No reference image quality assessment metric based on regional mutual information among images

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Abstract

With the inclusion of camera in daily life, an automatic no reference image quality evaluation index is required for automatic classification of images. The present manuscripts proposes a new No Reference Regional Mutual Information based technique for evaluating the quality of an image. We use regional mutual information on subsets of the complete image. Proposed technique is tested on four benchmark natural image databases, and one benchmark synthetic database. A comparative analysis with classical and state-of-art methods indicate superiority of the present technique for high quality images and comparable for other images of the respective databases.

1 Introduction

With the advent of inexpensive and good quality mobile cameras storage, transmission and compression of images has become a standard practice among technical and non technical masses. Large number of people have mobile phones with camera capturing trillions of photographs every year, approximately 24 billion selfies were uploaded to Google in year 2015 and increasing exponentially with every passing year. Unlimited space for uploading images on Google photos (and large space on other web servers; for example, Flickr, Pinterest, etc) facilitates and influences people to capture many photographs of the same situation. Searching the good quality images from this ever (exponentially) increasing large quantity is impossible task for a human being. Therefore, it becomes pertinent to design and develop better automatic and no-reference image quality assessment system. These systems will help; for example, in evaluating the image information and (possibly) retain the best out of plethora, find out the quality in real time, selecting camera settings for best results, etc. This drives researchers to develop better auto no reference image quality measurement techniques [1, 2, 3, 4, 5, 6, 7].

Researchers generally talk about three types of image quality assessment (IQA) techniques:

1. full reference [8, 9, 10, 11, 12, 13, 14, 15],

2. reduced reference IQA [16, 17], and

3. no-reference IQA [18, 19, 20, 21].

First type of IQA assumes that human beings are sensitive to degradations, second indicates that we are more sensitive to few key features extracted from the image. The current proposed technique lies in the last category.

Various techniques for objective image quality measurement are discussed in literature. Since human visual system is a complex set of decision making processes, available IQA methods are still not as good as the human visual decisions. We discuss some of the relevant and prevailing methods in rest of the present section.

Wu et al [22] used measurement of blocking effect in horizontal and vertical directions and differences at block boundaries in horizontal and vertical directions, respectively. Tan et al [23] analyzes magnitude and phase information in a harmonics to measure the quality of the image. Another [24] model was developed for measuring block effects in an image. Wang et al [25] used energy based measurements to find the blocking artifacts in an image. These blocking effects become fundamental building blocks for measurement of quality of an image.

While transmitting or storing, image quality (IQ) measurement plays a crucial role to evaluate and choose the correct image. The ultimate goal of IQ measurement is assigning a quantitative value to perception to human observers. Researchers perform this task with the help of crowd sourcing and acquiring Mean Opinion Score (MOS). MOS or its modified versions compared with the IQA values become basis for quality of the IQA index.

In the next section we discuss proposed method followed, in section 3, by experimental results and discussion. We close the manuscript with conclusion and references.

2 Methodology

The proposed index No Reference Regional Mutual Information (NrMI) predicts the quality of an image with the help of following procedure.

Given an image matrix $\Phi(x,y) \in \mathbb{Z}^{n\times m}$. Another version of matrix $\Phi(x,y)$ is created and is depicted by $\Phi'_\theta(x',y')$, where

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{1}$$

To make Φ and Φ'_θ of same size equations 2 and 3 are applied.

$$\Phi_{vec}(v) = vec(\Phi'_\theta(x',y')) \tag{2}$$

$$\Phi_{\theta v}(x,y) = vec^{-1}(\Phi_{vec}(v)) : \Phi_\theta(x,y) \in \mathbb{R}^{ab} \to \mathbb{R}^{n\times m} \tag{3}$$

We divide $\Phi(x,y)$ into disjoint group of n sub-matrices, $\eta_k^{a\times b}$: $k \in \mathbb{Z}^{>}$where $\eta_k : \eta_k \subset \Phi$. η_k contains q member of perfect subsets of Φ (such that $k/m \in \mathbb{Z}^{>}$), for it is obvious that if a subset is perfect, then there is no information loss. Every element of η_k represents a segment of original image Φ. $\Phi'_\theta(x',y')$ is divided into sub-matrices $\eta_{k,\theta}^{a\times b}$ ($\equiv \eta_k$).

We choose size of η_k (and consequently $\eta_{k,\theta}$) to be 3×3, which makes sure that the values within η_k will not be varying significantly except when sub-matrix lies at an edge in $\Phi(x,y)$ (or

$\Phi'_\theta(x', y')$). The value of θ is $\pi/2$, one can choose any value for θ but $\pi/2$ provides maximum shift, and equation 1 is rewritten as

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} -y \\ x \end{bmatrix} \tag{4}$$

which relates image matrices Φ and Φ'_θ by equation 5

$$\Phi(x, y) = \Phi'_\theta(-y, x) \tag{5}$$

Let sub-matrices η_k (and $\eta_{k,\theta}$) be represented by

$$\begin{aligned} \eta_k &= \begin{bmatrix} e_{11} & e_{12} & e_{13} \\ e_{21} & e_{22} & e_{23} \\ e_{31} & e_{32} & e_{33} \end{bmatrix} \\ \eta_{k,\theta} &= \begin{bmatrix} e_{11,\theta} & e_{12,\theta} & e_{13,\theta} \\ e_{21,\theta} & e_{22,\theta} & e_{23,\theta} \\ e_{31,\theta} & e_{32,\theta} & e_{33,\theta} \end{bmatrix} \end{aligned} \tag{6}$$

