www.ijecs.in
International Journal Of Engineering And Computer Science ISSN:2319-7242
Volume 03 Issue 07 July, 2014 Page No. 6950-6955

Multiple Quality Parameters for Image Quality assessment

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Abstract— **There has been an attention is boosted towards extending the IQA which follows two stage structures; in first stage, the reference and compressed images are taken as input by local quality measurement and the second stage advances it to the pooling stage and provides quality score. In the initial time, various methods such as MSE, PSNR, Correlation and Entropy are most used for the quality evaluation but this does not recommend any structural information of images. To diminish this restriction and offer structural information, initiative behind organizing this paper to accomplish most excellent overall performance is to progress the pictographic quality by merging information content weighting with structural similarity measurement.**

Keywords—Image quality assessment, structural similarity index measurement(SSIM), Feature extraction, Distortion, Quality index

I Introduction

It is renowned that images can endure from deformations due to numerous sources. Distortion is near in the images in different forms such as noise, blur, contrast change etc. This is able to disgrace the total quality of image. So, it is extremely indispensable to uncover the quality of images in this region. In this generation, curiosity towards the Image Quality Assessment is being boosted, so as to involuntarily anticipate individual activities in appraising image quality [1]-[3]. The field of Image Quality Assessment is hastily advancing. It is the measurement of elements of images like structure, contrast, local luminance, color etc. Image Quality Assessment plays a vital role in enormous applications in the appraisal, manage, blueprint and optimization of image which has the flair to accomplish miscellaneous operations such as image acquirement, communication, restoration, enhancement, analysis and progression and display systems. Image may be classified into full-reference (FR, where full access provided when estimating the deformed image), reduced-reference (RR, just fractional information on the reference image is obtainable here) and no-reference (NR, no admittance to the reference image is permitted here) algorithms are rest with the handiness of an ultimate quality reference image [3]. The frequent two-phase structure implemented via IQA measures (mainly FR algorithms). Locality might be characterized in space, spatial frequency and orientation or direction by the measurement of distortion and quality of image prepared in the first phase. There are the spatial domain methods that work out pixel or patch-wise distortion/quality measures in space [4], [5]. Mean squared error method is most exercised method that enumerates the quality of an image. By use of this method, measure of how two images are pixel-wise similar, is known and it does not offer any structural information of them. Therefore to reduce this limitation, a new quality assessment method projected which is founds on structural similarity of two images though localized quality/distortion measures across scale, space and orientation or direction described by block-discrete cosine transform [6] and wavelet-based [7]-[11] approaches. Image quality and localized measurement is all concerning what human see i.e. human visual system (HVS). In the primary visual cortex, it has been originated that the reaction of loads of neurons are exceedingly tuned to the stimuli that are slender band in frequency, space and orientation [12]. IQA is the process of measuring the quality/distortion in between the JPEG compressed image and reference image by computing two local quality/distortion measures, absolute and SSIM index which outcomes either in the spatial domain or in the transform domain by the assist of absolute error map and an SSIM map. The spatial variance of impertinent image quality is preferably reflected by using the SSIM index, portrayed from an attentive supervision or a survey. In the second stage of the IQA algorithm, an algorithm is engaged to bring forth a single quality score as of such quality/distortion maps.

In this paper, first stage defining the local quality/distortion measurement in the considerable evolution [1]-[3], and the second one is concerning pooling stage. There are different pooling approaches that exhibit adequacy of spatial pooling by inspecting with them [13]. IQA is segmented into two groups; subjective image quality assessment and objective image quality assessment. Subjective measurements are effectively stands on estimation by individual observer; the overall quality of a set of images is estimated and umpired by human being. The accurate result depends on the appropriate accomplishment but it puts away a lot of time which is the reason of being it's expensive. Objective measurement of image quality instead, approximates recognized quality though bypassing human assessors. A general assumption is so as to the entire pooling strategies are correlated through human visual system (HVS) and with subjective and objective measurements [14]-[16].

