# NO REFERENCE IMAGE QUALITY ASSESSMENT BASED ON LOCAL BINARY PATTERN STATISTICS

*Min Zhang[a], Jin Xie[b], Xiangrong Zhou[a] and Hiroshi Fujita[a]*
[a]Department of Intelligent Image Information, Division of Regeneration and Advanced Medical Sciences, Graduate School of Medicine, Gifu University, Gifu-shi, 501-1194 Japan
[b]Department of Computing, Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

## ABSTRACT

Multimedia, including audio, image and video, etc, is a ubiquitous part of modern life. Evaluations, both objective and subjective, are of fundamental importance for numerous multimedia applications. In this paper, based on statistics of local binary pattern (LBP), we propose a novel and efficient quality similarity index for no reference (NR) image quality assessment (IQA). First, with the Laplacian of Gaussian (LOG) filters, the image is decomposed into multi-scale sub-band images. Then, for these sub-band images across different scales, LBP maps are encoded and the LBP histograms are formed as the quality assessment concerning feature. Finally, by support vector regression (SVR), the extracted features are mapped to the image's subjective quality score for NR IQA. The experimental results on LIVE IQA database show that the proposed method is strongly related to subjective quality evaluations and competitive to most of the state-of-the-art NR IQA methods.

***Index Terms*****—** No reference, image quality, local binary pattern, support vector regression

## 1. INTRODUCTION

With the increase of multimedia applications in our daily life, perceived quality evaluation has been receiving more and more attention in the past years. However, how to accurately model and represent the user's reaction to the perceived quality is still challenging. Among these perceived quality evaluation tasks, image quality assessment (IQA) is one of the important issues. IQA methods aim to automatically evaluate and predict image perceived quality. Depending on the availability of a reference image, IQA methods can be divided into three categories: full-reference (FR, where the reference image is fully available when evaluating the perceptual quality of the distorted image), reduced-reference (RR, where only partial information about the reference image is available), and no-reference (NR) or blind image quality assessment (where no access to the reference image is allowed).

Conventional FR IQA indices such as mean squared error (MSE) and peak signal-to-noise ratio (PSNR) have been used for a long time but they do not conform well to the human visual perception. In the last decade, much effort and progress have been made on FR IQA and their performance has been validated across existing distortion types in the realistic world. In the bottom-up mechanism based FR metrics [1-10], the quality prediction is generally made up of all or some of the following HVS modules, such as CSF filtering, multi-channel decomposition, the visual detectability of error signal and error pooling, etc.[1-4]. The top-down mechanism based FR metrics mimic what the HVS is trying to accomplish when viewing a distorted image, such as Structural SIMilarity index (SSIM) [6] and non-shift edge ratio (NSER) [7]. It's assumed that HVS is highly adaptive to perceive the structure of nature images, and then the structural similarity was proposed to capture how much the structures are consistent between the reference image and the distorted one. Motivated by the natural scene statistics (NSS), the information fidelity criteria is also used to quantify the information shared between the distorted and the reference images [8].

RR IQA method is designed to predict the perceptual quality of distorted images with only partial information about the reference images. Certainly, the RR feature extraction is absolutely of most significance in RR metric. For example, Wang *et al*. proposed the concept of quality aware images in [11], where partial reference image information is embedded in the image and can be extracted reliably despite distortions. A couple of RR IQA methods favor the natural scene statistic (NSS) based RR feature extraction, which can provide a highly efficient way to capture the image information, and yield good performance [11, 12]. There is another noticeable trend to estimate RR IQA models from the state of the art FR IQA models, such as RR-SSIM method [13], which is reduced information estimation from SSIM index [6], and RRED indices [14], which is estimated from the visual information fidelity (VIF) index [9]. These methods are trying to find the relationship between the FR measure and their RR estimations. RR IQA attracted great scientific activity not only because it is a solution to IQA method, but more importantly, it could be considered as the preparations for the NR IQA solution. In fact, the proposed NR IQA method in this paper is derived from the previous RR IQA method [15].

