Unsupervised Blind Quality Estimation of NSS Images using Efficient Feature Extraction

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Abstract. In present-day date, public work more with images than with textual content. Often, the image which is transmitted over the internet or in wireless network demand a quality analysis to be done before accepting the same at the user’s end. A great quantity of work has been done in recent past to develop an unbiased image quality objective value that relate well with perceived quality measurement. In-spite of the tremendous effort, the success achieved is less in this direction. Through this paper, we discuss about the method, EBUQA, an objective analysis method by which the perceptual quality of Natural Scene Statistic image can be found. This method measures the amount of distortion and is quantized as a numeric parameter. Performance analysis and testing done on the method conforms well with the human observation.

1. Introduction

As per the surveys and observations, the amount of digital image content in the internet and social media is increasing overwhelmingly. According to the data published by Google Server, an average adult takes four photos or video a day and takes 2.4 selfies. It has become difficult to analyse and estimate the quality of this ever increasing visual content. Various quantitative methods to analyse the quality of image content is available. Full reference image quality analysis is a model which compares the distorted image with its good quality reference image. PSNR calculation compares the noise content in the image with the signal content. Structural similarity Index method is one method used in Full reference quality examination. Reduced reference image quality analysis indicates a model where the low quality image is compared against some reference parameters of the pristine image. No reference or Blind image quality calculation indicates the quality analysis of an image where information about the pristine version is not available.

In most of the real time manipulation and usage of images, getting the good quality reference image or a mean opinion score of the image is not always feasible. Also it is expensive and impractical to collect consistent and accurate opinion from a group of audience. It is the demand of the hour to develop an algorithm which can effectively simulate human opinion and there by predict the quality factor of the image. Hence judgement less blind quality assessment has always received special interest in the research community working in quality assessment. In most of the cases, media users will receive an image while the pristine version of the same image may not be available. It is highly rare that for quality assessment, distorted image and good quality image are received together. Hence our interest is mainly concerned about blindly assessing the quality in images, where any information about the pristine image is beyond reach.
NSS images or Natural Scene Statistic images is a category of image where studies with respect to quality assessments are significantly happening. This paper put forward a method to blindly assess the quality of NSS image based on some parameters extracted from the image.

2. Organization of the paper

The paper is organized as follows, section 3 discusses about the contributions given by different authors through their ideas that provide a thorough understanding about the work happening in the area of image quality analysis. Section 4 explains in detail about the proposed method, EBUQA with algorithm. Section 5 discusses result analysis, where the outcome of various test cases are analysed. Section 6 and 7 indicates the future perspectives and conclusion respectively.

3. Literature Survey

Image Quality Assessment centered on DCT: A method called BLIINDS is developed by Michele Saad, Christopher Charrier, Alan C. Bovik, [1] to effectively evaluate quality value of image in natural scene statistics (NSS). Here, discrete cosine transform or DCT is the basis for feature extraction. The histogram plot of the local DCT contrast value is compared and result is inferred from that.

Jayant Kumar, David and Le Kang in their paper[11] revealed an unsupervised method of Quality estimation, where a visual codebook is generated from features extracted from the image. The code book is encoded and finally regression analysis is done to obtain the quality score. The result shown is at par with the state of the art methods. Unsupervised method does not depend on the perspective of any person. Hence the result is unbiased.

Alan C. Bovik and Anush Krishna Moorthy [2] created a scheme for no-reference image quality assessment in the year 2012. This method relies on using wavelet transform (DIIVINE). Here the image is transformed to a time-frequent domain, wavelet transform is applied on to the image and the scale-space-orientation of the image is checked. The extracted statistical features form a vector. By means of this feature vector, quality score is calculated after finding the distortion type. Hence this algorithm has proven good in determining the type of distortion.

Natural Image Quality Evaluator (NIQE) suggested by M.A. Saad and A.C Bovik,[3] in 2012 is a blind image quality assessment that uses computable deviations from numerical consistencies perceived in natural images, without any training on subjective rated distorted images, and without any experience with distorted images

In 2013, Xuelong Li and Xinbo Gao effectively employed a method of Image Quality Analysis by a procedure called multiple Kernel Learning[5]. This paper creates a feature vector by adding the secondary and tertiary properties of wavelet transform. Secondary properties of Wavelet transform contributes Non-Gaussianity, Crowding and Persistency. Tertiary properties give EDC and strong persistency at finer scales. Quality score is totaled by extracting features to represent the above properties.

