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A Study on Various Image Quality Assessment Measures

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Abstract: Image quality assessment means estimating the quality of an image. Image Quality measures play important roles in various image processing applications.Image Quality assessment is an emerging field of signal processing. Though numerous algorithms or image quality metrics have been proposed, none truly correlates with the notion of quality as perceived by human vision system.There are two ways of measuring image quality ie subjective and objective. Objective method is more preferable than subjective because most of the time the original image is not available for the comparison and it is not that much expensive like the subjective method. In this paper we are studying the various image quality metrics.

Index Terms: Image Quality Metrics, Structural Similarity Index Metrics,Human Visual system

1. INTRODUCTION

Image quality assessment tries to quantify a visual quality or, analogically, an amount of distortion in a given picture. These distortions are inevitable part of any digital image processing pipeline (acquisition, compression, transmission, etc. of images). The only ”correct” method of evaluating the human-perceived visual quality of the pictures is the evaluation by the human beings. Measurement of image quality is crucial to many image processingsystems. Due to inherent physical limitations and economicreasons, the quality of images and videos could visibly degraderight from the point when they are captured to the point when theyare viewed by a human observer. Identifying the image qualitymeasures that have highest sensitivity to these distortions would help systematic design of coding, communication and imagingsystems and of improving or optimizing the image quality for adesired quality of service at a minimum cost. There are various approaches for calculating quality of image. All approaches however generally describe quality in terms of the pixel differences between an “original” image and its damaged or coded counterpart.For a given “signal” its original form is one that is free of any distortion and therefore assumed to be of perfect quality.There are two types of metrics used for quality assessment

i) Full reference metrics technique: That require both original and coded image.
ii) Reduced reference or no reference metrics technique: That requires only partial signal or none at all.

2. BACKGROUND

2.1 Definition of Quality

A common definition of quality, regardless of field, is that quality is the conformance to requirements.This definition is general, and has been adapted by many. Related definitionsare given by the International Organization for Standardization (ISO), who defines quality as the totality of characteristics of an entity that bear on its ability to satisfy stated or impliedneeds or as the ability of a set of inherent characteristics of a product, system or process to fulfill requirements of customers and other interested parties . All of these definitions relate quality to some sort of requirements.

2.2 Image quality

The image quality is defined by following definitions as follows

- Image quality is defined as the subjective impression found in the mind of the observer relating to the degree of excellence exhibited by an image.
- Image quality is defined as the integrated set of perceptions of the overall degree of excellence of the image.
- Image quality is defined as the impression of the overall merit or excellence of an image, as perceived by an observer neither associated with the act of photography, nor closely involved with the subject matter depicted.

Measurement of Image quality is very important to numerous image processing applications during acquisition, processing, storage, transmission and reproduction, of Digital images which may result in a degradation of visual quality due to various distortions.. Humans are highly visual creatures. The main function of human eye is to extract structural information from the viewing field, and the (HVS) human visual system ishighly adapted for this purpose. Therefore, for the applications in which images are ultimately to be viewed by human beings, the only "correct" method of quantifying visual image quality is through subjective evaluation. In practice, however, subjective evaluation is usually too inconvenient, time-consuming and expensive. In recent years, a lot of efforts have been made to develop objective image quality metrics that correlate with perceived quality. MSE, PSNR, and SSIM are some useful and most commonly used objective image quality measures.

3. SIGNIFICANCE OF QUALITY MEASURE

There is a lot of significance of image quality assessment. The importance of quality of images, videos and theassociated cost-quality balance, the obvious question that arises iswhy we need to measure quality. The answer is simple and couldbe illustrated by a few examples. If a designer is designing thishigh-end television, and wants to know what the quality-cost curvelooks like, he obviously needs a mechanism for measuring thequality of the output video when his design is running at certainconfiguration costing a certain resource. In another scenario, adesigner of a medical imaging device may want to decide whichof the two alternative X-ray devices gives better results. He tooneeds a way of scientifically comparing the quality of the twosystems. Basically, quality assessment algorithms are needed formainly three types of applications.

1. For optimization purpose, where one maximize quality at agiven cost.
2. For comparative analysis between different alternatives.
3. For quality monitoring in real-time applications.

4. APPROACHES OF IMAGE QUALITY MEASURE

There are basically two approaches for image Quality measurement:-

1. Subjective measurement
2. Objective measurement

4.1. Subjective measurement

A number of observers are selected, tested for their visualcapabilities, shown a series of test scenes and asked to score thequality of the scenes. It is the only "correct" method of quantifyingvisual image quality. However, subjective evaluation is usuallytoo inconvenient, time-consuming and expensive.

