An Efficient Image Quality Criterion in Spatial Domain

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Abstract

Due to rapid growth in multimedia technology, it becomes necessary to analyse image processing system. Important factor for analysis is image quality assessment as it plays a primary role in the design and quality monitoring of imaging and image acquisition systems. Image Quality assessment can be further referred for image processing systems. Quality analysis is achieved in two ways, subjectively and objectively. In subjective measurement expert people give their views of image quality i.e., MOS whereas objective techniques are applied with the help of mathematical algorithms. Commonly used objective quality metrics like FSIM, VIF, MSSIM etc. fail on some image impairments as seen in results. Paper proposes a similarity measure for image quality checking which is taking in to account perceived image features like edge, color, intensity, which are highly affected by commonly occurring variety of noise. HVS model is explicitly employed in the proposed measure. Experiments done on standard image quality assessment (IQA) database demonstrate that proposed criterion behaves in same way as subjective measure than existing similarity measures. The proposed methodology will further extend its support in video quality assessment too.

1. Introduction

Image quality analysis is significant to many image processing systems. Unavoidable physical limitations related to visual perception and economic reasons[1] results in image quality deterioration, from initial stage of capturing to the final state of viewing. There is great need to find image quality measures that are highly prone to these noises induced distortions, which further helps in the efficient and economic design of communication system and imaging systems. There are subjective and objective measures. In subjective measure, quality is judged by team of expert human observers, which is complex to implement, more time-consuming and less economical. Objective measures, in turn are mathematical measures that can predict the desired image quality automatically, and the objective here is to formulate full reference quantitative criterion that predicts image quality consistently with subjective human evaluation. Full reference (FR) here signifies that original reference image is available.

Objective quality assessment[2,4] is divided in to two categories: First category includes Simple statistics error metrics which are MSE, PSNR, VSNR, etc. Second category includes Human visual system (HVS) feature based metric like FSIM, MSSIM, and VIFP. HVS oriented methods used to take the benefit of the known characteristics of visual system, and try to calculate image quality by calculating discerning errors. But these similarity approaches became unsuccessful on some image noise which can be seen later in results section of this paper. Practically, image quality could degrade in almost every system, so, it becomes the duty of designers and developers to develop optimized system and also to maintain a healthy compromise between quality and cost in mind.

The paper is structured as follows. Section 2 emphases the various existing quantitative image quality measures.

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The proposed similarity measure in pixel or spatial domain is discussed in Section 3. Section 4 shows implementation and results analysis. Finally, conclusion and future scope is discussed in section 5.

2. Literature Review

Noise in digital images[5] is generally introduced in image acquisition and transmission. Thermal noise with Gaussian distribution, also named white noise has zero mean and signal independent. Impulse and Pepper noise is defined in two situations: data loss and saturation, and it occur in situations, where abrupt transients take place during imaging. It occurs mostly in mammogram images. Blur which is a structured a periodic noise highly affects the visibility of important image detail. Blur occurs due to motion of object which has to imaged or due to the motion of imaging system. Existing quantitative FR image quality indices for such noise contaminated images are as follows:

2.1 Mean Structural Similarity Index (MSSIM)

The idea of structural similarity proposed by Zhou Wang[6,7], is based on fact that the HVS is highly suited to gather structural information from visual scenes. MSSIM Index is formulated by focusing on both structural and non-structural distortions. MSSIM includes three parameters: luminance l (m, n), contrast c(m, n) and structure s(m, n). All parameters are similarity based. This proposed index can be applied to only grayscale images whereas humans can differentiate thousands of color shades.

Let,

$$M = \{m_i | i = 1,2,..K\} \text{ and } Y = \{n_i | i = 1,2,..K\}$$

be the original and test image signal respectively.

$$SSIM = [l(m, n)][c(m, n)][e(m, n)] \ldots \ldots (1)$$

$$MSSIM(M, N) = \frac{1}{w} \sum_{j=1}^{w} SSIM(m_j, n_j) \ldots .. (2)$$

2.2 Visual Information Fidelity in Pixel Domain (VIFP)

The VIFP considers two data variables[8]: One is the statistics between initial and the final stage of the visual channel when there is no distortion. Second variable is mutual data between the input of distortion block and the output of visual system block. Hypothetically, for reference image or in the absence of any noise, signal first passes through visual channel before entering the brain, which selects cerebral data from it. Where, in case of noisy images, source signal passes through another biased channel before coming in to perceptible channel. Combining the above stated two variables, a fidelity measure is extracted out. But, VIFP criterion fails on some image distortions like image blur, Gaussian noise and compression. This VIFP method requires number of assumptions and fails on realistic ground.

2.3 Feature Similarity Index (FSIM)

Feature-similarity (FSIM) measure for IQA proposed[9] is following the idea that human extract an image mainly according to its deep-level aspects. Low level aspects considered was phase congruency (PC), PC is a dimensionless quantity. PC reflects behavior of the image in frequency domain and it is computationally complicated. Gradient magnitude (GM) is used as subsequent aspect in FSIM. PC along with GM makes an agreeable fusion in constituting the image regional quality. But PC feature considered is contrast unwavering whereas contrast information alters human insight of image quality. Also, Perceptual results observed did not well match to subjective judgment.