NR image quality assessment (IQA) problem is to devise perceptual models that can predict the quality of distorted images only with the distorted stimulus. Although NR IQA would be potentially the most useful, it is an extremely difficult task so far. Most current NR IQA methods are distortion-specific [16-18]. They perform NR IQA quality prediction only if the distortion type of the image known in advance. While general-purpose NR IQA investigating is still the most important and hot research topic in this area. A kind of general-purpose NR IQA works favor the natural scene statistics (NSS). Examples of such methods based on the principle that natural images possess certain regular statistical properties that are measurably changed by the presence of distortion [19-23]. Statistical models to characterize the natural scene properties for IQA purpose have been investigated both in spatial domain (e.g., BRISQUE in [19]), and transform domain, such as wavelet [20,21], DCT [22] etc. They evaluate the "unnaturalness" extent of the test image without any prior knowledge.

Another way to NR IQA model is based on the learned regression model for the description of a set of relevant features that affecting the quality [24-26]. Features used in the training stage could be selected raw image patches in the given images (e.g., LBIQ in [24]); phase congruency feature and the entropy of the distorted image (e.g., GRNN in [25]); and image patches learned from visual codebook by *K*-means (e.g., CBIQ in [26]) etc. Nonetheless, the quality concerned feature extraction and selection are crucial in these approaches

Recently, a kind of low level local structure descriptor, local binary pattern (LBP) [27], has achieved great success in computer vision and pattern recognition. Although LBPs are only the sign component of local image information, it has been proved that LBPs preserve much more image local structural information than the magnitude component [28]. The most frequent local binary patterns correspond to primitive local structure, such as edges, corners, and spots; hence, they can be regarded as feature detectors that are triggered by the best matching pattern [27]. In addition, the computational simplicity of LBPs makes it rather competitive in real time applications.

From one viewpoint of visual perception, image local structural change could reflect the degradation of image quality and this has been validated by a serious of relevant IQA works, such as SSIM Index mentioned above [6], and Non-Shift Edge Ratio (NSER) [7], etc. Meanwhile LBP based statistics have been proved to be quite useful as a reduced reference IQA method [15]. Based on the above points, In this paper, we aim to fulfill NR IQA task using such statistics of image local structure with the nonlinear regression model. Preliminary results on LIVE image quality database show that the proposed method with statistics of LBPs is effective and efficient for general-purpose NR IQA.

## 2. NO REFERENCE IMAGE QUALTIY BASED ON LOCAL BINARY PATTERN STATISTICS

In this section, we first briefly review the local binary pattern descriptor. Then we present the proposed method in detail, including quality feature extraction and the quality prediction method with the support vector regression model.

### 2.1 Brief Review of Local Binary Pattern

Local binary texture patterns termed "uniform" have been recognized as the fundamental properties of local image feature [27]. These "uniform" patterns provide a vast majority, sometimes over 90 percent of image micro-structure patterns in examined image surface. Histograms from LBP codes provide statistical information of micro-structure orientation and coarseness. Formally, the operator takes the form

$$LBP_{P,R} = \sum_{p=0}^{P-1} S(t_i - t_c)2^p, \quad where \quad S(t) = \begin{cases} 1, & t \geq 0 \\ 0, & t < 0 \end{cases} \qquad (1)$$

$t_c$ is the gray value of the central pixel, $t_i$ is the value of its neighbors, $P$ is the total number of involved neighbors and $R$ is the radius of the neighborhood. The gray values of neighbors that are not in the image grids can be estimated by interpolation. At a center pixel $t_c$, each neighboring pixel $t_i$ is assigned with a binary label, which can be either "0" or "1," depending on whether the intensity value of the center pixel is greater than that of the neighboring pixel.

Suppose that the image is of size $M \times N$. After the LBP code of each pixel is identified, a histogram is built to represent the image

$$\begin{aligned} H(k) &= \sum_{m=1}^{M}\sum_{n=1}^{N} f(LBP(m,n),k), k \in [0,K], \\ f(x,y) &= \begin{cases} 1, x = y \\ 0, otherwise \end{cases} \end{aligned} \qquad (2)$$

in which $K$ is the number of different LBP codes.

The uniform LBP patterns refer to the patterns which have limited transitions or discontinuities (bitwise 0/1 changes) in the LBP. The "uniform" pattern is defined as a uniformity measure $U$ ("pattern")

$$U(LBP_{P,R}) = \left|S(t_{P-1} - t_c)\right| + \sum_{p=1}^{P-1}\left|S(t_p - t_c) - S(t_{p-1} - t_c)\right| \qquad (3)$$

$U$ value of at most 2 is defined as "uniform" patterns.