4.2. Objective measurement

These are automatic algorithms for quality assessment that couldanalyse images and report their quality without human involvement.Such methods could eliminate the need for expensive subjective studies. Objective image quality metrics can be classified accordingto the availability of an original (distortion-free) image, with whichthe distorted image is to be compared.

Most existing approaches are known as: -

(i) Full-reference: meaning that a complete reference image isassumed to be known.

(ii) No-reference: In many practical applications, however, thereference image is not available, and a no-reference or "blind"quality assessment approach is desirable.

(iii) Reduced-reference: In a third type of method, the referenceimage is only partially available, in the form of a set ofextracted features made available as side information helpto evaluate the quality of the distorted image.

5. CLASSIFICATION OF IMAGE QUALITY METRICS

Classification of existing IQ metrics is a good starting point for selecting the best metricsfor a given setting, such as to evaluate print quality. Without a classification of metrics onedoes not have an organized way to telling the difference between the different metrics.Such an organization illuminates the relationship between metrics, and thereby increasing theunderstanding of them. Classification helps in the decision making of what metric to use, butalso in the development of new and improved metrics.

5.1 Existing classification of image quality metrics

Since IQ metrics have been proposed based on different approaches they can be divided into different groups. These groups usually reflect different aspects of the metrics, such as their intended use or construction. Several different researchers have classified metrics into groups, even though it can be difficult to find sharp boundaries between the numerous IQ metrics in the literature.

Avcibas et al. divided IQ metrics into six groups based on the information they use:

• Pixel difference-based measures such as mean square distortion.
• Correlation-based measures, that is, correlation of pixel values, or of the vector angular directions.
• Edge-based measures, that is, measure of the displacement of edge positions or their consistency across resolution levels.
• Spectral distance-based measures, that is, the Fourier magnitude and/or phase spectral discrepancy on a block basis.

• Context-based measures are based on various functionals of the multidimensional context probability.
• HVS-based measures are measures that are either based on the HVS-weighted spectraldistortion measures or (dis)similarity criteria used in image base browsing functions.

5.2 Proposal for classification of image quality metrics

There are many different ways to group IQ metrics. In order to present thevarious approaches we have divided the IQ metrics into four groups

- Mathematically based metrics, which operate only on the intensity of the distortions.These metrics are usually simple, such as the Mean Squared Error (MSE) and PeakSignal to Noise Ratio (PSNR).
- Low-level based metrics, which take into account the visibility of the distortions using for example Contrast Sensitivity Functions (CSFs) .
- High-level based metrics, which quantify quality based on the idea that our HVS isadapted to extract information or structures from the image. The Structural Similarity (SSIM), which is based on structural content, or the Visual Image Fidelity(VIF) , which is based on scene statistics, are examples of metrics in this group.
- Other metrics, which are either based on other strategies or combine two or more of theabove groups. One example is the Visual Signal-to-Noise Ratio (VSNR) , which takes into account both low- and mid-level visual properties, and the final stage incorporatesa mathematically based metric.

6. MATHEMATICALLY BASED METRICS

The first group of metrics, mathematically based ones, has been very popular probably dueto their easy implementation, and they are convenient to use for optimization. These metricsusually only work on the intensity of the distortion *E* given by

$$E(x,y) = I_O(x,y) - I_R(x,y),$$

where$I_O$is the original image, $I_R$is the reproduction, x and y indicate the pixel position.

(a) Original (b) Modified

Figure 1: Test target from Halonen et al. to differentiate between IQ metrics. The original image has been processed by applying an ICC profile with the relative colorimetric rendering intent.

6.1 Mean squared error

MSE is a mathematically based metric; it calculates the cumulative squared error between theoriginal image and the distorted image. Most of the metrics in this group are strict metrics, thatis, where ($\rho(I_O(x), I_R(y))$) is essentially an abstract distance, with the following properties:
$\rho(I_O(x), I_R(y)) = 0$ if $I_O(x) = I_R(y)$, symmetry, triangle inequality, and non-negativity. MSEis given as:

$$MSE = \frac{1}{MN}\sum_{y=0}^{M-1}\sum_{x=0}^{N-1}[E(x,y)]^2$$

where *x* and *y* indicate the pixel position, *M* and *N* are the image width and height.

