BLIND QUALITY ASSESSMENT OF COMPRESSED IMAGES VIA PSEUDO STRUCTURAL SIMILARITY

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ABSTRACT

Block-based compression causes severe pseudo structures. We find that the pseudo structures of images compressed by different levels show some degree of similarity. So we propose to evaluate the quality of compressed images via the similarity between pseudo structures of two images. To obtain a "reference" image, we introduce the most distorted image (MDI), which is derived from the distorted image and suffers from the highest degree of compression. The proposed pseudo structural similarity (PSS) model calculates the similarity between pseudo structures of the distorted image and MDI. Pseudo structures of the distorted image become similar to the MDI's under the condition of severe compression. Via comparative tests, the proposed PSS model, on one hand, is shown to be comparable to state-of-the-art competitors, and on the other hand, it is not only good at assessing natural scene images but also performs the best in the hotly-researched screen content image (SCI) database. It deserves to mention that PSS is able to boost the performance of mainstream general-purpose no-reference (NR) quality measures.

Index Terms— IQA, blockiness, pseudo structural similarity, most distorted image, screen content image

1. INTRODUCTION

Image quality assessment (IQA) can be of great use in implementing and optimizing numerous visual communication systems [1–4]. The ultimate goal of objective IQA is to provide computational measures with results that are well correlated to human perceptions. In the past two decades, a great deal of IQA algorithms have been proposed and applied [5]. Among all types, NR IQA measures are more valuable since the original images are often not available in the practical systems. In this paper, we specifically design NR IQA measure for compressed images. Because of its widely use in various communication systems, we mainly take JPEG as examples and assess the quality of JPEG compressed images.

Block-based compression causes blocking and blurring artifacts which degrade image quality. Measurement of the degradation can be in return applied to improve and optimize existing compression related systems. In recent years, plenty of metrics have been proposed to assess the quality of JPEG compressed images [6–15]. The most intuitive way is to evaluate the blocking and blurring artifacts spatially.

Block-based compression introduces blocking artifacts at the block boundaries since the blocks are quantized independently during compression. Lee and Park [12] detected and measured the strength of blocking artifacts based on the finding that the pixel value changed abruptly acorss the boundary and the pixel values remained unchanged along the entire boundary. Liu and Heynderickx [10] combined pixel-based distortion of the artifact with its local visibility by means of visual masking, where the local distortion was measured by the strength of gradient at the artifact. To reduce the computation complexity, they also included a grid detector to locate the blocking artifact. Instead of using pixel discontinuity at the block boundaries, Pan *et al.* [9] used the edge orientation of those pixels at the boundaries to measure blocking artifacts. Li *et al.* [14] evaluated blockiness by measuring the regularities of pseudo structures. The ratio of color-missing blocks was also incorporated since heavier blocking artifacts resulted in more color-missing blocks.

Blurring artifacts are also introduced within blocks due to the discard of high frequency DCT coefficients. Some researchers measured both the blocking and blurring effects. In Wang *et al.*'s method [7], the blockiness was estimated as the average differences across block boundaries, and the blurring effect was evaluated by two parts: the average absolute difference between in-block image samples and the zero-crossing rate of the differencing signal. In [8], Perra *et al.* convolved the compressed image with Sobel masks, then blockiness was measured by quantifying both luminance variation of block boundaries and luminance variation of remaining pixels. In [16], Zhang and Bull characterized blurring artifacts and no-

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ticeable distortion to predict the quality of video.

Compressed images can also be evaluated in the transform domain. Bovik and Liu [6] proposed a blockiness measurement in the DCT-domain. The blocking artifact was modeled as a 2-D step function by constructing a new block from two adjacent blocks. The new block constructing and parameters extracting were derived in the DCT-domain. Chen and Bloom [11] first calculated the absolute difference between adjacent pixels along each column or row. Then one-dimensional discrete Fourier transform was used to derive the blockiness measure. Golestaneh and Chandler [13] counted the number of zero-valued DCT coefficients in each block, and then used a quality relevance map to weight the counts. The quality relevance map indicates whether the blocks are natural or generated by JPEG compression. Li *et al.* [15] used Tchebichef moments to measure blocking artifacts based on the finding that Tchebichef kernels are able to capture blockiness.

In this paper, we propose to evaluate JPEG compressed images blindly via pseudo structural similarity (PSS). Traditional full-reference (FR) IQA algorithms can measure image quality accurately because of the information provided by the reference image which has perfect quality. IQA metric can be interpreted as a "distance" measure in the "quality space", then FR algorithm calculates the distance between the reference image and the distorted image. Since the reference image is often not available, we propose to measure the "distance" between the distorted image and the most distorted image (MDI), which is calculated from the distorted image and suffers from the most severe distortion.