To achieve rotation invariance, a locally rotation invariant pattern could be defined as

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{P-1} S(t_p - t_c) & if \quad U(LBP_{P,R}) \leq 2 \\ P+1 & otherwise \end{cases} \qquad (4)$$

Superscript $^{riu2}$ reflects the use of rotation invariant "uniform" patterns that have $U$ value of at most 2.

### 2.2. Statistics of Quality Concerned Feature from LBP

The procedure of quality concerned feature extraction is as follows.

*2.2.1. Multi-scale decomposition*

It has been proved that the neuronal responses in V1 of visual cortex perform multi-scale decompositions of the visual data [29]. From a computational point of view, the response of classical cortical receptive field (CRF) can be modeled by a series of hierarchical filters, i.e. the Laplacian of Gaussian (LOG) filters, which are defined as

$$\nabla^2 G(r,\sigma) = -\frac{1}{\pi\sigma^4}\left(1-\frac{r^2}{2\sigma^2}\right)\exp\left(-\frac{r^2}{2\sigma^2}\right) \tag{5}$$

where $G(r,\sigma) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{r^2}{2\sigma^2}\right)$ is the Gaussian kernel. $r$ is the $l_2$ norm of $\boldsymbol{X}$, i.e., $r = \|\boldsymbol{X}\|_2$ . $\boldsymbol{X}$ is the position of the test image $\boldsymbol{I}$.

Filter response $\boldsymbol{F}$ can be obtained by the convolution of the filter kernel $\nabla^2 G(r,\sigma)$ and the image $\boldsymbol{I}$ in the following form:

$$\boldsymbol{F}(\boldsymbol{X},\sigma) = \nabla^2 G(r,\sigma) \otimes \boldsymbol{I}(\boldsymbol{X}) \tag{6}$$

in which $\otimes$ represents the convolution operator.

*2.2.2. Encoding maps of LBPs in the Transform Domain*

After multi-scale decomposition, a modified LBP operator is executed in every decomposed sub-band images.

$$LBP_{P,R,\sigma}(\boldsymbol{X}_c) = \sum_{p=0}^{P-1} S(\mathrm{abs}(\boldsymbol{F}(\boldsymbol{X}_i,\sigma) - \boldsymbol{F}(\boldsymbol{X}_c,\sigma)))2^P,$$

$$Where \quad S(t) = \begin{cases} 1, & t \ge 0 \\ 0, & t < 0 \end{cases} \tag{7}$$

At a center pixel $\boldsymbol{F}(\boldsymbol{X}_c,\sigma)$ in the filtered sub-band image, each neighboring pixel $\boldsymbol{F}(\boldsymbol{X}_i,\sigma)$ is assigned with a binary label of either “0” or “1”, depending on whether the center pixel $\boldsymbol{F}(\boldsymbol{X}_c,\sigma)$ is greater than the neighboring pixel $\boldsymbol{F}(\boldsymbol{X}_i,\sigma)$ .

*2.2.3. Quality concerned feature from LBP histograms*

Finally, the histograms of the LBP encoding map for every sub-band images are normalized and formed as the quality concerned features.

$$H_\sigma(t) = \sum_{\mathrm{X}} f(LBP_{P,R,\sigma}(\boldsymbol{F}(\boldsymbol{X},\sigma),t))/(MN), t \in [0,T] \tag{8}$$

in which $T$ is the number of different LBP codes and the sub-band image $\boldsymbol{F}(\boldsymbol{X},\sigma)$ is supposed of size $M \times N$ . In this way, $H_\sigma$ is served as the NR quality concerned feature.

### 2.3. Quality Prediction with Support Vector Regression

However, how to model the mapping function between the subjective score and quality concerned features is another crucial issue in NR IQA methods. To fulfill this task, we turn to a nonlinear regression model - support vector regression (SVR) for the quality prediction. SVR has been proposed in 1997 by Vapnik and other co-workers [30], which is learning in the high dimensional feature space. An overview of the basic ideas underlying support vector (SV) machines for regression and function estimation can be referred to [31].

