Fast Image Quality Assessment via Hash Code

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Abstract. No-reference image quality assessment (NR-IQA) is significant for image processing and yet very challenging, especially for real-time application and big image data processing. Traditional NR-IQA metrics usually train complex models such as support vector machine, neural network, and probability graph, which result in long training and testing time and lack robustness. Hence, this paper proposed a novel no-reference image quality via hash code (NRHC). First, the image is divided into some overlapped patches and the features of blind/ referenceless image spatial quality evaluator (BRISQUE) are extracted for each patch. Then the features are encoded to produce binary hash codes via an improved iterative quantization (IITQ) method. Finally, comparing the hash codes of the test image with those of the original undistorted images, the final image quality can be obtained. Thorough experiments on standard databases, e.g. LIVE II, show that the proposed NRHC obtains promising performance for NR-IQA. And it has high computational efficiency and robustness for different databases and different distortions.

Keywords: No-reference · Image quality assessment · Hash code

1 Introduction

With the tremendous development of intelligent network, ultra-high resolution display, and wearable devices, high quality and credible visual information (image, video, etc.) is significant for the end user to obtain a satisfactory quality of experience (QoE). Where, assessing the quality of visual information, especially no-reference or blind image quality assessment (NR-IQA or BIQA), plays an important role in numerous visual information processing system and applications [1]. Moreover, effective (high quality prediction accuracy) and efficient (low computational complexity) NR-IQA is essential and has attracted a large number of attentions.

NR-IQA metric is designed to automatically and accurately predict image quality without reference images. Hence, it is a difficult and challenging work and has attracted many researchers' attentions. Traditional methods focus on designing distortion-specific methods [2]-[4], which means that these methods evaluate images with only one kind of distortions effectively, such as JPEG compression, JPEG2000 compression, white noise, and Gaussian blurring. Therefore,

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it is imperative to build the general purpose NR-IQA metric to handle different types of distortions and even multi-distortions.

Recently, great effort has been made to design general purpose NR-IQA metrics. A series of methods are presented in the literature [5]-[18]. Almost all of the reported NR-IQA methods include quality-aware feature extraction and effective evaluation model designing, which are the most important processing for building a NR-IQA method. Generally, natural scene statistical (NSS) properties [19] are most popular utilized features, which are extracted by generalized Gaussian distribution in wavelet domain usually. Also other features are extracted through Gabor in spatial domain [11] or statistical characteristics in discrete cosine transformation (DCT) domain [10]. Another key point is designing the prediction model. The latest methods can be divided into two categories, two-steps strategy and transductive approach. The former first determines the distortion type of a test image and then employs an associated distortion-specific no-reference image quality assessment metric to predict the quality of the given image, e.g. BIQI [5] and DIIVINE [6]. The BIQI trains a support vector machine (SVM) model to divide five different distortions and trains five different support vector regressions (SVR) model for a particular distortion to predict image quality. The DIIVINE, which is the extended work of BIQI, also is built in the two-steps framework. While the transductive approach aims to build a model to directly map image features to image quality without distinguishing different types of distortions, such as LBIQ [7], BLINDS [8], BLINDS-II [10], CORNIA [11], and SRNSS [12]. In those metrics, a large number of machine learning methods are utilized to train the quality prediction model, such as multiple kernels learning (MKL), neural network (NN), and the probabilistic model. Therefore, the reported metrics face a significant problem that they need long training and test time. This is because that complex machine learning model is adopted, the parameters are mostly defined by experience, and a large number of samples are utilized to train the prediction model. And these methods also would reduce the robustness of the quality evaluation system.

In order to solve the above problems, this paper proposed a novel no-reference image quality assessment metric via hash codes, which is simple yet very fast. The proposed method first divides the image into overlapped patches and extracts the blind/referenceless image spatial quality evaluator (BRISQUE) [9] features for each patch. Then the features are encoded into hash codes via an improved iterative quantization (IITQ) [20] method. The Hamming distance between the hash code of the test image and the original undistorted image is calculated to predict image quality. In the proposed method, the quality prediction includes hash coding and the Hamming distance calculation. They have the properties of fast speed and high efficiency. Hence, the proposed can satisfy the real-time applications and big image data processing.

