EFFECTIVE FEATURE ANALYSIS COMPLETELY BLIND IMAGE QUALITY EVALUATOR

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ABSTRACT
In our daily lives, we accompany the digital visual information. Various distortions are introduced during the exchange, transmission or storage of this digital information. Image quality evaluation refers to the evaluation of image quality. This is because some image processing applications depend on this information. Image quality can be measured in two ways: subjective method and objective method. A subjective method is one by which human judge the image quality using average opinion scoring method (MOS).
In recent years, there has been growing interest in the development of objective image quality assessment (IQA) models that not only monitor image quality degradation and reference image processing systems but also optimize various algorithms and systems, Past results are worthy of praise, but there are some important issues when applying existing IQA models to real-world applications. These include obvious things such as tasks that greatly reduce the complexity of existing IQA algorithms and are easy to use and easy to understand.
Unfortunately, so far, BIQA's method, which does not consider opinion, did not consistently demonstrate high-quality prediction accuracy over the method of opinion. Here, we aim to develop BIQA's unknown opinion method that can compete with existing opinion methods and possibly overcome. Multivariate Gaussian model of image patch is learned from the natural image set by integrating statistical features of the natural image obtained from plural signals. The proposed BIQA method does not require distorted sample images or subjective quality scores for training, but extensive experiments demonstrate superior quality prediction performance for the BIQA method with cutting edge view.

KEYWORDS: Blind image quality assessment, natural image statistics, multivariate Gaussian.

1. INTRODUCTION
The quality of an image is lost due to the occurrence of noise, and these noises are generated during information accumulation, transmission, or exchange of information between the devices. A wide range of applications depends on this digital information being transmitted. Therefore, in order to evaluate and control the quality of these images, quality measurement is necessary. Evaluation of image quality is a model that predicts distorted image quality. In the image quality evaluation method, evaluation of quality by humans is obtained by the mean opinion score method (MOS), human subjective evaluation is obtained by MOS (mean opinion score method), human subjective evaluation is distorted the image will be perceived by the average person.
Quantitative assessment of image perception quality was one of the most difficult problems of modern image processing and computational study of vision. The perceptual image quality assessment (IQA) method is classified into two categories: subjective evaluation by human and objective evaluation by an algorithm designed to imitate subjective judgment. Subjective assessment is the last standard of image quality, but it is time consuming, cumbersome, expensive and cannot be implemented in systems that require real-time evaluation of image or video quality. However, as the amount of image / video data generated everyday increases exponentially, it is impossible to solve these quality problems in a timely manner by slow, annoying and expensive subjective visual tests. On the other hand, only the reliable model of IQA can satisfy these needs.
The most important message in this document shows that a "completely blind" IQA model that does not take into account opinions can achieve robust quality prediction performance over opinion sensitive models.

Such models and algorithms can be used for countless practical applications. These results hope that IQA researchers and image experts will more thoroughly consider the possibility of a "fully blind" BIQA model that does not take into account the opinion.

2. SYSTEM IMPLEMENTATION

It is shown that the natural scene statistics (NSS) are excellent indicators of the degree of degradation of the quality of distorted images. As a result, the NSS model has been widely used in the design of the BIQA algorithm. For example, parameters of generalized Gaussian distribution (GGD) that effectively models natural wave coefficients and DCT coefficients of images have been used as characteristics of quality prediction. For complex pyramid wavelets, transformations were used to extract similar NSS properties. All of these BIQA methods based on the NSS model are opinion methods and learn a regression model that associates vectors of extracted NSS characteristics with subjective quality scores. To extract image characteristics related to multiple scales and quality directions, we use a log-Gabor filter and extract the statistical properties of the filter response. Color distortion is described using statistical properties derived from the image intensity distribution in the logarithmic scale opposite color space.

In general, five types of characteristics are used. All of these characteristics are well known in the NSS literature, but are initially adapted together for a completely blind BIQA task. Our experiments show that new features can greatly improve the performance of image quality prediction.

3. EXPERIMENTAL DETAILS

4.

3.1 STATISTICS OF NORMALIZED LUMINANCE

It noted that the locally normalized luminance of the gray scale natural photographic image matches the Gaussian distribution. This normalization process can be written as follows.

$$I(i, j) = \frac{I(i, j) - \mu(i, j)}{\sigma(i, j) + 1} \quad (1)$$

are the local image mean and contrast, where $\omega = \{\omega_{k,l} | k = -K, ..., K, l = -L, ..., L\}$ defines a unit-volume Gaussianwindow. The so-called MSCN coefficients $I(i, j)$ have been observed to follow a unit normal distribution on natural images that have not suffered noticeable quality distortions.