7. Low-level based metrics

Metrics classified as low-level based metrics simulates the low level features of the HVS, suchas CSFs or masking. However, most of these metrics use a mathematically based metric.

8. High level based metrics

High-level based metrics quantify quality based on the idea that our HVS is adapted to extractinformation or structures from the image.

9. VISUAL INFORMATION FIDELITY

Sheikh and Bovik proposed the Visual Information Fidelity (VIF) criterion, which is an extension of the Information Fidelity Criterion (IFC) by the same authors. It quantifies the Shannon information present in the reproduction relative to the information present in the original. The natural scene model used is a Gaussian Scale Mixture model in the wavelet domain, and as a HVS model they use an additive white Gaussian noise model. The reference image is modeled by a Gaussian Scale Mixture in the wavelet domain. *c* isa collection of *M* neighboring wavelet coefficients from a local patch in a subband. Then *c* ismodeled as

$$c = \sqrt{z}u$$

where *u* is a zero-mean Gaussian vector and *z* is an independent scalar random variable. The VIF assumes that the distortion of the image can be described locally. as a combination of a uniformwavelet domain energy attenuation with added independent additive noise. So that visual distortion is modeled as a stationary, zero-mean, additive white
Gaussian noise process in the wavelet domain:
$e = c+n$ and $f = d + n$, where *e* and *f* are the random coefficient vectors for the same wavelet subband in the perceived original and perceived distorted image. *c* and *d* are random vectors from the same location in the same subband for the original and distorted image. The VIF is calculated as the ratio of the summed mutual information in the subbands, which can be written as following.

$$VIF = \frac{I(C;F|z)}{I(C;E|z)} = \frac{\sum_{i=1}^{N} I(c_i;f_i|z_i)}{\sum_{i=1}^{N} I(c_i;e_i|z_i)},$$

where *i* is the index of local coefficients patches, including all subbands.

10. Peak Signal to Noise Ratio (PSNR):
The PSNR is evaluatedin decibels and is inversely proportional the Mean Squared Error.It is given by the equation.

$$PSNR = 10\log_{10}\frac{(2^n - 1)^2}{\sqrt{MSE}}$$

11. SIMPLIFYING THE STRUCTURAL SIMILARITY METRIC
The structural similarity (SSIM) metric and its multi-scale extension(MS-SSIM) evaluate visual quality with a modifiedlocal measure of spatial correlation consisting of three components:mean, variance, and cross-correlation. The structural similarity (SSIM) metric and its multiscaleextension (MS-SSIM) evaluate visual quality basedon the premise that the human visual system (HVS) has evolvedto process structural information from natural images, and,hence, a high-quality image is one whose structure closelymatches that of the original. To this end, SSIM employs amodified measure of spatial correlation between the pixels ofthe reference and test images to quantify the degradation of animage's structure. MS-SSIM extends SSIM through a multiscaleevaluation of this modified spatial correlation measure. SSIM evaluates perceptual quality using three spatially localevaluations: mean, variance, and cross-correlation. Despiteits simple mathematical form, SSIM objectively predictssubjective ratings as well as more sophisticated QA algorithms.

11.1 SSIM and MS-SSIM

The SSIM has received a lot of attention since its introduction, gone through extensiveevaluation, and it has influenced a number of other metrics, such as the color version SSIMIPT by Bonnier et al. and the color version of UIQ by Toet and Lucassen. The SSIM index proposed by Wang et al. attempts to quantify the visible difference between a distorted image and a reference image. This index is based on the Universal Image Quality (UIQ) index. The algorithm defines the structural information in an image as those attributes that represent the structure.
of the objects in the scene, independent of the average luminance and contrast. The index is based on a combination of luminance, contrast, and structure comparison. The comparisons are done for local windows in the image, theoverall IQ is the mean of all these local windows. The SSIM is specified as

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

where$\mu$is the mean intensity for signals *x* and *y*, and σ is the standard deviation of the signals*x* and *y*. *C* is a constant defined as

$$C_1 = (K_1 L)^2$$

whereL is the dynamic range of the image, and k1 <<_1. C2 is similar to C1 and is defined as

$$C_2 = (K_2 L)^2$$

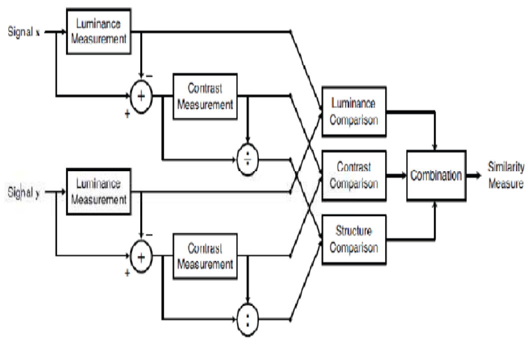

Figure 2. SSIM flowchart, signal x and y goes through a luminance and contrast measurement before comparison of luminance, contrast and structure. A combination of these results in the final similarity measure.