Here, we explore the applicability of the LBP features for NR IQA purpose with the SVR training model. With SVR, the LBP feature vector is mapped to the quality score to train the quality prediction model. For simplicity, only the histograms of sub-band image LBP maps are used as the training quality features for our preliminary testification.

## 3. EXPERIMENTAL SETUP

### 3.1. Test Image Database

The LIVE IQA database is used to test the performance of the proposed method, which consists of 29 reference images with 779 distorted images, crossing five different distortion categories – JPEG2000 (JP2K) and JPEG compression, additive white Gaussian noise (WN), Gaussian blur (Blur), and a Rayleigh fast-fading channel distortion (FF). Each of the distorted images has an associated difference mean opinion score (DMOS) which represents the subjective quality of the image.

### 3.2. Simulation Details and Parameters

Since the proposed approach requires a training procedure, the LIVE database is split into two randomly chosen subsets: 80% training and 20% testing. And there is no overlap between the training set and testing data set in each split and evaluation. The random train-test procedure is repeated 1000 times and the median of the performance across these 1000 iterations is reported in order to eliminate performance bias. LIBSVM package [32] is utilized to implement SVR. In our experimentations, we perform ε-SVR with a radial-basis function (RBF) kernel. The parameters (cost, gamma) of ε-SVR are tuned by a 2D grid search in the logarithm space.

The proposed NR method is compared with NSS based NR IQA methods, including LBIQ [23], LD-TS [21], BLIINDS [22], DIIVINE [20], visual codebook based metric (CBIQ) [26], regression neural network based metric (GRNN) [25] and spatial domain metric BRISQUE [19]. The results listed in Table 1 and Table 2 for NR metrics are from their available publications with the same testification procedures for a fair comparison.

Table 1 Median spearman rank ordered correlation coefficient (SROCC) across 1000 train-test combination on the LIVE IQA database.

| | Type | JP2K | JPEG | WN | Blur | FF | All |
|---|---|---|---|---|---|---|---|
| PSNR | FR | 0.8646 | 0.8831 | 0.9410 | 0.7515 | 0.8736 | 0.8636 |
| SSIM [6] | | 0.9389 | 0.9466 | 0.9635 | 0.9046 | 0.9393 | 0.9129 |
| CBIQ [26] | NR | 0.8935 | **0.9418** | 0.9582 | **0.9324** | 0.8727 | 0.8954 |
| LBIQ [23] | | 0.9040 | 0.9291 | 0.9702 | 0.8983 | 0.8222 | 0.9063 |
| LD-TS [21] | | 0.8202 | 0.8334 | 0.9566 | 0.9251 | **0.8863** | 0.8833 |
| GRNN [25] | | 0.8156 | 0.8721 | **0.9794** | 0.8331 | 0.7354 | 0.8268 |
| BLIINDS-II (SVM) [22] | | **0.9285** | **0.9422** | 0.9691 | 0.9231 | **0.8893** | **0.9306** |
| DIIVINE [20] | | 0.913 | 0.910 | **0.984** | 0.921 | 0.863 | 0.916 |
| BRISQUE [19] | | **0.9139** | **0.9647** | **0.9786** | **0.9511** | 0.8768 | **0.9395** |
| NR-LBPS$^{riu2}$ | | **0.9275** | 0.9338 | 0.9484 | **0.9426** | **0.8890** | **0.9323** |

Table 2 Median linear correlation coefficient (LCC) across 1000 train-test combination on the LIVE IQA database

| | Type | JP2K | JPEG | WN | Blur | FF | All |
|---|---|---|---|---|---|---|---|
| PSNR | FR | 0.8762 | 0.9029 | 0.9173 | 0.7801 | 0.8795 | 0.8592 |
| SSIM [6] | | 0.9405 | 0.9462 | 0.9824 | 0.9004 | 0.9514 | 0.9066 |
| CBIQ [26] | NR | 0.8898 | 0.9454 | 0.9533 | 0.9338 | 0.8951 | 0.8955 |
| LBIQ [23] | | 0.9103 | 0.9345 | 0.9761 | 0.9104 | 0.8382 | 0.9087 |
| LD-TS [21] | | 0.8273 | 0.8507 | 0.9544 | 0.9315 | 0.8784 | 0.8774 |
| GRNN [25] | | 0.8276 | 0.8798 | **0.9887** | 0.8250 | 0.8189 | 0.8374 |
| BLIINDS-II (SVM) [22] | | **0.9348** | **0.9676** | 0.9799 | **0.9381** | **0.8955** | **0.9302** |
| DIIVINE [20] | | 0.922 | 0.921 | **0.988** | 0.923 | 0.888 | 0.917 |
| BRISQUE [19] | | **0.9229** | **0.9734** | **0.9851** | **0.9506** | **0.9030** | **0.9424** |
| NR-LBPS$^{riu2}$ | | **0.9327** | **0.9498** | 0.9646 | **0.9436** | **0.9127** | **0.9370** |