3. Proposed Work

Quality assessment has wide application area. Quality criterion can be used by image processing system to adjust itself inevitably for retrieving upgraded quality images and also helps in design and to evaluate image acquisition systems, display devices and algorithms[11]. Also, bandwidth efficiency of communication system can be improved by using IQA techniques.

Quality criterion proposed to assess quality of various deteriorated images works on color images since color information[13] will ease image prediction e.g., object classification and eradication on the basis of color. Firstly, RGB color image are converted in to YIQ color model since it separates the intensity segment (Y) from color section (I and Q). Now, two factors considered for comparison of original and noisy image are intensity comparison and color comparison noise has significant effect on luminance and color.

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.274 & -0.332 \\ 0.211 & -0.523 & 0.312 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \qquad (3)$$

Let, f_1, f_2 represents reference and distorted image respectively. I_1, I_2, Q_1, Q_2 be I and Q chromatic channels of the image f_1, f_2. Similarly, Y_1, Y_2 be intensity component of f_1 and f_2 respectively. Similarity between chromatic and intensity features is given as:

$$S_I = \frac{2\,I_1 I_2}{I_1^2 + I_2^2} \qquad \dots\dots.. (4)$$

$$S_Q = \frac{2\,Q_2 Q_2}{Q_1^2 + Q_2^2} \qquad \dots\dots. (5)$$

$$S_Y = \frac{2\,Y_1 Y_2}{Y_1^2 + Y_2^2} \qquad \dots\dots. (6)$$

Third Factor considered is gradient or edge information acting as a strong visual stimulus. Edge information[10,12,14] is quite rich as interest points on the image content and they ease any further interpretation by focusing on specific area in image. Gradient of an image is calculated by obtaining partial derivative df/dx and df/dy at every pixel location, thus gradient provides variety of slim details and become highly values criterions of image analysis.

Partial derivative G_x and G_y of image f_1 along horizontal and vertical direction using scharr gradient operator is:

$$G_x = \frac{1}{16}\begin{bmatrix} 3 & 0 & -3 \\ 10 & 0 & -10 \\ 3 & 0 & -3 \end{bmatrix} f_1 \dots\dots\dots (7)$$

$$G_y = \frac{1}{16}\begin{bmatrix} 3 & 10 & 3 \\ 0 & 0 & 0 \\ -3 & -10 & -3 \end{bmatrix} f_1 \dots\dots\dots (8)$$

Gradient magnitude of reference image f1 is then,

$$G_1 = \sqrt{\left(G_x^2 + G_y^2\right)} \dots\dots\dots\dots. (9)$$

Similarly, gradient magnitude G_2 of distorted image can be obtained. Finally, Gradient similarity can be calculated as:

$$S_G = \frac{2 G_1 G_2}{G_1^2 + G_2^2} \dots\dots\dots\dots\dots. (10)$$

Then, different weights are given to similarity measures according to HVS perception[15]. Finally image

quality criterion (Q) is submitted by representing an image contamination as amalgam of above calculated similarity measures as:

$$Q = S_G^2 \times (S_I \times S_Q \times S_Y)^\lambda \dots\dots\dots (11)$$

Where, $\lambda > 0$, this parameter used to regulate the value of chrominance and intensity components. Here, $\lambda = 0.02$.

4. Results and Discussion

Performance of proposed quality criterion Q, is assessed by applying Q criterion on standard 24 bit colored 512 x 384 test image. Standard images are taken from TID 2008 database[16]. Original image along with images contaminated by a number of noises is shown in figure 1.
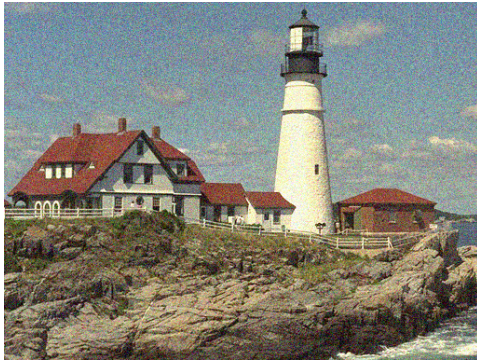

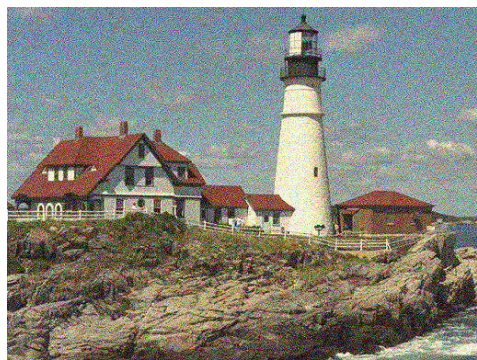(a)_Thakur

(b)_Thakur

(c)_Thakur

(d)_Thakur

(h)_Thakur

(e)_Thakur

(i)_Thakur

Figure 1. (a) A reference image; (b - i) are the distorted versions of (a) in the TID2008 database. Distortion types of (b - i) are mean shift, masked noise, additive gaussian noise, impulse noise, HF noise, gaussian blur, image denoising, and JPEG compression, respectively