MS-SSIM extends SSIM by computing the variance andcross-correlation components at K image scales, where thekth scale image corresponds to low-pass filtering and subsampling,by a factor of 2 in both spatial directions, the originalimage (k − 1) times. The mean component is only computedat the coarsest scale, K. The MS-SSIM index is given by

$$\text{MS-SSIM} = m_K(X,Y)^{\alpha_K} \prod_{k=1}^{K} v_k(X,Y)^{\beta_k} r_k(X,Y)^{\gamma_k}$$

where mk(X, Y), vk(X, Y), and rk(X, Y) respectively correspondto the mean, variance, and cross-correlation componentcomputed and pooled across patches from scale k withk = 1as the full-resolution image.

11.2 SSIM Component Gradient Analysis

The SSIM quality metric as given in Eq. (1) combines three components to quantify the visual quality of an image, but it is not immediately obvious how each component evaluates visual quality. A gradient analysis illustrated that for a fixed MSE, the total SSIM quality metric favors an image with increasedvisual quality. However, a gradient analysis of theindividual components of SSIM was not performed. A gradient analysis, inspired by, is performed to examinethe visual quality evaluation corresponding with theindividual components. An original natural image X is selected,and a random image Y is formed whose pixel valuesare independently and identically drawn from a uniform distributionwith mean 128 and standard deviation 1/12. Forexample, to optimize according to the mean component ofSSIM, m(X, Y) the image Y is updated at iteration k viagradient ascent according to

$$Y \leftarrow Y + \eta(k) \nabla_Y m(X,Y)$$

Eq (1)

Whereŋ is the learning rate at iteration k and $Y m(X,Y)denotes the gradient of the mean component with respect toY . Here,m(X, Y) denotes the average of the individual patchmeans m(x, y).

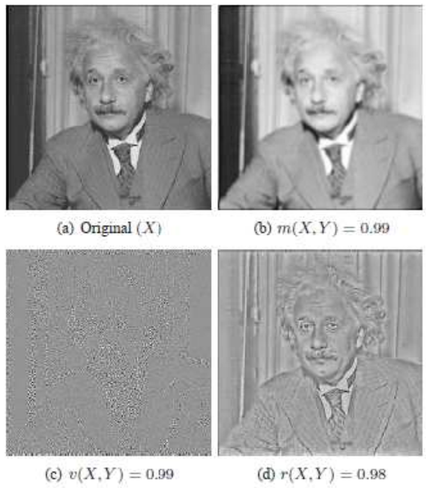

Figure3. Gradient analysis of the individual SSIM components: mean m(X, Y), variance v(X, Y), and cross-correlation r(X, Y). Images (b) – (d) have been rescaled for visibility

Figure 3 illustrates the effect of maximizing the individual components of SSIM for the natural image ofEinstein. At first glance, using the mean component generates an image (Figure 1(b)) that most resembles the original in Figure 1(a) among the three components. However, the maximum for m(X, Y) does not produce a sharp image. The optimization with the SSIM variance component yields a textured image (Figure 1(c)), where the textures occur along the image edges. The variance component optimization does not adequately restrict the possible pixel value configurations to produce an easily recognizable image. The image optimizingthe cross-correlation component captures most of the detailsfrom the original image. For instance, notice the details inthe hair, eyes and mustache in Figure 1(d). Moreover, the facial expression has a more accurate phenomenal appearancein Figure 1(a) with respect to the original than in Figure 1(b),where the expression appears melancholy rather than alert.The SSIM cross-correlation component clearly assesses qualityaccording to the preservation of the reference image edges.

CONCLUSION

Image Quality assessment is an emerging field of Image and signal processing. Although numerous algorithms or image quality metrics have been proposed, none of them truly correlates with the idea of quality as perceived by human vision system. In this paper we have studied the subjective and objective approaches of Image quality assessment. we have found that SSIM and MS SSIM is a better choice.

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