3.2 STATISTICS OF MSCN PRODUCTS

As pointed out in [10] and [15], image quality informationis also captured by the distribution of the products of pairs ofadjacent MSCN coefficients, in particular $I(i, j)I(i, j + 1)$,$I(i, j)I(i + 1, j)$, $I(i, j)I(i + 1, j + 1)$, and$I(i, j)I(i + 1, j - 1)$. On both pristine and distorted images,these products are well modeled as following a zero mode

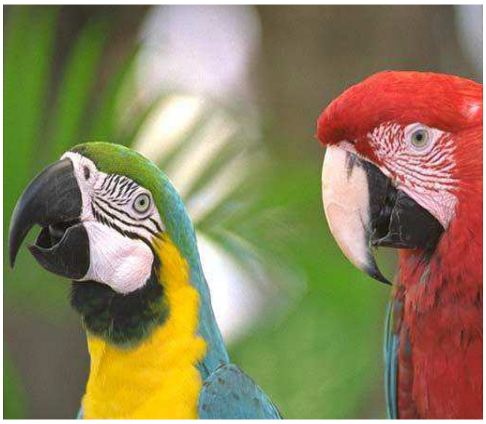
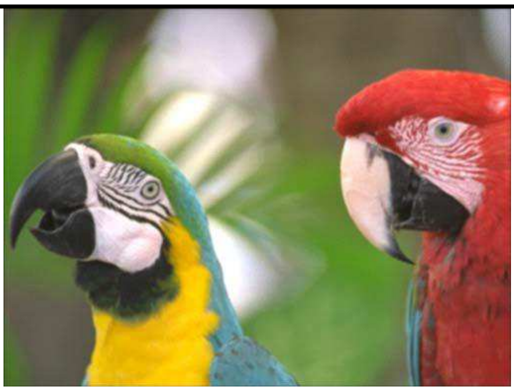
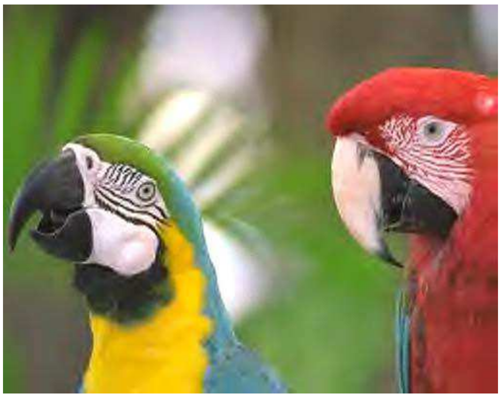


Fig. 1. (a) A reference image. Distorted versions of (a)



(b) minor Gaussian blur,

(c) severe Gaussian blur



(d) minor JPEG2K compression

(e) severe JPEG2K compression.

3.3 GRADIENT STATISTICS

The gradient of the image is a rich descriptor of the structure of the local image and is, therefore, a descriptor of the local quality of the image. We found that by introducing distortion into the image, the distribution of the gradient component (partial derivative) and the magnitude of the gradient are modified. I will give you an example to demonstrate this fact. First, when strain is introduced, the empirical distribution of the component of the gradient of the image and the magnitude of the gradient magnitude is affected. Second, the most severe distortion causes a big change in distribution over less severe strain.

3.4 STATISTICS OF LOG-GABOR FILTER RESPONSES

Because visual cortex neurons selectively respond to stimulus direction and frequency, statistics of multi-directional and multi-rate filter responses to images are also useful for generating quality-aware BIQA features. Here we implement perceptually related Log-Gabor filters to achieve multiscale and multi-orientation filtering.

3.5 STATISTICS OF COLORS

To capture even more the statistical properties that are particularly related to the color in the image, we used a simple classic that showed that the distribution of the photographic image data coincides with the Gaussian probability model in the logarithmic color space. It depends on the NSS model.Given an RGB image having three channels $R(i, j)$, $G(i, j)$,and $B(i, j)$, first convert it into a logarithmic signal with mean subtracted:

$R(i, j) = log\ R(i, j) - \mu R$

$G(i, j) = logG(i, j) - \mu G$

$B(i, j) = log\ B(i, j) - \mu B$

whereμR, $\mu G$and $\mu B$are the mean values of log $R(i, j)$,log $G(i, j)$ and log $B(i, j)$, respectively, over the entire image. Then, image pixels expressed in (R, G, B) space are projectedonto an opponent color space:

$l1(x, y) = (R + G + B)/\sqrt{3}$

$l2(x, y) = (R + G - 2B)/\sqrt{6}$

$l3(x, y) = (R - G)/\sqrt{2}$

PRISTINE MVG MODEL LEARNING

We will learn the original MVG model to create a representation of the NSS characteristics of the original image of nature. In IL-NIQE, the original MVG model acts as a "reference" to evaluate the quality of a given natural image patch. In order to know the desired model, we will collect a set of high-quality natural images from the internet. Four volunteers participated and were asked to look for 100 high-quality images in each of four categories: people, plants, animals, and artifacts. This is similar to the process used to create the original corpus from which the NIQE index was created. Most natural images fall into these categories. Next, each of the 400 images taken was visually inspected by seven volunteer observers. If five or more of the seven observers found that the image quality was very good, the images were saved.

5. RESULT

A. DATABASES

Four benchmark large-scale IQA datasets are used to evaluate the proposed IL-NIQE index, including TID2013, CSIQ, LIVE, and LIVE Multiply Distortion.

B. PERFORMANCE ON EACH INDIVIDUAL DATASET

Because opinion methods need to use distorted images in the data set to learn the model, divide the data set into a training subset and a test subset. We present this result in three partitions. Distorted images related to 80%, 50%, 10% of the reference images are used for training and the rest are used for testing. Partitions are run 1,000 times at random and the average results are reported in Table 1. IL-NIQE, NIQE, and QAC do not require dataset training but report the results in a subset of comparison consistent.

Table 1 Results of Performance Evaluation on Each Individual Dataset

Datasets	Methods	80%		50%		10%	
		SRCC	PLCC	SRCC	PLCC	SRCC	PLCC
TID2013	BIQI	0.349	0.366	0.332	0.332	0.199	0.250
	BRISQUE	0.573	0.651	0.563	0.645	0.513	0.587
	BLIINDS2	0.536	0.628	0.458	0.480	0.402	0.447
	DIIVINE	0.549	0.654	0.503	0.602	0.330	0.391
	CORNIA	0.549	0.613	0.573	0.652	0.508	0.603
	NIQE	0.317	0.426	0.317	0.420	0.313	0.398
	QAC	0.390	0.495	0.390	0.489	0.372	0.435
	IL-NIQE	0.521	0.648	0.513	0.641	0.494	0.590
CSIQ	BIQI	0.092	0.237	0.092	0.396	0.020	0.311
	BRISQUE	0.775	0.817	0.736	0.781	0.545	0.596
	BLIINDS2	0.780	0.832	0.749	0.806	0.628	0.688
	DIIVINE	0.757	0.795	0.652	0.716	0.441	0.492
	CORNIA	0.714	0.781	0.678	0.754	0.638	0.732
	NIQE	0.627	0.725	0.626	0.716	0.624	0.714
	QAC	0.486	0.654	0.494	0.706	0.490	0.707
	IL-NIQE	0.822	0.865	0.814	0.854	0.813	0.852
LIVE	BIQI	0.825	0.840	0.739	0.764	0.547	0.623
	BRISQUE	0.933	0.931	0.917	0.919	0.806	0.816
	BLIINDS2	0.924	0.927	0.901	0.901	0.836	0.834
	DIIVINE	0.884	0.893	0.858	0.866	0.695	0.701
	CORNIA	0.940	0.944	0.933	0.934	0.893	0.894
	NIQE	0.908	0.908	0.905	0.904	0.905	0.903
	QAC	0.874	0.868	0.869	0.864	0.866	0.860
	IL-NIQE	0.902	0.906	0.899	0.903	0.899	0.903
MD1	BIQI	0.769	0.831	0.580	0.663	0.159	0.457
	BRISQUE	0.887	0.921	0.851	0.873	0.829	0.860
	BLIINDS2	0.885	0.925	0.841	0.879	0.823	0.859
	DIIVINE	0.846	0.891	0.805	0.836	0.631	0.675
	CORNIA	0.904	0.931	0.878	0.905	0.855	0.889
	NIQE	0.909	0.942	0.883	0.921	0.874	0.912
	QAC	0.418	0.597	0.406	0.552	0.397	0.541
	IL-NIQE	0.911	0.930	0.899	0.916	0.893	0.907
MD2	BIQI	0.897	0.919	0.835	0.860	0.769	0.773
	BRISQUE	0.888	0.915	0.864	0.881	0.849	0.867
	BLIINDS2	0.893	0.910	0.852	0.874	0.850	0.868
	DIIVINE	0.888	0.916	0.855	0.880	0.832	0.851
	CORNIA	0.908	0.920	0.876	0.890	0.843	0.866
	NIQE	0.834	0.884	0.808	0.860	0.796	0.852
	QAC	0.501	0.718	0.480	0.689	0.473	0.678
	IL-NIQE	0.928	0.915	0.890	0.895	0.882	0.896