The rest of the paper is organized as follows. Section 2 illustrates the proposed no-reference image quality assessment. Detailed experimental results are summarized and discussed in Section 3, and section 4 concludes the paper.

2 NR-IQA via Hash Code

In order to assess the image quality effectively and efficiently, a novel no-reference image quality assessment method is presented in the paper. The proposed method includes three major steps: feature extraction, hashing coding, and quality evaluation. For convenience, the proposed metric is named **NRHC**, which is short for fast **N**o-**R**eference image quality assessment via **H**ash **C**ode. And the framework of proposed NRHC is shown in figure 1.

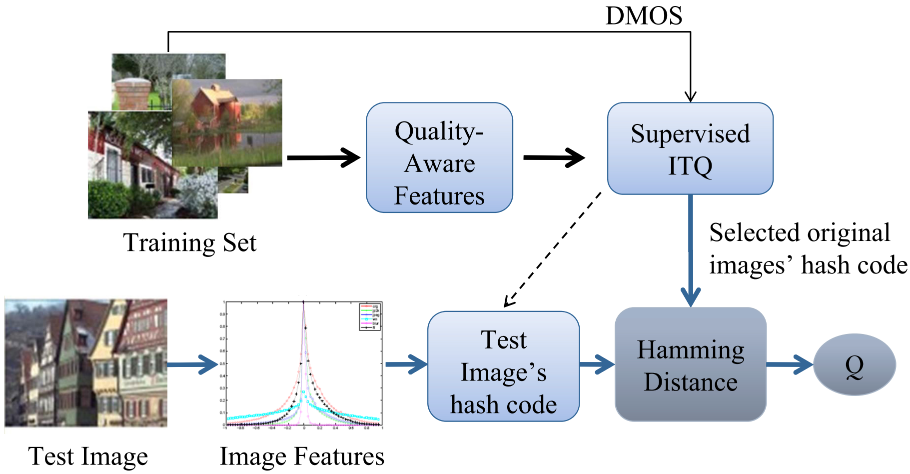

Fig. 1. The framework of the proposed NRHC.

2.1 Features Extraction

Generally, the image has some statistical properties [19], especially for natural scene images. The natural scene statistic is sensitivity to the presence of distortions, such as JPEG2000 compression. Hence, quantifying deviations from the normal natural scene statistics can assess the image quality, which is sufficient to quantify naturalness of the image. However, the NSS feature is extracted from the coefficient of some transform domain, such as DCT, wavelet and contourlet. And it has a defect that time of transformation is huge. Hence, this paper introduces the NSS properties into the BRISQUE [9] to describe the naturalness of images.

Let $\mathbf{X}$ denotes the training set of images including n images. First, every image in the training set is divided into overlapped patches with the size $\omega \times \omega$ and an over-lapping size of ω_0 pixels between neighboring patches. Then the local BRISQUE features are extracted for every patch. The local patch is processed by local mean subtraction and variance normalization on log-contrast values to produces decorrelated coefficients which follow Gaussian like distributions. Given a local patch $x_{l,k}$ (l-th image and k-th patch), the process is as follows

$$\hat{x}_{l,k}(i,j) = \frac{x_{l,k}(i,j) - \mu_{l,k}(i,j)}{\sigma_{l,k}(i,j) + \sigma_0}. \tag{1}$$

Where, i and j are the spatial indices in local patch. σ_0 is a constant that is used to prevent instabilities. μ and σ are the mean and variance with a Gaussian filter. The normalized luminance coefficients obey the asymmetric generalized Gaussian distribution (AGGD). And all the parameters are estimated for the AGGD with zero mode

$$p_X(x;\alpha,\sigma_l^2,\sigma_r^2) = \begin{cases} \frac{\alpha}{(\beta_l+\beta_r)\gamma(1/\alpha)} \exp(-(\frac{-x}{\beta_l})^{\alpha}) & x < 0 \\ \frac{\alpha}{(\beta_l+\beta_r)\gamma(1/\alpha)} \exp(-(\frac{-x}{\beta_r})^{\alpha}) & x \geq 0 \end{cases} \tag{2}$$

Let $\mathbf{f}_l = (f_{l,1}, \cdots, f_{l,k_l})$ represents the feature set of the l-th image. k_l is the number of patches for the l-th image. $f_{l,k}$ is the BRISQUE feature vector of the k-th patch in the l-th image. In this paper, the dimension of the feature is thirty-six for every patch.