As already discussed, pseudo structures are introduced during JPEG compression. Image content structure and pseudo structure are easy to distinguish since pseudo structure exists only at the block boundaries while image content structure can be anywhere. Pseudo structures of the distorted image and MDI become more similar as the degree of compression increases. So we propose to calcultate the similarity between pseudo structures of the distorted image and MDI.

The remainder of this paper is organized as follows. Section 2 describes the proposed PSS model. In Section 3, PSS model is tested and verified with several large and widely used datasets. In Section 4, we present an application. We propose to boost the mainstream NR IQA measures using the PSS model. The boosting effect is also reported in this section. Section 5 concludes this paper.

2. THE PSS MODEL

As described in previous section, the proposed PSS method computes the similarity between the distorted image and MDI. Details are discussed below.

2.1. Most Distorted Image

Traditional FR IQA metrics generally assess the quality of a distorted image by evaluating how well does it agree with the reference image. Using different consistence measurements, we can get diverse FR IQA methods. As illustrated in Fig. 1, if the consistence or agreement are described in a "quality axis", FR IQA metrics measure the "distance" between the distorted and the reference images. If the reference image is not available, FR IQA is no longer practicable. But we can find another image as a "reference" in the "quality axis".

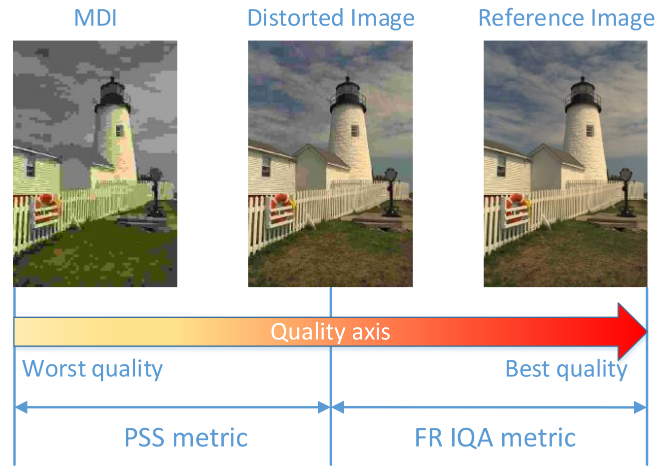


Fig. 1. A compare of the proposed PSS metric and FR IQA metric. FR IQA metric calculates the "distance" between the distorted and reference image, while PSS calculates the "distance" between the distorted and most distorted image.

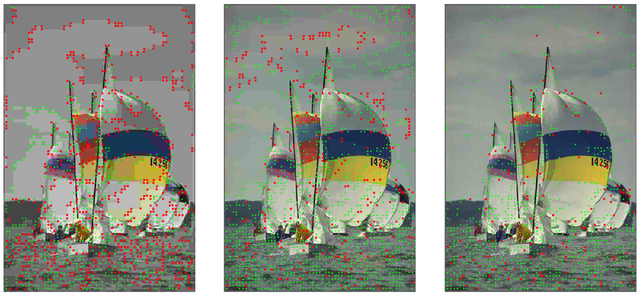
In this paper, we introduce the most distorted image (MDI) as a new "reference". Different from the traditional reference image which has the best quality, MDI locates in an opposite position in the "quality axis". MDI has the worst quality and it is generated from the distorted image. More specifically, we compress the distorted image to the utmost. We use "imwrite" function from MATLAB R2014a as an encoder. The 'Quality' parameter is set to 0, which denotes the most severe distortion. The leftmost image in Fig. 1 shows an example of MDI. As shown in this figure, the proposed PSS metric calculates the "distance" form the distorted image to MDI to represent the quality. Note that all information including the MDI all comes from the distorted image, so the proposed PSS model is still a NR IQA measure.

2.2. PSS Model

Excessive compression introduces pseudo structures, which can be used to assess the quality of the compressed image. We use the framework showed in Fig. 1, and the "distance" described above is calculated as the similarity between pseudo structures of the distorted image and MDI.

