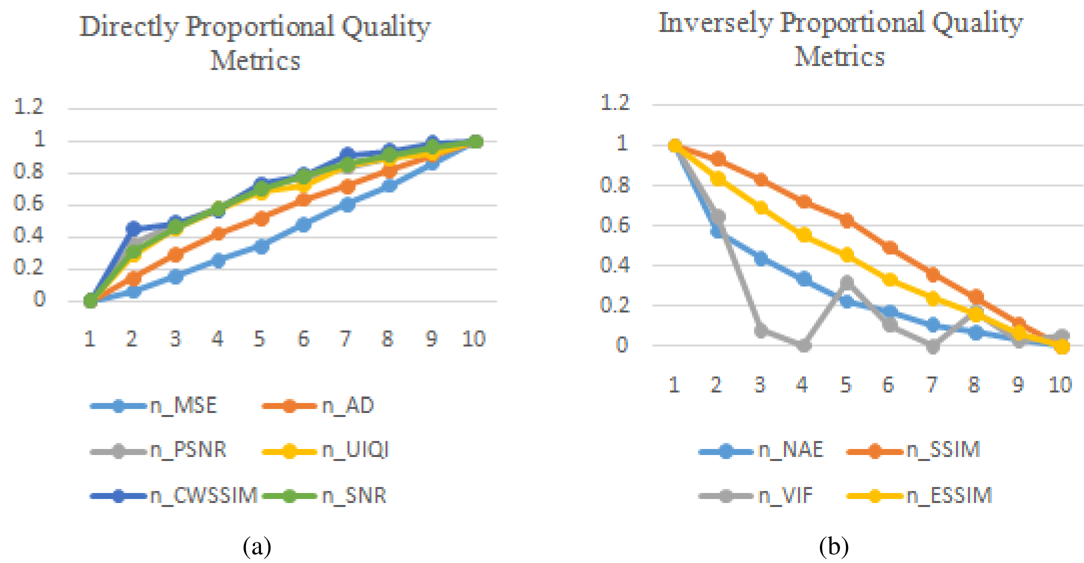


Figure 4. (a) Shows comparison of different normalized quality metrics which are directly proportional to noise variance and (b) gives comparison of different normalized quality metrics which are inversely proportional to noise variance for X-ray image.

A good quality metric is one which detects small changes in the image caused by the increment of noise by small amount. From above tables 2 to 7 and figures 2 to 4, following points are observed.

1. It is observed that all above quality metrics could be classified into two broad categories because some of them are directly proportional to noise variance and some are inversely proportional.

2. For general and ultrasound images AD, MSE, NAE quality metrics behave well in the category of directly proportional quality metrics. Similarly PSNR, SSIM, VIF, UIQI, ESSIM, FSIM, SNR behaves well in the category of inversely proportional quality metrics.

3. In case of X-ray images, Poisson noise is signal dependent. Hence, when images are scaled to low intensity, Poisson noise is dominant and when images are scaled at higher intensity, effect of noise is less. MSE, AD, PSNR, CWSSIM, UIQI, SNR are good quality metrics in directly proportional category whereas NAE, SSIM are good in inversely proportional category.

4. For general images, abrupt behaviour is observed for MD, Beta and CWSSIM quality metrics.

5. In ultrasound images, abrupt behaviour is observed in MD, SDI, Beta and CWSSIM quality metrics.

6. For X-ray images, MD, FSIM, Beta and VIF quality metrics behave abruptly.

Above stated observations can be justified as explained below.

- AD, MSE, NAE, PSNR are pixel difference based quality metrics. As noise variance increases, pixel difference increases hence their performance is better for all three datatypes.

- In case of general images, MD behaves abruptly. Value of MD depends upon maximum pixel intensity difference between reference and estimated images. As it is expected that by increasing noise variance, pixel intensity difference should increase, but in actual practice, noise may increase or decrease original pixel intensity value. Hence, abrupt behaviour of MD is justified.

- Performance of CWSSIM depends upon level of decomposition, number of orientation and robustness factor (K). Depending upon values of these parameters, performance of CWSSIM quality metric varies.

- Though Speckle Degradation Index (SDI) is speckle noise dependent quality metric, its behaviour for ultrasound images is not up to the mark as compared with general images.

- Visual Information Fidelity (VIF) [7] gives score depending upon information present in estimated image as compared to that of reference image. Information in image depends upon structural contents, edges, etc. present in the image. General and ultrasound images are rich in information as compared to that of X-ray images. So, VIF does not perform well in case of X-ray images.

5. CONCLUSIONS

To identify suited quality metric for natural, ultrasound and X-ray images is primary goal of this paper. We conclude that structural similarity index (SSIM) is suited for all three types of images. Visual information fidelity (VIF) and normalized absolute error (NAE) works well than other quality metrics for natural and ultrasound images. In case of X-ray images, normalized absolute error (NAE) and peak signal to noise ratio (PSNR) shows better performance than that of other quality metrics.

We also conclude that, there is huge scope to develop noise dependent quality metrics. In future, authors will work to develop Poisson noise dependent quality metric.

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