All the features extracted from the training images are then clustered into c classes using the k-means clustering algorithm with the squared Euclidean distance metric. The cluster centers are used as the "quality-aware" visual words. Every patch is assigned to the nearest cluster center by vector quantization, and an empirical distribution over the visual words is calculated for each training image, denoted as $\mathbf{s}_l$ for every image.

2.2 Hashing Coding

The BRISQUE statistical features have a weak positive correlation with the differential mean opinion scores (DMOS) which are produced human evaluation. To get more accuracy prediction quality, it needs to design the evaluation model and learning algorithm. Most existing models are built through complex machine learning methods. Aiming to design as efficient and fast quality assessment model, the iterative quantization [20] hash code algorithm is adopted in this paper because of the fast properties. However, ITQ is an unsupervised method. To obtain accuracy image quality, ITQ is improved (named IITQ) with the supervised information (e.g. DMOS) to learning similarity binary codes for images with similarity DMOS.

Training

Given the training image set $S = [s_1, s_2, \cdots, s_n] \in \mathbb{R}^{c\times n}$ and corresponding DMOS $\{q_1, q_2, \cdots, q_n\}$, our goal is to learn a binary code matrix $B \in \{-1, 1\}^{n\times d}$, where d denotes the code length. For each bit r, the binary encoding function is built by h_r. Combining all bits, we can get hash functions $H = \{h_1, h_2, \cdots, h_d\}$. Following [19], we will apply linear dimensionality reduction to data, and then perform improved binary quantization in the resulting space. First, the PCA projection matrix $W \in \mathbb{R}^{c \times d}$ is utilized to maximum the variance as follows

$$\begin{array}{l} \max F(W) = \frac{1}{n} tr\left(W^T S S^T W\right) \\ s.t.\ W^T W = I. \end{array} \tag{3}$$

Where, maximizing the objective function F is a typical Eigen-problem which can be easily and efficiently solved by computing the eigenvectors of SS^T corresponding to the largest d eigenvalues. After getting PCA projection vectors W, we can get the low-dimensional embeddings $V = S^T W$. Then we orthogonally transform the projected data by an orthogonal rotation matrix $C \in \mathbb{R}^{d \times d}$ to minimize the quantization loss

$$\begin{array}{l} \min Q\left(B, C\right) = \|B - VC\|_F^2 \\ s.t.\ C^T C = CC^T = I. \end{array} \tag{4}$$

Meanwhile, we intend to make the Hamming distance between a pair of binary codes preserving the DMOS difference of two images, that is

$$\min \delta\left(C\right) = tr(\mathrm{sgn}(VC)^T \tilde{S} \mathrm{sgn}(VC)), \tag{5}$$

where $\tilde{S} \in \mathbb{R}^{n \times n}$ is the difference matrix of DMOS. As the Eq. (5) is difficult to solve, we approximate binary codes B and rotation matrix C simultaneously

$$\min \tilde{\delta}\left(B, C\right) = tr(\mathrm{sgn}(VC)^T \tilde{S} VC) = tr(B^T \tilde{S} VC). \tag{6}$$

Then the overall objective function for minimizing the quantization loss and preserving the difference of DMOS simultaneously would be

$$\begin{array}{l} \min L(B, C) = \|B - VC\|_F^2 + 2\eta tr(B^T \tilde{S} VC) \\ s.t.\ C^T C = CC^T = I. \end{array} \tag{7}$$

Where, η is a scaling parameter to balance the two contributions. Although the problem is NP-hard, its sub-problems w.r.t. each of B and C are convex. Therefore, we can minimize it by the alternating procedure.

Testing
Given a test image, we can obtain the features $s_t \in \mathbb{R}^{c \times 1}$. Then, its hash code can be obtained by

$$b_t = \mathrm{sgn}(s_t^T W C). \tag{8}$$

2.3 Quality Evaluation

For a new image y, we extract its features and quantify those features to get statistic properties of empirical distribution over the "quality-aware" visual words. Then the features are coded through the previous testing processing and we can obtain the hash code of the new image, indicated as b_t.