Another image assessment procedure by means of the method Deep Learning was introduced recently by W. Hou and X. Gao. This paper[9] inspects the method of evaluating the quality of a possibly distorted image by developing rules from linguistic explanations. Normally, subjects are used for providing linguistic descriptions, here this method learns the qualitative evaluations and outputs numerical scores for comparison [9]. The exponential decay characteristic of wavelet coefficients are used here to represent the image. The decay rate of magnitudes of the wavelet coefficients of NSS images is exponentially across scale. Furthermore, the exponential decay is less dependent on particular image content and is therefore suitable for constructing a universal BIQA method.
4. Proposed Method – EBUQA (Efficient Blind Unsupervised Quality Assessment)

Image quality depends on various factors where the image was captured or generated. It depends greatly on the surroundings, brightness and other factors. The Scene Statistics mentions the way a picture is perceived. Natural Scene Statistics demands much interest here as NSS (Natural Scene Statistics) images are a category of images which respond and shows the statistical behaviour correctly in the absenteeism of distortion. This property of NSS is exploited in our proposed method as the statistical property get troubled due to distortion and this disturbance or variation can be quantized as the quality value.

Surveys have exposed that distortions in the image can be quantized by applying proper statistical methods. Here we have proposed an algorithm which can effectively calculate the quality estimate value of the given image. From studies it is understood that proper analysis of the received possibly distorted NSS images will give an in-depth information about the amount of distortion that has affected the image. Most of the currently available Quality Assessment algorithms convert the image domain to frequency and then manipulations are done. Our method does manipulations in spatial domain as visual cortex responds well in spatial domain. As per the reviews, its agreed that these distortions are well captured by local features like contrast, multi scale orientations, decompositions, colour statistics etc.

i. Finding the normalized luminance: For a (conceivably distorted) image, we compute local luminance value by subtracting local mean and division by deviation value. It is perceived that implementing a local non-linear operation to luminance and removing local mean has an astonishing effect to the correlation of image coefficients. Such an operation may be applied to a given intensity image I (i, j) to produce:

\[ \tilde{I}(i,j) = (I(i,j) - \mu(i,j)) \ast (\sigma(i,j) + C)^{-1} \]  

Where I and j are spatial indices and i=1,2,…M and n=1,2,…N.

Where \( \mu(i,j) \) represents the

\[ \mu(i,j) = \sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} I_{k,l}(i,j) \]  

and \( \sigma(i,j) \) is obtained as

\[ \sigma(i,j) = (\sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} I_{k,l}(i,j) - \mu(i,j))^2 \]  


Where \( w = \{ w_{k,l} | k = -K, \ldots, K, l = -L, \ldots L \} \) is a 2D circularly-symmetric Gaussian weighting function. We set \( K \) and \( L \) as 3 in our implementation. These coefficients are also called as mean subtracted contrast normalized. This MSCN coefficients exhibit peculiar characteristics of the image[4]. The characteristics can be extracted and can be used to estimate the quality. From investigation, it is perceived that each of the different kinds of distortion affect the outline of the curve in a different way. The shape parameter \( \alpha \) controls the shape of the distribution while \( \sigma^2 \) control the variance. The shape parameter \( \alpha \) is also used to represent the decay rate in image: the smaller \( \alpha \) value signifies a more peaked distribution and a larger \( \alpha \) signifies a flatter distribution, so it is also termed as the ‘decay rate’. For NSS images, yet another vital advantage is that there exists a numerical dependency relationship between neighboring pixels and these dependencies gets disturbed in the presence of distortion[1].

\[ \begin{align*}
H(i,j) &= \overline{I(i,j-1)} \overline{I(i,j)} \\
V(i,j) &= \overline{I(i-1,j)} \overline{I(i,j)} \\
D1(i,j) &= \overline{I(i-1,j-1)} \overline{I(i,j)} \\
D2(i,j) &= \overline{I(i-1,j+1)} \overline{I(i,j)}
\end{align*} \tag{4} \tag{7}
\]

for \( i \in \{1, 2 \ldots M\} \) and \( j \in \{1, 2 \ldots N\} \).

The values are fitted against a generalized Gaussian Distribution and the characteristic parametric values of the estimation curve is extracted. Thus the four parameters \( (\gamma, \beta l, \beta r, \eta) \) extracted from the

![Figure1: The response of MSCN coefficients of a good quality and low quality NSS image.](image)
GGD distribution in all the four directions will serve to provide a total of 16 features extracted from the image. The image is down sampled by two for better analysis of image and the mentioned 18 features are extracted again. Thus yielding a total of 36 features. Figure 2 gives a better understanding of the correlation relationship between the neighbouring pixels of image. A perfect peaked histogram centred around mean zero represents a good quality image. As distortions increases, deviations also increase.

![Figure 2: Comparison of MSCN and neighbouring pixel correlation for a good quality and poor quality image.](image)

### iii. Derivative statistics

The derivative information extracted from any image gives information about changes in intensity of the image or the edge statistics of the image. Feature extraction will be finest when the image is converted to opponent colour space from RGB and then manipulations are done. Thus second order derivative taken in any NSS image stands as a strong candidate for distortion identification since the edge contours or edges boundaries are likely to be affected badly by distortion. The gradient statistics is computed along both the vertical direction and horizontal direction by doing convolution with Gaussian derivative filters along x and y axis. Gradient magnitude is computed as

$$I = \left( \| I_h \|^2 + \| I_v \|^2 \right)^{1/2}$$

This magnitude value is fitted against a Weibull distribution and the parameters $a$ and $b$ of Weibull distribution is extracted to represent the characteristic of the curve. This characteristic parameters in turn characterizes the extent of distortion in the image.