2.2.1. *Pseudo corners*

Corner is a frequently-used image feature in various computer vision applications, such as motion detection and video track-



(a) Q=5, PSS=0.11 (b) Q=15, PSS=0.23 (c) Q=25, PSS=0.48

Fig. 2. Pseudo structures. Q denotes the quality parameter of "imwrite" function. The red and green dots denote the pseudo corners. Specially, the red ones indicate that they overlap with pseudo corners of corresponding MDIs. There are more overlapping pseudo corners in more distorted images.

ing. It can be used to represent image structures. Corners are also highly correlated with blocking artifacts. In [14], the authors found that corners were distributed without regularity in natural images. While in JPEG images, corners were more regularly found at the block boundaries because of the blockiness introduced by JPEG compression. In their work, the authors proposed to describe blocking artifacts using the ratio of regular corners, i.e. pseudo corners.

2.2.2. *Pseudo structural similarity*

In this paper, we also use corners to represent image structures. Genuine structures from image content and artificial pseudo structures introduced by blockiness are superimposed in JPEG images. But they can be differentiated according to their regularity. The detected corners are identified as pseudo corners if they are distributed at the corners of 8×8 blocks. Otherwise, they are regarded as ordinary corners. All pseudo corners in an image can efficiently describes its pseudo structures, which is what we are mainly interested in. We define the pseudo structure of image $\mathbf{A} = (a_{ij})_{h\times w}$ as $\mathbf{P} = (p_{ij})_{h\times w}$, where h, w denote the image height and width. The elements are defined by:

$$p_{ij} = \begin{cases} 1 & \text{if } a_{ij} \in C, mod(i,N) < 2, mod(j,N) < 2 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where $a_{ij} \in C$ indicates that a_{ij} is a corner; mod calculates the remainder and $N = 8$. Instead of using the ratio of regular corners considered in [14], we propose to measure blockiness by the distribution of regular corners, i.e. pseudo structures.

Fig. 2 illustrates examples of pseudo structures. Three images with varying compression degrees are used as examples. The red and green dots represent the pseudo corners. We use Shi and Tomasi's minimum eigenvalue method [17] to detect corners in this paper. We use $\mathbf{P}_d = (p_{dij})_{h\times w}$ and $\mathbf{P}_m = (p_{mij})_{h\times w}$ to denote the pseudo structures of the distorted image and the MDI. In Fig. 2, the red and green dots together describe $\mathbf{P}_d$.

We compare $\mathbf{P}_d$ and $\mathbf{P}_m$, and we find that certain similarity exists between them, especially in image with great distortion. We use $\mathbf{P}_o = (p_{oij})_{h\times w}$ to denote the overlap between $\mathbf{P}_d = (p_{dij})_{h\times w}$ and $\mathbf{P}_m = (p_{mij})_{h\times w}$:

$$\mathbf{P}_o = (p_{oij})_{h\times w} = (p_{dij} * p_{mij})_{h\times w} \tag{2}$$

As illustrated in Fig. 2, the red dots describe $\mathbf{P}_o$. It indicates that there are pseudo corners at the positions in both the distorted image and MDI. Note that there are more overlapping pseudo corners (red dots) in more distorted images. It means that $\mathbf{P}_d$ becomes more similar to $\mathbf{P}_m$ as the distortions become heavier.

So we propose to use pseudo structural similarity (PSS) as a blockiness measure. More detailedly, if we define the following two variables:

$$N_o = \sum_{i,j} p_{oij}\,; \quad N_m = \sum_{i,j} p_{mij} \tag{3}$$

where N_o indicates the number of overlapping pseudo corners between $\mathbf{P}_d$ and $\mathbf{P}_m$ and N_m indicates the number of pseudo corners in $\mathbf{P}_m$. Then the pseudo structural similarity (PSS) can be described as:

$$PSS = \frac{N_o}{N_m} \tag{4}$$

PSS indicates the ratio of overlapping pseudo corners in the MDI. Higher PSS value indicates more severe blockiness. As shown in Fig. 2, PSS shows good correlation with perceptual quality. Quantitative verification of the PSS model is given in next section.

3. EXPERIMENT RESULTS

In this section, we compare the PSS model with state-of-the-art competitors. Comparisons will be performed in both natural scene and screen content images. Details are given below.

3.1. Experiment settings

3.1.1. *Databases*

JPEG subset of five large IQA databases are used as testbeds in this paper, including one screen content image IQA database: LIVE [18], CSIQ [19] TID2008 [20], TID2013 [21] and SIQAD [22]. All databases have more than 100 JPEG images. Note that only JPEG compressed images are used in this paper. In LIVE, CSIQ and SIQAD, difference mean opinion score (DMOS) serves as human judgement score. Whereas in TID2008 and TID2013, mean opinion score (MOS) is used.

Table 1. Performance comparison in natural scene and screen content images. We bold the top three performed models.