The original images from the training set are selected, indicated as b_i $(r = 1, \cdots, r)$, where r is the number of original images in the training set. Finally, the image quality can be obtained as follows

$$Q = \frac{100}{d}\frac{1}{r}\sum_{i=1}^{r}\text{Hamming}(b_i,b_t). \tag{9}$$

Where, $\text{Hamming}(b_i, b_t)$ denotes the Hamming distance between b_i and b_t. And d is the number of hash code bits.

3 Experimental Results and Analysis

To validate the effectiveness and robustness of the proposed NR-IQA method, some experiments are conducted, including the consistency experiment, database independence, and time cost experiment.

Databases: LIVE II [23], TID [24], CSIQ [25], IVC [26], and MICT [27] are used as the standard databases. The LIVE (the Laboratory of Image and Video Engineering at the University of TEXAS at Austin) II database is the most popular adopted database and it is used as the benchmark database. It contains 29 high-resolution 24-bits/pixel RGB color original images and a series of distorted images (#982): JPEG2000 compression (JP2K, #227), JPEG compression (JPEG, #233), white noised in the RGB components (WN, #174), Gaussian blurring (Gblur, #174) and transmission error in the JPEG2000 bit stream using a fast-fading Rayleigh channel (FF, #174). All the images are presented with differential mean opinion scores.

Criterion: Video quality expert group (VQEG) [22] provides the comparison criterion in Phase-I and -II. A nonlinear mapping is first built between the predicted quality and DMOS using logistic non-linear regression analysis. And the criteria of LCC and SROCC are used to compare the performance of metrics. The Pearson linear correlation coefficient (**LCC**) provides an evaluation of prediction accuracy. The Spearman rank-order correlation coefficient (**SROCC**) is considered as a measure of prediction monotonicity. A larger value indicates better performance.

Settings: The bit size of binary hash code will directly affect the performance of the proposed NRHC. Generally, the size is larger than 100 for the proposed metric. On the other hand, the size of hash code is limited to the dimension of the image features. When all of these conditions are considered together, the size of hash code is set to 120 in this paper. And this setting can lead to a good performance.

3.1 Consistency

The subjective score (DMOS or MOS) is the most reliable evaluation because human beings are the ultimate recipients of the image. Therefore, the consistency

Table 1. Comparison of the Performance (LCC) on the LIVE II Database.

Metric	Type	JP2K	JPEG	WN	Gblur	FF	All
PSNR	FR	0.8962	0.8596	0.9858	0.7834	0.8895	0.8240
SSIM	FR	0.9367	0.9283	0.9695	0.8740	0.9428	0.8634
BIQI	NR	0.8086	0.9011	0.9538	0.8293	0.7328	0.8205
LBIQ	NR	–	–	–	–	–	–
DIIVINE	NR	0.9220	0.9210	0.9880	0.9230	0.8880	0.9170
BLIINDS	NR	0.8070	0.5970	0.9140	0.8700	0.7430	0.6800
LQF	NR	0.8424	0.8310	0.8523	0.8459	0.7976	0.8021
QAC	NR	0.8648	0.9435	0.9180	0.9105	0.8248	0.8625
NRHC	**NR**	**0.9006**	**0.8674**	**0.8845**	**0.8887**	**0.8955**	**0.8714**

Table 2. Comparison of the Performance (SRCC) on the LIVE II Database.

Metric	Type	JP2K	JPEG	WN	Gblur	FF	All
PSNR	FR	0.8898	0.8409	0.9853	0.7816	0.8903	0.8197
SSIM	FR	0.9317	0.9028	0.9629	0.8942	0.9411	0.8510
BIQI	NR	0.7995	0.8914	0.9510	0.8463	0.7067	0.8195
LBIQ	NR	0.9000	0.9200	0.9700	0.8800	0.7800	0.8900
DIIVINE	NR	0.9130	0.9100	0.9840	0.9210	0.8630	0.9160
BLIINDS	NR	0.8050	0.5520	0.8900	0.8340	0.6780	0.6630
LQF	NR	0.8389	0.8323	0.8472	0.8456	0.8018	0.8156
NIQE	NR	0.9187	0.9422	0.9718	0.9329	0.8639	0.9086
QAC	NR	0.8621	0.9362	0.9509	0.9134	0.8231	0.8683
NRHC	**NR**	**0.8622**	**0.8428**	**0.8518**	**0.8806**	**0.8651**	**0.8776**