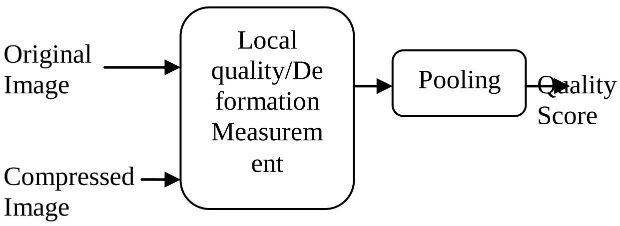


Fig. 1 Two stage structure of IQA

II Image Quality Assessment

The weighing up of image information substance is a matter of excellent statistical image sculpts. IQA consist two stage structures as described in this paper. For the second stage i.e. spatial pooling of IQA, it is deemed that a coarse spatial domain local Gaussian sculpts is exercised [13]. IQA [34] [37] [38] and image denoising [36] have some topical booming advances that stimulate to absorb the Gaussian scale mixture (GSM) model for expected images. A Markov hypothesis is prepared to condense the high dimensionality of expected images through the probability density of a pixel is entirely found out by the pixels within a spatial locality. A set of neighboring coefficients within a multi-resolution image transform domain, erects the locality. For this intention, GSM has initiated to be an influential sculpt [39]. It has been revealed so as to the GSM skeleton know how to approve description effortlessly meant for the subsidiary information of multi-resolution transform coefficients of expected images, where strong non-Gaussianity revealed with pointed peak at zero and weighty tails, from the density. To portray the amplitude-dependency linking neighboring coefficients, GSM is too potent [39].

In our methodology,we intordouce four multiple parameter, Which is following:

1) SSIM - A new quality assessment method projected which founds structural similarity of two images though localized quality/distortion measures, is known as Structural Similarity Index Measurement. SSIM accomplish the process by splitting its tasks into three distinctions that are luminance, contrast and structure. The product of the illumination and the reflectance is acknowledged as the luminance of the surface of an object that is being pragmatic. The structural information is characterized by those aspects that symbolize the structures of the object. It does not distress by the average luminance and contrast because the values of these are fluctuating across a scene.
2) We necessitate describing the three functions $l(x,y)$, $c(x,y)$ and $s(x,y)$ to complete the definition of similarity measures and also satisfies the following conditions:
   1. Symmetry: $S(x,y)=S(y,x)$;
   2. Boundedness: $S(x,y)\le 1$;
   3. Unique maximum: $S(x,y)=1$ if and only if x=y (in discrete representations, $x_i = y_i$ for all $i=1,2,\ldots\ldots N$).

At last, the three components are pooled to yield an overall similarity measure:

S(X,Y) = f(l(x,y),c(x,y),s(x,y))

The SSIM indices measure the structural similarity between two image signals. If one of the image signals is regarded as of perfect quality, then the SSIM index can be viewed as an indication of the quality of the other image signal being compared. When applying the SSIM index approach to large-size images, it is useful to compute it locally rather $\sum$than globally.

2) MSE - In statistics, the mean squared error is one of the most ways to enumerate the variation between values disguised by an estimator and the true values of the extent being guessed.
MSE is defined as below :

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(X_i - Y_i)^2$$

Where x_i and y_i be the ith pixel in the reference x image and the distorted image y, respectively.
The ratio between the highest achievable power of a signal and the power of demeaning noise that influences the reliability of its demonstration illustrates the expression of peak signal to noise ratio.

3) Standard deviation/mean- In statistics, the standard deviation (SD) be evidence for the measure of variation or dispersion of a set of data from its mean. A low standard deviation signifies that the data points tend to be extremely close to the mean (also known as expected value); a high standard deviation signifies that the data points are broaden away above a vast range of values.
Standard deviation is calculated as given below:

$$\sigma = \sqrt{\sum_{i=1}^{N} P_i\,(X_i - \mu)^2}$$

Where $\mu = \sum_{i=1}^{N} p_i x_i$,

x_i - Finite data set and

p_i - Probability.

4) Skewness- Skewness is an attribute of a distribution. A distribution that is symmetric around its mean has skewness zero, and is 'not skewed'. Skewness is calculated as E[(x-mu)3]/s3 where mu is the mean and s is the standard deviation. Skewness is asymmetry in a statistical

distribution, in which the curve appears distorted or skewed either to the left or to the right. Skewness can be quantified to define the extent to which a distribution differs from a normal distribution. In a normal distribution, the graph appears as a classical, symmetrical "bell-shaped curve." The mean, or average, and the mode, or maximum point on the curve, are equal. In a perfect normal distribution (green solid curve in the illustration below), the tails on either side of the curve are exact mirror images of each other. When a distribution is skewed to the left (red dashed curve), the tail on the curve's left-hand side is longer than the tail on the right-hand side, and the mean is less than the mode. This situation is also called negative skewness. When a distribution is skewed to the right (blue dotted curve), the tail on the curve's right-hand side is longer than the tail on the left-hand side, and the mean is greater than the mode. This situation is also called positive skewness.