From matrices of equation 6 calculate matrix M_e

$$M_e = [e_{11}\ e_{12}\ e_{13}\ e_{11,\theta}\ e_{12,\theta}\ e_{13,\theta}\ e_{21} \ldots e_{23}\ e_{21,\theta}\ \ldots\ e_{33,\theta}] \tag{7}$$

Center the values at the origin and represent it by $M_{e,0}$ by

$$M_{e,0} = M_e - \frac{1}{N}\sum_i^N p_i \tag{8}$$

where p_i are elements of matrix M_e and $N = 9 + 9 = 18$.
Find covariance

$$C = \frac{1}{N} M_{e,0} M_{e,0}^T \tag{9}$$

Estimate joint entropy [1]

$$H_g(C)$$

Estimate marginal entropy1 $H_g(C_A)$ and $H_g(C_B)$, where C_A and C_B are top left and bottom right $\frac{d}{2} \times \frac{d}{2}$ matrices of C. d is a relationship defined as

$$d = 2(2r + 1)^2 \tag{11}$$

where, r is the size of sub matrix under consideration; that is, the size of MB for which we are going to calculate the similarity within the matrix.
Calculate Regional Mutual Information

$$M_{rmi} = H_g(C_A) + H_g(C_B) - H_g(C) \tag{12}$$

[1] Joint and marginal entropy is given by [26]

$$H_g(\Sigma_d) = log((2\pi e)^{\frac{d}{2}} det(\Sigma_d)^{\frac{1}{2}}) \tag{10}$$

which represents the entropy of a normally distributed set of points in $\Re^d$ with covariance matrix Σ_d.

M_{rmi} gives a measure of regional mutual information between $\Phi(x, y)$ and $\Phi_\theta(x', y')$.

A weight function for RMI is calculated with equation of $\Phi_{vec}(v)$ is calculated next

$$\Phi_{wg} = \mathbf{E}\left[(\Phi_{vec}(v) - \mathbf{E}[\Phi_{vec}])^2\right] \tag{13}$$

The relative quality of an image is given by

$$NrMI_i = M_{rmi,i} * \Phi_{wg,i} \tag{14}$$

where $i \in i^{th}$ image in the image sequence.

3 Experimental Results

In this section we validate our method through application on various benchmark state-of-art and classical databases. Experiments are conducted with five standard databases of natural and one of synthetic images. The natural image databases are TID 2008 [27] with 1699 images, TID 2013 [28] with 2483 images, CID 2013 [29], LIVE [30], MEFD with 550 images each. While ESPL [31], a database consisting of 550 synthetic images, is used for evaluation of the current algorithm.

For objective evaluation SRCC (Spearman's Rank Correlation Coefficient) and PLCC (Pearson Linear Correlation Coefficient) matrices are used. These metrics give a measure of prediction monotonicity and linearity, respectively.

Table 1 presents a comparative view of various index of quantitative quality measures. Blue color values in table 1 indicate best results. Since no-reference quality measurement system requires complex set of interdependent parameters to work as efficiently as human beings, therefore every system has certain advantage over others under certain conditions. From the table it becomes clear that proposed method evaluates the images better than SSIM for most of the databases. Since the proposed method uses underlying regional geometric information by splitting the set into disjoint group of sub-sets; therefore every small change in geometry (including presence of undetectable noise for human visual system) changes the qualitative measure.

Specifically with images of high quality (databases MEFD and ESPL) the proposed method performs much better than SSIM [32] and other state-of-art techniques. Since proposed technique considers underlying geometry of the image, high quality images distorted by small amount of noise produce lower value of the quality index. This lower value in turn will be helpful to take corrective measures to develop noise removal or better compression algorithms.

4 Conclusion

Present manuscript investigates the problem of no-reference quality assessment. A novel technique has been proposed for the assessment based on underlying geometry of the image. The technique is applied on various databases with different types of images. Results show interesting trend and promising performance when compared with existing literature. Since method utilizes mutual information approach it was able to render better results for high quality images.

In future we aim to study the effects of current technique by calculating RMI on weighted image segments. The weights will be calculated based on the importance of the region in the images, which in turn depends on point of focus in human visual system.

Database	Statistical Measurement	SSIM [32]	NR [33]	NJQA [34]	NR [35]	MUG NR [36]	MUG^{+} NR [36]	PM
TID 2008 [27]	PLCC	0.954	0.952	0.944	0.951	0.941	0.953	0.868
	SRCC	0.925	0.913	0.8993	0.917	0.917	0.924	0.832
TID 2013 [28]	PLCC	0.954	0.953	0.948	0.955	0.942	0.955	0.887
	SRCC	0.9200	0.927	0.886	0.931	0.908	0.919	0.842
CID 2013 [29]	PLCC	0.979	0.975	0.954	0.979	0.9679	0.972	0.789
	SRCC	0.955	0.955	0.925	0.957	0.930	0.937	0.798
LIVE [30]	PLCC	0.979	0.979	0.956	0.976	0.965	0.973	0.962
	SRCC	0.946	0.974	0.956	0.973	0.959	0.968	0.959
ESPL [31]	PLCC	0.943	0.960	0.809	0.962	0.940	0.937	0.962
	SRCC	0.904	0.933	0.739	0.933	0.928	0.927	0.959

Table 1: Performance comparison of no reference image quality measure for TID 2008 [27], TID 2013 [28], CID 2013 [29], LIVE [30], MEFD, and ESPL [31] databases. Blue color values represent best performing technique in terms of corresponding SRCC and PLCC statistical measures.

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