between the objective evaluations and the subjective scores is the most important performance. To verify that the algorithms are robust to the image content, a cross-validation experiment is conducted on the database. Part of original images and their corresponding distorted images (80%) are randomly selected for model training, with for the remainder being used as test images. The performance of LCC and SROCC is the average of the experimental results with 100 times of random cross-validation. The results are shown in Table 1 and 2. Where, PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural SIMilarity) [21] are typical full-reference image quality assessment metrics, and BIQI (the Blind Image Quality Indices) [5], LBIQ (Learning based Blind Image Quality measure) [7], DIIVINE (the Distortion Identification-based Image Verity and INtegrity Evaluation) [6], BLIINDS (BLind Image Integrity Notator using DCT Statistics) [8] [10], LQF (Latent Quality Factors) [15] and QAC (Quality-Aware Clustering method) [17] are no-reference image quality assessment metrics.

Table 1 and 2 show the comparison of performances on the sub (JP2K, JPEG, WN, Gblur, FF) and the entire LIVE II database. It can be found that different NR-IQAs present the best performance on some distorted sub database. The proposed NRHC obtains better performance than the state-of-the-art methods on most conditions. Furthermore, the proposed NRHC has similar performance on different distortions. Hence, the proposed NRHC has greater robustness than other metrics.

3.2 Database Independence

Most of the NR-IQA metrics need to determine model parameters through learning algorithm on the training set. Hence, it is necessary to verify the robustness and generalization. It means that whether the learned model is sensitive to different databases or database independence.

The metrics are trained on the LIVE II database and tested on other databases including TID (1700 distorted images with 17 different distortions), CSIQ (900 distorted images with 6 different distortions), IVC (195 distorted images with 4 different distortions), and MICT (168 distorted images with 2 different distortions). The experimental results of PSNR, SSIM, BIQI, DIIVINE, BLIINDS, LQF, QAC and the proposed NRHC on these publicly available databases are shown in Table 3. It can be found that the proposed metric has better stability than other metrics.

Table 3. LCC on other Public Databases.

Metric	Type	TID	CSIQ	IVC	MICT
PSNR	FR	0.5643	0.8772	0.7192	0.6355
SSIM	FR	0.6387	0.8060	0.7924	0.7979
BIQI	NR	0.4192	0.6601	0.5346	0.6853
DIIVINE	NR	0.7749	0.8284	0.3300	0.6416
BLIINDS	NR	0.5086	0.7529	0.7013	0.7924
LQF	NR	0.4231	0.6396	0.6191	0.7042
QAC	NR	0.8538	0.8416	0.7676	0.5189
NRHC	**NR**	**0.5387**	**0.6826**	**0.6237**	**0.7187**

Table 4. Computational time on LIVE II Databases.

Metric	Type	Training	Testing
PSNR	FR	–	1.86s/100p
SSIM	FR	–	7.20s/100p
BIQI	NR	–	74.25s/100p
BLIINDS	NR	–	85.27s/100p
NRHC	**NR**	**1.75s/100p**	**0.21s/100p**

3.3 Computational Time

Time cost will greatly affect the effectiveness and efficiency and plays a significant role in the real-time application and big image data processing system. In this subsection, we test and compare the computing time of some existing methods with the proposed NRHC. The computational time experiment is conducted on the LIVE II database and the same runtime environment. The results are shown in Table 4. The computational time is recorded and presented under processing for every 100 images. From the table, we can find that the proposed NRHC has the best performance on computational time cost.

4 Conclusions

This paper proposed a novel no-reference image quality assessment method via hash codes. The proposed NRHC is effective and efficient which are demonstrated by the analysis and experiments. The proposed NRHC first extract the spatial natural scene statistics features, embed the features into hash codes via an improved iterative quantization method, and calculate the Hamming distance between the hash code of the test image and the original undistorted image to predict image quality. The hash coding and the Hamming distance calculation have the properties of fast speed and high efficiency. Hence, the proposed NRHC can satisfy the real-time applications and big image data processing. However, the proposed NRHC has not considered the characteristics of the human visual system (HVS), such as visual saliency. Therefore, the method combining the fast algorithm and the properties of HVS need to be studied. Additionally, in order to assess stereo images, video and high definition, the proposed method also needs to be extended to fit new applications.

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