Database & metric		Bovik[6]	Wang[7]	Perra[8]	Pan[9]	Liu[10]	Chen[11]	Lee[12]	NJQA[13]	Li[14]	PSS
LIVE	SRCC	0.9476	**0.9735**	0.8688	0.9011	0.9404	0.9305	0.9470	0.9562	**0.9610**	**0.9711**
	PLCC	0.9532	**0.9787**	0.8712	0.9024	0.8792	0.9363	**0.9679**	0.9627	0.9658	**0.9784**
	RMSE	9.6290	**6.5382**	15.639	13.723	15.174	11.187	**8.0060**	8.6232	8.2590	**6.5900**
CSIQ	SRCC	0.9454	**0.9551**	0.8517	0.8625	0.9241	0.9228	**0.9479**	0.9249	0.9313	**0.9514**
	PLCC	0.9716	**0.9799**	0.8927	0.8888	0.9518	0.9091	**0.9759**	0.9539	0.9490	**0.9746**
	RMSE	0.0725	**0.0610**	0.1379	0.1402	0.0939	0.1275	**0.0667**	0.0918	0.0965	**0.0685**
TID2008	SRCC	0.8807	**0.9129**	0.7576	0.8075	0.8916	0.8559	**0.9112**	0.8993	0.8699	**0.9207**
	PLCC	0.9232	**0.9518**	0.7956	0.8478	0.8916	0.9060	0.9319	**0.9442**	0.9082	**0.9608**
	RMSE	0.6547	**0.5223**	1.0320	0.9032	**0.5526**	0.7210	0.6179	0.5610	0.7130	**0.4727**
TID2013	SRCC	0.8821	**0.9267**	0.7601	0.8136	0.8619	0.8560	0.8758	**0.8860**	0.8644	**0.9117**
	PLCC	0.9311	**0.9530**	0.8170	0.8641	0.9355	0.9120	0.9213	**0.9477**	0.9156	**0.9647**
	RMSE	5.4918	**4.5650**	8.6841	7.5804	5.3219	6.1766	5.8551	**4.8076**	6.0564	**3.9635**
SIQAD	SRCC	0.4655	**0.7452**	0.2401	0.3987	0.4127	0.1629	**0.7464**	0.6144	0.6261	**0.7625**
	PLCC	0.4587	**0.7412**	0.3108	0.4209	0.5052	0.1300	**0.7467**	0.6208	0.6206	**0.7689**
	RMSE	8.3498	**6.3077**	8.9312	8.5235	8.1095	9.3168	**6.2497**	7.3665	7.3683	**6.0082**

3.1.2. Evaluation criteria

To evaluate the IQA models, we adopt several evaluation criteria. As suggested by the video quality experts group (VQEG) [23], we first map the predicted scores nonlinearly using a four-parameter logistic function, then calculate the following commonly used performance metrics: SRCC, PLCC and RMSE.

3.1.3. Comparing algorithms

In this paper, we compare the proposed PSS model with state-of-the-art NR JPEG IQA measures including: Bovik [6], Wang [7], Perra [8], Pan [9], Liu [10], Chen[11], Lee [12], NJQA [13] and Li [14]. All models are briefly reviewed in Section 1. Many models evaluate the strength of blockiness at the block boundaries, and several models also further consider the blurring effect within blocks.

3.2. Quality prediction in natural scene images

As discussed in Section 3.1.1, four natural scene IQA databases which have more than 100 distorted images are chosen as testbeds. Table 1 lists the experiment results. From this table, we can see that the proposed PSS model is comparable to the best performed metrics, especially in TID2008 and TID2013 database. On the whole, PSS, Wang [7] and Lee[12] show the best performances.

3.3. Quality prediction in screen content images

Screen content IQA has became a hot research topic because of its widely use in various communication systems [22]. SCI is peculiar because it is a mix of natural scenes, texts, graphics, etc. Yang *et al.* [22] constructed a screen image quality assessment database (SIQAD) for the facility of screen content IQA research. We also test and compare all metrics in the JPEG subset of SIQAD. As listed in Table 1, PSS shows the best performance in terms of all metrics. It means that PSS is more consistent across different image content types.

4. APPLICATION

Although PSS is designed to measure the quality of JPEG images, we find that it can be used to boost the performance of mainstream general-purpose NR quality metrics. As discussed in Section 2, PSS calculates the "distance" between the distorted image and the image with highest degree of compression. It can be generalized to measure general distortions. We calculate the "distance" from image with general distortions to the most compressed image.