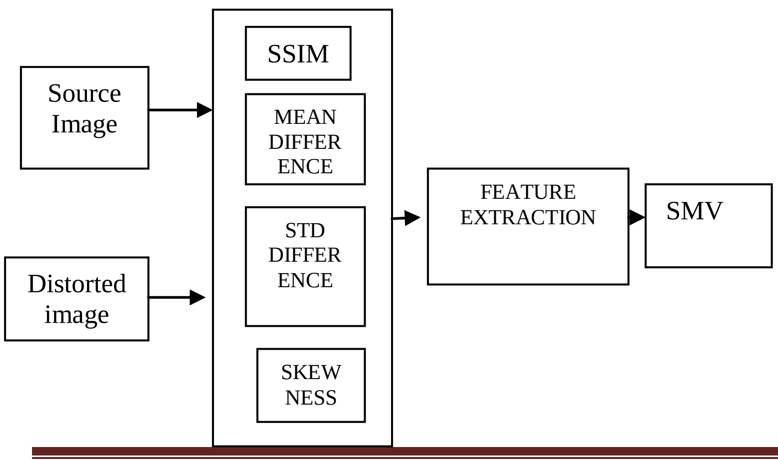
The **moment coefficient of skewness** of a data set is skewness: $g_1 = m_3 / m_2^{3/2}$

where $m_3 = \sum(x-\overline{x})^3 / n$ and $m_2 = \sum(x-\overline{x})^2 / n$

$\overline{x}$ is the mean and n is the sample size, as usual. m_3 is called the **third moment** of the data set. m_2 is the **variance**, the square of the standard deviation. We have to choose one of two different measures of standard deviation, depending on whether you have data for the whole population or just a sample. The same is true of skewness.

III METHEDOLOGY

The proposed method, is to merge the quality score obtained by the index of structural similarity with the distortion amount measured in order to obtain a quality measure that takes account the perception of local luminance , contrast, variance and structure. The most important assumption is that the human eye is typically suitable for the extraction of structural information of an image. It is then necessary to measure the degradation of this structural information. The idea is to extract local structural attributes of the image from which each block is described by its brightness, contrast and structure. The good IQM must be accurate and consistent in predicting the quality. Most IQ metrics are related to the difference between two images (the original and the distorted image).



SMV – Similar Measure Values

Fig .2 Basic Structure

In this methedology,we are having a source image and distorted image.We are going to comapre some parameters of those images.First,we divide each image in grid 4*4 size, Each grid has four parameters,that we want to comapre those particular parameters,namely they are :

1) SSIM
2) Standard Deviation
3) Mean Difference
4) Skewness

We extract the features from source image and distorted image and substracts the values of distorted image parameter to source image parameter and finally,we get similar measures value(SMV).

IV RESULT

In this literature, how to develop the superiority of picture is portrayed by using Image Quality Assessment. IQA is the sub-category of the image processing which facilitates to diminish the distortion by full-reference quality assessment. There different methods used in IQA are entropy, mean squared error (MSE) and peak signal to noise ratio (PSNR), correlation, standard deviation/mean and structural similarity index measurement (SSIM). Mean squared error and all the methods are most used method and all specifies the quality of an image. As a result of all this methods, assess of how two images are pixel-wise similar, is known but it does not offer any structural information of them. Therefore to drop off this restriction and provide structural information to produce an excellent quality, a new quality assessment method anticipated which is establishes on structural similarity of two images however localized quality/distortion measures across scale, space and orientation. Result of all the measurements are revealed in the below images and the graphs.

Fig 3 Image Quality Assessment

Two images are taken such as original image and distorted image as shown in fig. 3 and it generates the result in the terms of SSIM, Standard Deviation, MSE and Skewness org as shown in fig. 4.