C. CROSS-DATASETS PERFORMANCE EVALUATION

Table 2 Evaluation Results when Trained on LIVE

	TID2013		CSIQ		MD1		MD2	
	SRCC	PLCC	SRCC	PLCC	SRCC	PLCC	SRCC	PLCC
BIQI	0.394	0.468	0.619	0.695	0.654	0.774	0.490	0.766
BRISQUE	0.367	0.475	0.557	0.742	0.791	0.866	0.299	0.459
BLIINDS2	0.393	0.470	0.577	0.724	0.665	0.710	0.015	0.302
DIIVINE	0.355	0.545	0.596	0.697	0.708	0.767	0.602	0.702
CORNIA	**0.429**	**0.575**	**0.663**	**0.764**	0.839	0.871	**0.841**	**0.864**
NIQE	0.311	0.398	0.627	0.716	**0.871**	**0.909**	0.795	0.848
QAC	0.372	0.437	0.490	0.708	0.396	0.538	0.471	0.672
IL-NIQE	**0.494**	**0.589**	**0.815**	**0.854**	**0.891**	**0.905**	**0.882**	**0.897**

Table 3 Weighted-average Performance Evaluation Based on Table 2

	BIQI	BRISQUE	BLIINDS2	DIIVINE	CORNIA	NIQE	QAC	**IL-NIQE**
SRCC	0.458	0.424	0.424	0.435	0.519	0.429	0.402	**0.599**
PLCC	0.545	0.548	0.525	0.595	0.643	0.512	0.509	**0.675**

Table 4 Evaluation Results when Trained on TID2013

	LIVE		CSIQ		MD1		MD2	
	SRCC	PLCC	SRCC	PLCC	SRCC	PLCC	SRCC	PLCC
BIQI	0.047	0.311	0.010	0.181	0.156	0.175	0.332	0.380
BRISQUE	0.088	0.108	0.639	0.728	0.625	0.807	0.184	0.591
BLIINDS2	0.076	0.089	0.456	0.527	0.507	0.690	0.032	0.222
DIIVINE	0.042	0.093	0.146	0.255	0.639	0.669	0.252	0.367
CORNIA	0.097	0.132	**0.656**	**0.750**	0.772	0.847	0.655	0.719
NIQE	**0.906**	**0.904**	0.627	0.716	**0.871**	**0.909**	**0.795**	**0.848**
QAC	0.868	0.863	0.490	0.708	0.396	0.538	0.471	0.672
IL-NIQE	**0.898**	**0.903**	**0.815**	**0.854**	**0.891**	**0.905**	**0.882**	**0.897**

Table 5 Weighted-average Performance Evaluation Based on Table 4

	BIQI	BRISQUE	BLIINDS2	DIIVINE	CORNIA	NIQE	QAC	**IL-NIQE**
SRCC	0.074	0.384	0.275	0.172	0.461	0.775	0.618	**0.861**
PLCC	0.250	0.491	0.349	0.251	0.527	0.821	0.744	**0.882**

For five optionally conscious BIQA methods, the original author provides a quality prediction model formed through the LIVE data set. Therefore, test them with other data sets directly using them. The results are shown in Table 2. For each performance index, the two best results are highlighted in bold. In Table 3 we present a weighted average SRCC and PLCC index for all methods in the four data sets and the weight assigned to each data set is linearly dependent on the number of distorted images included in that data set. In addition, we train opinion methods on the entire TID 2013 dataset and run tests on the remaining datasets. The results are shown in Tables 4 and 5.

6. CONCLUSION

We proposed a new effective BIQA method to expand and improve the new "fully blind" concept of the introduced IQA. The new model IL-NIQE is used to extract five types of NSS characteristics from the original natural picture collection, to learn the multivariate Gaussian model (MVG) of the original image. For a given test image, the quality of those patches is evaluated, then the patch quality scores are averaged and a general quality score is obtained.

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