Thus a total of 38 structures are mined from each image whose quality estimation is to be done. This feature set helps in learning the image and converting that to a quality score. In our method, we have used a General processing model, which includes the application of a learning function from the training data consisting of image features and their quality scores are estimated. The whole process is summarized as algorithm and is shown below.

**Procedure EBUQA**

Input: A collection of NSS Images  
Output: A vector of Quality scores

I:procedure FEATURE SELECTION

Input: Image I, total number of images N , Output: Selected features f1 - fj

For each image, do the following,
1: Apply statistical manipulations on the image and extract the features $f_1$ the shape and $f_2$ the variance
2: Extract all statistical features that signifies the correlation between adjacent pixels ie $f_3$ – $f_{18}$ Eq. [4] to [7]
3: Down-sampling the image by 2 and repeat the steps 4.1 and 4.2 to get the features $f_{19}$ – $f_{36}$.
4: Find the derivative statistics of the image and fit it against Weibull distribution. The parameters ‘a’ and ‘b’ of the distribution are extracted as features $f_{37}$ – $f_{38}$.
5. end for
6. end procedure FEATURE SELECTION

II: Procedure QUALITY COMPUTATION
Input: The extracted 38 features of an NSS image, Output: Numeric Quality score
For each set of 38 features corresponding to an image, do the following,
1. Compute the numeric quality score as a function of the set of 38 input values.
2. The quality score is written in to a vector.
3. end for
4. end procedure QUALITY COMPUTATION
end Procedure EBUQA

5. Result Analysis

Our proposed method EBUQA (Efficient Blind Unsupervised Quality Assessment) is implemented by taking train image and test image from LIVE database release2 dataset. 29 input images were used to create the LIVE dataset. Distortion types like JPEG2000, JPEG, white noise, Gaussian Blur etc. are applied on these 29 images and its distorted sub categories are made.

We have implemented and have done analysis of the result by collecting 20 images from LIVE dataset, ref. Figure 3. Four pristine images with five version for each image. 4 distorted version and one pristine version. The results obtained are collected in the Table 1. For better understanding, the pictorial form of the same is shown in the chart. The result is again compared with the current state of the art methods like BRISQUE, BLIINDS and CORNIA to prove its versatility and uniqueness (ref Table 2). The comparison shows that proposed method is at par with the other standard methods.
Figure 3. Collection of images taken from LIVE release2 for testing the proposed method.

The 20 images that we chose were all White Noisy and in the scale fair, good, bad, poor and excellent. The images were entered in the same order. As shown, the result obtained from the algorithm settles very well with human observation. The more the numerical value, the more the image is disturbed. Thus the proposed method is doing well in predicting the quality score in an unsupervised manner.

Chart 1: Shows the comparison of distortion value calculated for 5 version of four images taken from LIVE release2 dataset.
Table 1. Quantitative value of quality score for the images taken for testing.

| Result Obtained | IMAGE1     | IMAGE2     | IMAGE3     | IMAGE4     |
|-----------------|------------|------------|------------|------------|
| Fair            | 112.1803   | 131.0274   | 116.1927   | 87.48084   |
| Good            | 116.362    | 128.1181   | 116.5868   | 88.11355   |
| Bad             | 114.7519   | 142.1659   | 118.4022   | 119.3466   |
| Poor            | 107.2055   | 135.9803   | 115.8466   | 94.00431   |
| Excellent       | 108.6724   | 129.7436   | 115.9546   | 96.81554   |

Table 2. Comparison of proposed method (EBUQA) with other existing methods

| Perspective for comparison | BRISQUE | BLIINDS | CORNIA | EBUQA                  |
|----------------------------|---------|---------|--------|------------------------|
| Accuracy of result         | 97.8%   | 97.35%  | 91.3%  | 100* (gave proper result for the given input set) |
| Execution time (in seconds)| 1       | 20      | 1.59   | 5                      |

6. Future Enhancement

A careful and selective filtering of features from image is highly desired for getting the proper quality score. More features can be identified and addition of these features to the feature vector has to be done after ensuring its viability. The response of features varies according to the type of distortion. Thus after detecting the distortion occurred in the image, repair action can be done for reducing the effect of distortion. Further, one more enhancement is to make the algorithm semi supervised one with the help of Mean Opinion Score available in LIVE Release2 dataset.

7. Conclusion

Through this paper, we discussed about the method, EBUQA (Efficient Blind Unsupervised Quality Assessment) for extracting or mining a set of 38 feature values from an image for quality evaluation method and then effectively classifying the scores thereby predicting the quality of that image. Objective analysis value can be taken into justification only by verifying the same with subjective assessment. Hence the scores predicted are plotted in a graphical chart and the same is compared against human observation. Our results have proven that this observation is at par with subjective opinion. The efficiency of the method depends prominently on the feature set extracted from the image. Here, we found that our method give promising result.

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