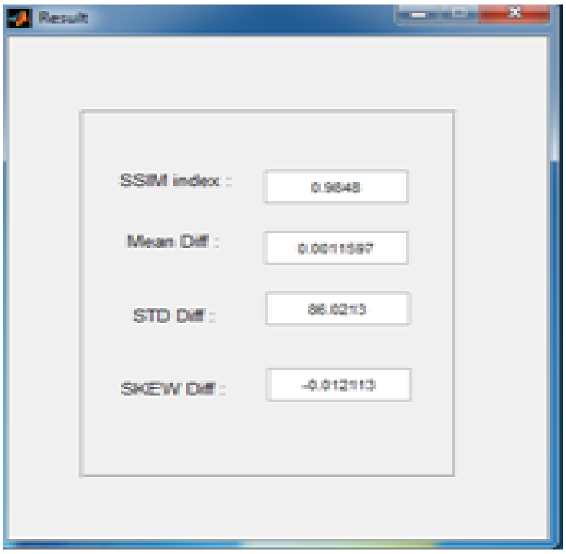


Fig. 4 Result

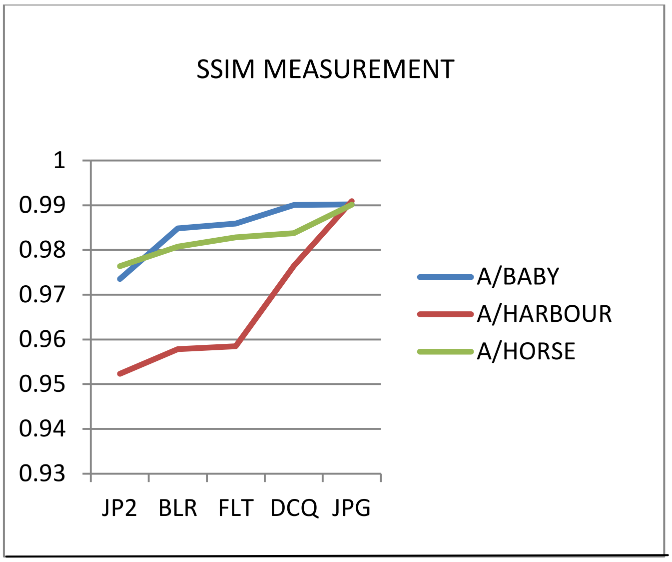


Fig. 5

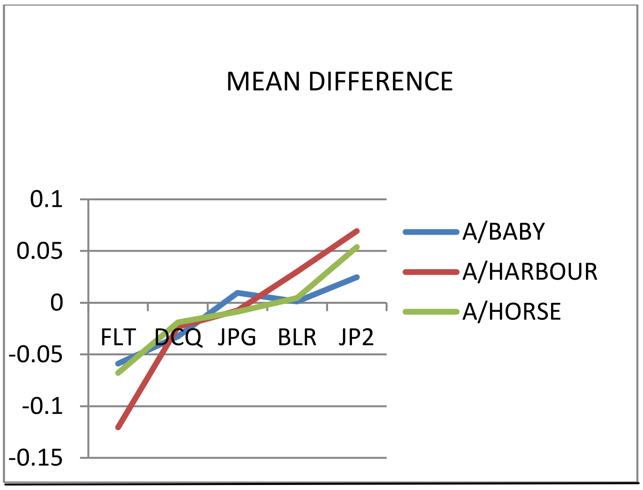


Fig. 6

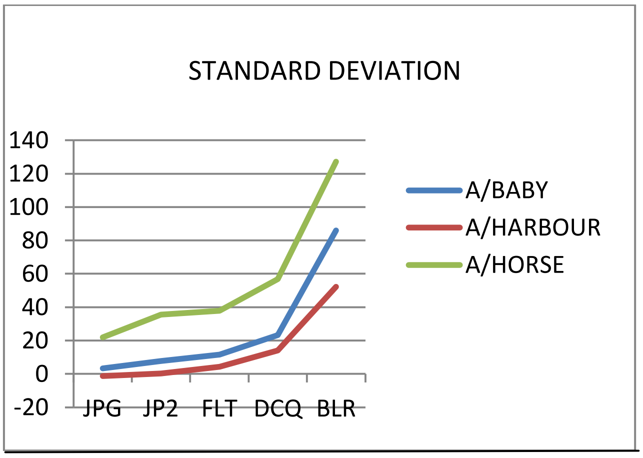


Fig. 7

V CONCLUSION

For the progression of the image quality, IQA with information content weighted SSIM is a most succeed method.In this literature, various algorithms such as entropy, standard deviation/mean, MSE and correlation are present for image quality assessment they work just like SSIM but they does not endow with any structural information of the images and correlation has the disadvantage that is computationally intensive. Orienting and situating two images so they overlie. In the result, there are three graphs which symbolize the SSIM have the peak value of JPG, mean difference has the peak value of JP2 and the standard deviation has the peak value of BLR. Therefore the structural similarity measurement with information weight (IW-SSIM) is engaged to shrink all these margins and endow with excellent overall performance.

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