(f)_Thakur

Distortions considered are additive Gaussian noise, mean shift, masked noise, salt-pepper noise, HF noise, blurring, JPEG compression etc. Performance of proposed criterion Q will be checked and matched with three commonly used IQA metrics, MSSIM, VIFP and FSIM. Also, consistency of Q with subjective score MOS is also checked.
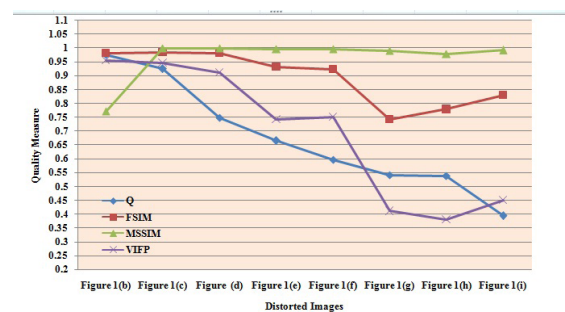

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Figure 2. A subjective score of test images figure 1(b-i)

Table 1. Quality evaluation of images in figure 1.

Metric	Figure 1(b)	Figure 1(c)	Figure 1(d)	Figure 1(e)	Figure 1(f)	Figure 1(g)	Figure 1(h)	Figure 1(i)
MOS	5.3125	4.9063	4.6875	3.9355	3.433	2.4063	2.375	1.322
Q	0.9758	0.9253	0.7483	0.6656	0.5962	0.5419	0.5395	0.3937
FSIM	0.9825	0.9840	0.9822	0.9318	0.9230	0.7426	0.7792	0.8297
MSSIM	0.7711	0.9997	0.9996	0.9972	0.9973	0.9906	0.9792	0.9925
VIFP	0.9554	0.9468	0.9111	0.7485	0.7516	0.4113	0.3819	0.4514

Table 2. Assorting of images in accordance to their quality calculated by each metric

Metric	Figure 1(b)	Figure 1(c)	Figure 1(d)	Figure 1(e)	Figure 1(f)	Figure 1(g)	Figure 1(h)	Figure 1(i)
MOS	1	2	3	4	5	6	7	8
Q	1	2	3	4	5	6	7	8
FSIM	2	1	3	4	5	8	7	6
MSSIM	7	1	2	4	3	6	7	5
VIFP	1	2	3	5	4	7	8	6

Proposed Q is validated as well as compared with existing objective measures FSIM, MSSIM and VIFP. From Table 1, it is clear that proposed image quality criterion Q is showing consistent results with subjective results represented by mean opinion score (MOS). Since Subjective result values (MOS) in figure 2 are consistently decreasing from figure 1(b) to figure 1(i) and proposed Q values from figure 3 are also decreasing from figure 1(b) to figure 1(i). Thus it can be seen that Q agrees with the human perception. Other IQA metrics, such as FSSIM results did not agree human perception in figure 1(g) and figure 1(i). Also, MSSIM show inconsistency in case of figure 1(b-f) and figure 1(i). Finally, VIFP fails in distortions which can be visualized from figure 1(e) and figure 1(i).
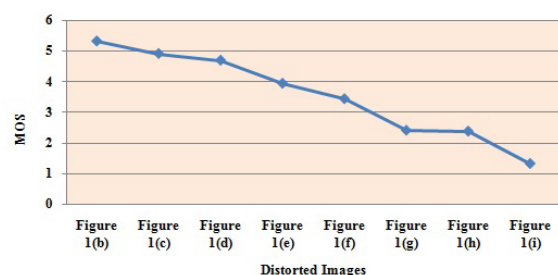
Figure 3. Performance comparison of IQA metrics on test images figure 1(b– i)

In order to show the correspondence of each IQA metric with the subjective results clearly, in Table 2, ranking of the images is done in accordance to their quality values computed by each metric and also subjective result. Also, time elapsed for running the new quality metric Q is 0.382s where as in FSIM time elapsed is 0.968s, MSSIM take 0.3499s, and time elapsed for running VIFP is 0.533s.

5. Conclusion

Objective of this proposed work is to see basic approaches of image quality measurement algorithms and suggest appropriate criterion Q by taking in to account the fact that gradient and color are significant attribute of human visual perception of quality. Proposed criterion is simple to implement, consume less time and shows full correlation with subjective results. Thus, knowledge considered in formulating image quality calculation methods are: insight of human visual models; knowledge about high-quality images whether full, reduced and no reference; and awareness about image distortions. Numerous issues to consider for image quality prediction includes to achieve good level of quality at minimum cost, application scope, application goal for quality check ,algorithm optimization and speed requirements.

IQA has wide application area. It can be applied to, many fields such as science, medical, remote sensing, forensic study, material Science, military, film-making industry, etc. Benchmarking and monitoring of image compression, communication, acquisition, display, resto-

ration and detection system can be accomplished also. In future perspective, proposed color image quality criterion can focus upon video quality computation.

6. References

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