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Measuring Quality Using Attributesfor No-Reference EnhancedImages

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Abstract —*Human vision can easily judge the quality of the image without a need for a reference image. But the idea of designing an algorithm to measure image quality without any reference is a challenge. Most of the available No-Reference image quality algorithms depend on prior knowledge of the type of distortion available in the image.*
Our research aims to develop a NR measurement index for TIF non-compressed images – to avoid any type of noise that might be caused by compression process. The research starts by establishing a TIFF image database out of a collection of available databases such as LIVE [1]*, CSIQ* [2]*, and DRIQ database* [3]*, and then conducting a subjective experiment on this database. In our research we propose an index that measures the quality of the image depending on its contrast, colour, naturalness and noise of the image. Furthermore, we present a computational NR image quality metric model for TIFF images. A subjective result – Mean opinion Score (MOS) - is used to test the metric, which achieved good quality prediction performance among other full-reference image quality metrices.*

Keywords-*No-reference, metric, enhancement, quality, natural scene.*

I. INTRODUCTION

In the last decade, there has been a rapid improvement in developing object measurement techniques for predicting image/video quality. There is a vast area of application to implement these methods such as monitoring image/video quality for quality control systems, benchmarking image/video processing systems and be embedded into image/video processing systems, and to optimize algorithms and parameter settings. Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) are the most used algorithms for image quality measurement, but they are not efficient to correlate with perceived quality measurement, despite that this research will use them beside Mean Structural Similarity index (MSSIM) in a comparison with proposed index. A great effort has been made in the field of objective image/video quality assessment that incorporate perceptual quality measures by considering characteristics.

Most of the proposed image quality metrics requires the presence of the original image as a reference to evaluate the distorted image; this is called Full-reference image quality metric like it is in PSNR, MSE, and MSSIM. Fortunately, human mind can assess the quality of the image without using any reference. But on the other hand, designing a No-Reference (NR) quality algorithm is considered difficult task because of the limitation of understanding human visual system. It is assumed that the No-Reference quality assessment is truthful if there is training for the human mind for the type of distortion, noise or miss-convenient that should be look for. A limited number of algorithms presented in the past decades for objective NR quality assessment, but recently many researchers started to work at this side [4], [5], [6], [7], [8].

The main purpose of this research is to develop an objective NR quality index for Tagger Image Format (TIFF) non-compressed images that is capable to predict perceived image quality effectively. Despite that blurring and ringing are considered the most known artefacts generated during compression process, but in our research, we care for the artefacts that show because of unnatural enhancement of the image.

An efficient way is presented to measure some of the main noticeable attributes by human observers in the image. And then we combine these measurements in a linear equation to constitute an index that can predict the quality of the image. Despite that there are many physical attributes for any natural scene, but after questioning about the most noticeable attributes by human observers, we found that colourfulness, contrast, brightness, and sharpness are the most important thing that human eye notice when there is no specific type of noise referred to. Subjective experimental results were used to evaluate the proposed index, which achieved very good quality prediction performance.

II. SUBJECTIVE EXPERIMENT

The subjective experiment was conducted on coloured images. There were 120 test images in the database; thirty-three of them were original images, which were randomly distributed in the database. The bitmapped images were converted into TIF using Photoshop software, some of test images are shown in Figure 1.

The experiment was a single stimulus, and the thirty subjects were given a little training, and then were shown the database randomly one image at a time; most of the subjects were college students, they were asked to evaluate each image to a score between 1 and 100 (100 presents the best quality where 1 is the worst). The 30 scores of each image were averaged to a final Mean Opinion Score (MOS) of the image.

Despite that the main goal of this research is to develop a NR objective image quality index and the computation of PSNR, MSE and MSSIM requires a reference image, it is nice to see how these algorithms correlate with the MOS values specially since PSNR is widely used in different image processing applications, and it has been employed as a reference model to evaluate the effectiveness of other objective image/video quality assessment approaches [9].

The implementation for the proposed metric was done using Matlab.

Figure 1: Some of the images used in the experiment

Despite it is well known that PSNR, MSE, and MSSIM are acceptable in predicting image quality for compressed images, there visual predictively ability degrades when applied to non-compressed images**.**

III. OBJECTIVE NR QUALITY ASSESSMENT

Images used in the experiment were contrast reduced using *imadjust* in Matlab, and then each of these reduced contrast images was enhanced using Histogram Equalizer (HE).The enhancement of the image produced different types of images were some were better than the original (the contrast reduced image), and others were worse. Enhancement does not always produce better results.

There are many distortions caused by over enhancement that causes unnatural results such as excessive brightness, noise artefacts, and brightness saturation [11].

Steps for designing quality indices in the proposed index are:

A. Colourfulness Index:
  1- Convert the image from sRGB colour space into RGB colour space.
  2- Convert the image from RGB colour space into XYZ colour space.
  3- Convert image from XYZ colour space into CIELab colour space.