For the proposed method, the training image is decomposed into 4 scales. For each scale, the LBP codes could be computed with different R and P. In this paper, $R = 1, 2, 3$ and $P = 4$ are selected for computational simplicity. The 72-dimensional rotation invariant uniform LBP features are extracted in each image. In this way the proposed method is indicated as NR-LBPS$^{riu2}$.

### 3.3. Evaluation of Performance

The spearman rank order correlation coefficient (SROCC), the linear correlation coefficient (LCC) between the objective scores predicted by the computational model and the subjective scores predicted by observers after nonlinear regression are used to evaluate the performance of these IQA methods. A value close to 1 for SROCC and LCC indicates good performance in terms of correlation with human opinion.

According to the VQEG report [33], the nonlinear logistic regression is allowed to transform the values of the metric score to the predicted quality values. The mapping function is defined as follow:

$$Quality(x) = a_1\left(\frac{1}{2} - \frac{1}{1+\exp(a_2(x-a_3))}\right) + a_4 x + a_5 \quad (9)$$

Where $a_1, a_2$ and $a_3$ are optimized by a nonlinear regression routine.

## 4. EXPERIMENTAL RESULTS AND DICUSSION

A preliminary evaluation of the proposed method is undertaken in terms of correlation with human perception. Table 1 and Table 2 compare both the performance of the overall prediction accuracy and the specific distortion prediction accuracy of the proposed method with that of the competitive NR IQA methods, as well as two FR indexes – PSNR and SSIM [6]. The greatest three correlations for the compared NR methods are marked in bold in the tables.

From Table 1 and Table 2, it is clear that the proposed method performs well in terms of correlation with human perception of quality. The performance of the proposed NR method is statistically better than PSNR and comparable to most of other state-of-the-art NR IQA methods and SSIM index [6].

Although the proposed method seems only from certain statistics of the image micro-structure description model, several important HVS modules, such as multi-channel decomposition, visual sensibility and masking effect are implicated in the statistical features. The uniform LBP are the most discriminative features to form a histogram that provide better discrimination in comparison to the histogram of all individual patterns. This may correspond to the visual masking effect in HVS [34]. In HVS, human perceptual ability is bounded to some extent. Some concepts, such as just-noticeable-difference (JND) [35] and visual masking effect [34] are introduced to explain this visual phenomenon in different ways. With uniform LBP, features upon and below human perceptual discriminative ability are statistically grouped into "uniform" or "non-uniform" ones and all non-uniform patterns are labelled with a single label to improve the consistency with human perception. That would be the reason why the proposed method works. While comparing with other NR IQA methods, the performance of the proposed method seems not overwhelming, since such kind of statistical features from LBPs miss most of the contrast information of the images. They are only the sign components for preserving image local structural information. Hence, there is still room for the improvement of this method.

It is noted that the data rate and the computational complexity of the proposed method are fairly low. Only 24 scalar features are used in the training stage for each image in the proposed implementation. And the average computational time, over all the images in the LIVE database, is around 1 second/image using a laptop with the Intel i5 processor at 2.60 GHz for feature extraction. The high speed process makes the proposed method highly competitive in real time applications.

It is noteworthy that the proposed method has not been fully optimized yet. More work will be done upon this framework in the future. And the performance is also needed to further investigate and validate across different databases.

## 5. CONCLUSION

This paper proposed a local binary pattern statistic based distortion generic no-reference (NR) quality assessment index. The tentative experimental results on LIVE subject-rated image database show that the proposed NR IQA index exhibits good correlations with subjective evaluation over a wide variety of image distortions with low data rate and high efficiency. It outperforms the popular FR methods, including PSNR and SSIM index and is competitive to most of the state of the art NR IQA methods.

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