We choose 4 mainstream general-purpose NR quality measures: DIIVINE [24], BLIINDS-II [25], BRISQUE [26] and NFERM [27]. They are all feature integration based measures. 88, 24, 36 and 23 features are used respectively. PSS is considered in a multi-scale manner to adapt the variations of different viewing conditions. In detail, we set parameter N in Eq. (1) as $1, 8, 16, 32$ and thus 4 PSS features of different scales are derived. Extracted PSS features are integrated with the original features of each measure. Similar to the original models, we use SVM [28] to integrate the PSS and original features. We adopt 80% train - 20% test splits. We repeat the splits for 1000 times and report the mean results. In all repeats, images of the same content are split to the same set.

The split-train-test procedure is processed in the whole databases which include all kinds of distortions. Table 2 lists the average results. Most measures perform better after incorporating PSS features. We also perform one-way ANOVA

Table 2. Performance boosting effect of PSS features. Orig / Orig+: without / with considering PSS features. Sig: significance test results; +1 / -1 denote "Orig+" is significantly ($p < 0.05$) better / worse than "Orig"; 0 indicates no significant changes.

Database & metric		DIIVINE [24]			BLIINDS-II [25]			BRISQUE [26]			NFERM [27]		
		Orig	Orig+	Sig	Orig	Orig+	Sig	Orig	Orig+	Sig	Orig	Orig+	Sig
LIVE	SRCC	0.8579	0.9012	+1	0.9166	0.9199	+1	0.9375	0.9383	0	0.9329	0.9320	0
	PLCC	0.8693	0.9096	+1	0.9237	0.9264	+1	0.9423	0.9437	0	0.9373	0.9376	0
	RMSE	13.136	11.199	+1	10.305	10.132	+1	9.0349	8.9118	+1	9.3863	9.3601	0
CSIQ	SRCC	0.6607	0.6888	+1	0.7352	0.7371	0	0.6647	0.6633	0	0.7841	0.7739	-1
	PLCC	0.7175	0.7426	+1	0.7874	0.7888	0	0.7139	0.7128	0	0.8222	0.8139	-1
	RMSE	0.1755	0.1682	+1	0.1590	0.1589	0	0.1779	0.1789	0	0.1456	0.1483	-1
TID2008	SRCC	0.4411	0.4353	0	0.6484	0.6778	+1	0.5517	0.6094	+1	0.6402	0.6661	+1
	PLCC	0.5054	0.4996	0	0.6558	0.6905	+1	0.6099	0.6687	+1	0.7013	0.7213	+1
	RMSE	1.1435	1.1497	0	0.9658	0.9199	+1	1.0442	0.9807	+1	0.9398	0.9097	+1
TID2013	SRCC	0.4107	0.4162	0	0.5424	0.5663	+1	0.5329	0.5703	+1	0.5855	0.6027	+1
	PLCC	0.4923	0.4862	0	0.6362	0.6563	+1	0.5982	0.6410	+1	0.6803	0.6885	+1
	RMSE	1.0652	1.0702	0	0.9402	0.9178	+1	0.9743	0.9334	+1	0.8985	0.8850	+1
SIQAD	SRCC	0.6421	0.7428	+1	0.6725	0.7014	+1	0.7427	0.7473	0	0.7612	0.7886	+1
	PLCC	0.6938	0.7667	+1	0.7356	0.7398	0	0.7877	0.7799	0	0.7932	0.8118	+1
	RMSE	8.9699	8.9432	+1	9.5760	9.4562	+1	8.6584	8.7327	0	8.5687	8.2234	+1

(analysis on variance) [29] to test if the influence of incorporating PSS features is significant ($p < 0.05$). Performance of one random split is taken as one sample. Significance test results are also listed in Table 2. In terms of all databases, quality measures and evaluation criteria, 46 out of 60 metrics become better and 36 of them become significantly better. It means that PSS features can boost most quality measures, and the improvements of more than half the measures are significant. So the PSS model can be used as a supplement to general-purpose NR IQA measures.

5. CONCLUSION

In this paper, we present a blind compressed image quality measure via pseudo structural similarity (PSS). We first introduce a most distorted image (MDI) with the highest compression degree and then compare the similarity between pseudo structures of the distorted image and MDI. Experiments in the JPEG subsets of several large IQA databases show that PSS is good at measuring the quality of compressed images, being comparable to state-of-the-art competitors. Further experiments show that the proposed PSS model performs well with screen content image, which is more challenging but widely used in the communication systems. What is more, we also proposed to consider PSS in a multi-scale manner and integrate them with mainstream SVM-based general-purpose NR quality metrics to measure general distortions. Experiments also verify that PSS model can boost mainstream general-purpose NR IQA measures, which means that PSS can be used as good supplements to existing quality measures.

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