B. Naturalness Index:
1- Convert the image from sRGB colour space into RGB colour space.
2- Convert the image from RGB colour space into XYZ colour space.
3- Convert image from XYZ colour space into CIELuv colour space.
4- Compute image characteristics such as luminance, hue, saturation, and Chroma.
5- Using image characteristics in computing main natural attributes with main colour such as skin, grass, and sky colour ranges.
6- Using pixels for the three main fields (skin, grass, and sky) image quality metric is computed.

Figure 2 and Figure 3 show images in different colour spaces.

Figure 2: Original image sRGB to the left, converted to RGB image to the right

Converting the sRGB to RGB which is more intensive colour space. RGB has a wider range of colours than sRGB - is done using the following equation:

$$d(K) = \begin{cases} \left(\frac{K+0.055}{1.055}\right)^{2.4}, & \text{if } K > 0.04045 \\ \frac{K}{12.92}, & \text{otherwise} \end{cases} \tag{1}$$

Images in Fig. 6 show to the left the image in RGB colour space, whereas the image to the right is the image in XYZ colour spaceWhile the following metrix was used to convert into XYZ color space:

Figure 3*: Image to the left in RGB while the one to the right in XYZ colour space*

Conversion equations into XYZ colour space was presented in [11], in addition to equation for converting XYZ colour space into CIELuv colour space.

C. Contrast Index:
In order to compute contrast index, the Michelson contrast was used as in the following equation[12]:

$$C_M = \frac{L_{max} - L_{min}}{L_{max} + L_{min}} \tag{2}$$

To find colour index the standard deviation and the mean were used as expressed in the following equation:

$$Cl_y = \sigma_{rgyb} + 0.3 * \mu_{rgyb} , \quad (3)$$

where μ is the mean and σ is the standard deviation.

Items naturalness and contrast required to compute the quality metric are ready.

D. Noise Index:

The last index is the noise index which is described in the following equation:

$$NR = \mu(\sigma(im(:))) \quad (4)$$

Now we have all the indices required for computing quality metric. Indices were combined to form image quality index as in the following equation:

$$Q_i = (1 - w_q) * N_i + w_q * \left(\frac{Cl_i}{Cl_{max}}\right) + 0.5 * C - NR \quad (11)$$

where $w_q = 0.75$. Constants used in the equation are experimental constants that have been tried 100 times to reach the best fraction that gives the best results for quality metric equation.

Now after getting **MATLAB**software was used to get fitting. **Fittedmodel** is the model resulted after applying curve fitting tool. Data computed was compared with Mean Opinion Score MOS as in the following steps:

- Selecting the data where the x-axis our sample and the y-axis is MOS
- Create a new fit by selecting Custom Equation as the type of fit
- General Equation: type the equation used in the metric
- Selecting the fitting options where Robust =>**On** and the Algorithm =>**levenburg Marquadrt** (this could be changed to the others to see the result)
- The Coefficients (with 95% confidence bounds)
- Goodness of fit are: SSE: 13.02, R-square: 0.5126, Adjusted R-square: 0.4882, and RMSE: 0.5704
- Do the correlation (**Pearson**, **Spearman**) and get the RMSE

IV. RESULTS

Applying proposed metric over the data sets of test images provided in the experiment gave prediction results displayed in Figure 4.

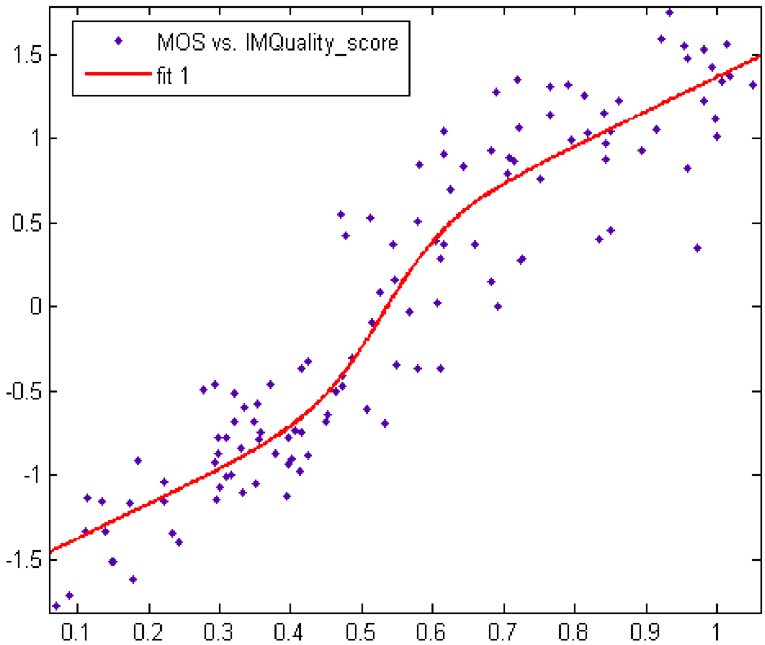

Figure 4: Model prediction resulted from proposed image quality metric NRIQuality vs. MOS

Comparing proposed metric with available image quality algorithms PSNR, MSE, and MSSIM is displayed in Table 1, whereas Figure 5 shows results in columns.

Table 1: Correlation coefficient for the proposed metric vs. PSNR, MSE, and MISSIM

	PEARSON PLCC	SPEARMAN SROCC	RMSE
NRIQUALITY	0.9453	0.9288	0.3489
PSNR	0.7980	0.7251	0.593
MSE	0.8250	0.8400	0.5609
MSSIM	0.8132	0.8422	0.5712

From Table. 1, the proposed metric for measuring image quality for no-reference images gave a better Pearson and Spearman correlation results with 0.9453 and 0.9288 whereas the Root Mean Square error (RMSE) was the less than other metrices PSNR, MSE and MSSIM Full-Reference matrices.See Figure 5.

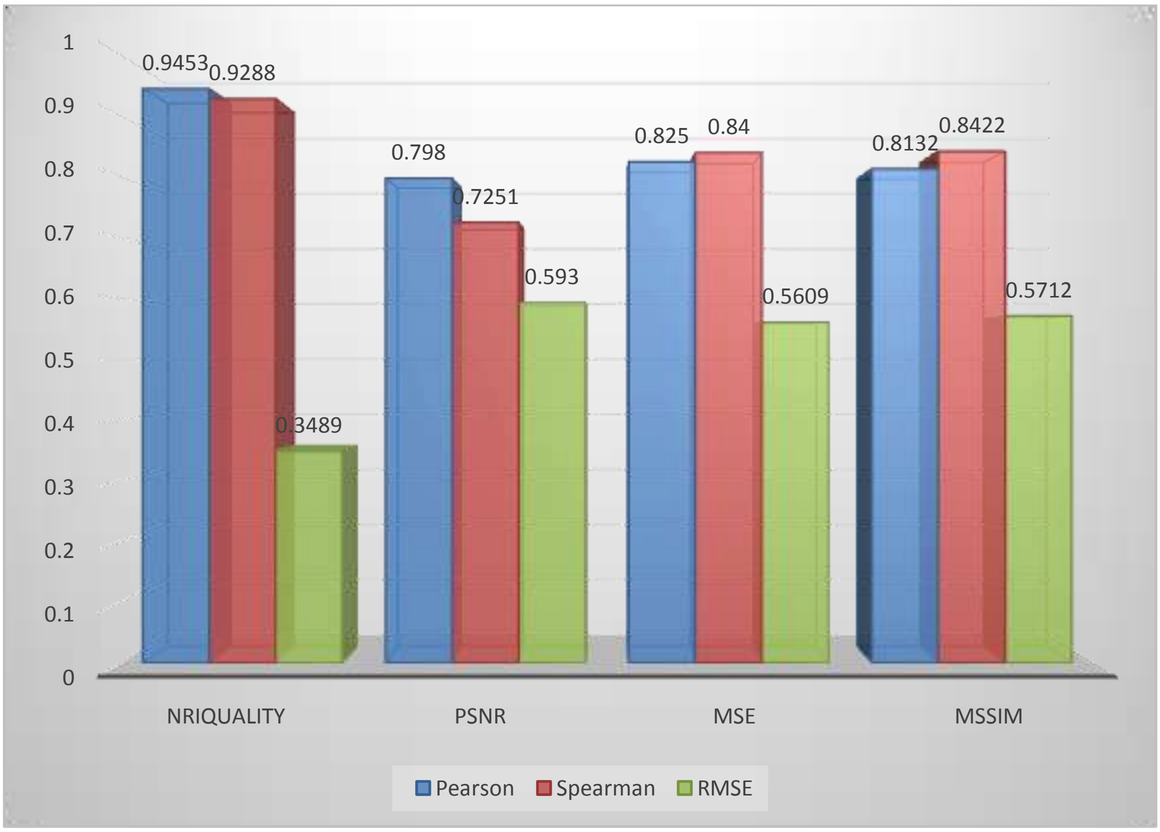

Figure 5: A Chart the shows a comparison between proposed NRIQUALY metric and other metrices

V. CONCLUSIONS

This paper proposed a novel NR perceptual quality assessment metric scheme for TIF non-compressed images. Subjective experiment was conducted to evaluate the quality of the TIF images. The attributes described in the paper (naturalness, contrast, colour, and noise) were the most noticeable attributes used in evaluating any image and the non-linear (curve-fitting-tool).

The proposed metric NRIQUALITY gave a good correlation with MOS scores.The proposed metric is computationally efficient since indices were computed in their proper colour spaces. The basic methodology of the proposed index can be used to develop other NR quality indices for compressed images.

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