A No-Reference Blocking Artifacts Metric Using Selective Gradient and Plainness Measures*

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Abstract. This paper presents a novel no-reference blocking artifacts metric using selective gradient and plainness (BAM_SGP) measures for DCT-coded images. A boundary selection criterion is introduced to distinguish the blocking artifacts boundaries from the true-edge boundaries, which ensures that the most potential artifacts boundaries are involved in the measurement. Next, the artifacts are evaluated by the gradient and plainness measures indicating different aspects of blocking artifacts characteristics. Then these two measures are fused into a metric of blocking artifacts. Compared with some existing metrics, experiments on the LIVE database and our own test set show that the proposed metric can keep better consistent with Mean Opinion Score (MOS).

Keywords: Blocking artifacts metric, gradient measures, plainness measures.

1 Introduction

Blocking artifacts is one of the prominent visible distortions in block-based discrete cosine transform (DCT) image/video compression schemes. The metric of blocking artifacts is used in a wide range of applications. In general, the metrics are classified into two categories: reference ones and no-reference ones. The reference metrics [1] require some information of original image. By contrast, the no-reference metrics [2-4] do not rely on the original image, and are especially useful for quality assessment, optimization and post-processing when the original images are not available.

Although the no-reference metrics have achieved good performance of artifacts measurement, they ignored the fact that the intensity discontinuity at block boundaries is caused by not only the blocking artifacts but also possibly the original image signal. In order to obtain an accurate measurement, it needs to exclude true-edge boundaries

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in the artifacts metric. Inspired by this, we propose a novel no-reference Blocking Artifacts Metric using Selective Gradient and Plainness (BAM_SGP) measures, in which a blocking artifacts boundary selection followed by a combination of gradient measures and plainness measures is utilized. In the experiments on the LIVE database [5] and our own test set, the proposed metric outperforms some existing objective metrics and can keep well consistent with Mean Opinion Score (MOS) [6].

In the rest of the paper, Section 2 gives details of the proposed BAM_SGP metric. Section 3 presents experimental results and finally Section 4 concludes the paper.

2 The Proposed Metric

As shown in Fig.1, the proposed BAM_SGP is composed of four steps: (1) Boundary Selection; (2) Gradient Measures; (3) Plainness Measures; (4) Metric Fusion. In order to avoid overlapping, only two boundaries of block A are utilized to measure the artifacts at horizontal and vertical directions, respectively, as the bold lines in Fig.2.

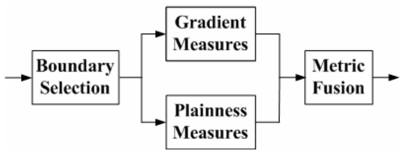

Fig. 1. Flow chart of the proposed metric

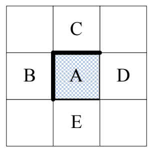

Fig. 2. An 8x8 block and its neighbors

2.1 Boundary Selection

Considering various contents in different images, an adaptive threshold is defined as,

$$T = g_{\min} + r_1 \cdot (g_{\max} - g_{\min}) . \tag{1}$$

Where $g_{min}=MIN(g_{i,j})$and $g_{max}=MAX(g_{i,j})$, $g_{i,j}$ is the intensity of the image gradient extracted by Sobel operator. Then the block boundaries can be divided into true-edge boundaries and artifacts boundaries. According to the properties of human vision system (HVS), only artifacts boundaries should be utilized for the measurement.

2.2 Gradient Measures

The horizontal gradient measure G_h across boundary between A and B is defined as:

$$G_h = E_h \cdot [1 - S(W_h, 0)] / W_h . \tag{2}$$

with

$$S(x, y) = \begin{cases} 1, & if \quad x = y \\ 0, & otherwise \end{cases} \tag{3}$$

$$E_h = r_2 \cdot \sum_{\{1 \le i \le 8\} \cap \{g_{i,j} < T\}} D(i, j) \tag{4}$$

$$W_h = r_3 \cdot \sum_{\{1\le i\le 8\}\cap\{g_{i,j}<T\}} \sum_{k=-3}^{3} D(i, j+k) + (1-r_3) \cdot \sum_{\{1\le i\le 8\}\cap\{g_{i,j}<T\}} D(i, j) \tag{5}$$

$$D(i, j) = \left|3P_{i,(j-1)} - 3P_{i,j} - P_{i,(j-2)} + P_{i,(j+1)}\right| / 2 \tag{6}$$

Where *S(x,y)* is an equivalence function, E_h and W_h are defined as the pixel gradient at the block boundary and within the adjacent blocks, respectively. Here *T* is defined in Eq.1 and $g_{i,j}<T$ ensures that pixel $P_{i,j}$ belongs to the potential artifacts boundaries. *D(i,j)* is the intensity discontinuity between adjacent pixels $P_{i,(j-1)}$ and $P_{i,j}$, which is based on the observation that blocking artifacts visibility is due to not only the block boundary gradient, but also the different pixel structures within adjacent blocks.

The vertical gradient measure G_v between block *A* and *C* is obtained in the same way, then the gradient measure G_{BLK} can be summarized as the mean of G_h and G_v.

2.3 Plainness Measures

At low bit rates, gradient discontinuity becomes less severe and many blocks merge together into some large uniform regions, therefore the plainness will be the dominant one for the artifacts measurement. The horizontal plainness measure P_h for block boundary between Block *A* and *B* is calculated as:

$$P_h = \frac{r_4}{56} \cdot \sum_{\{1\le i\le 8\}\cap\{g_{i,j}<T\}} \left(\sum_{k=-3}^{3} S(P_{i,(j+k-1)}, P_{i,(j+k)}) \right). \tag{7}$$

Where *S(x,y)* is also the equivalence function mentioned above. The vertical plainness measure P_v and the overall plainness measure P_{BLK} are obtained in the same way.

2.4 Metric Fusion

The overall blocking artifacts measurement BA_{BLK} of Block *A* can be obtained by combining the gradient measure value G_{BLK} and plainness measure value P_{BLK}. Based on extensive experiments, the fusion can be performed as

$$BA_{BLK} = MAX(G_{BLK}, P_{BLK}) \cdot \tag{8}$$

3 Experimental Results

The performance of the proposed metric is evaluated in LIVE database [5] and our own data set, and compared with three state-of-the-art metrics described in [2][3][4] (referred as BAM_SGP, GBIM, S and Q_Image). In order to keep the range of the proposed metric identical to that of MOS [6], the parameters in Eq.1, 4, 5 and 7 are set to r_1=0.135, r_2=5, r_3=2/3 *and* r_4=5, respectively. Three indicators defined in VQEG [7] are used: *Prediction Accuracy, Monotonicity* and *Consistency*, which are quantitatively measured by *Pearson* correlation coefficient, *Spearman* rank order correlation coefficient and *Outlier Ratio* of outlier-points to total points respectively.

Table 1. Indicator values of four metrics for LIVE database

Metric/ Indicator	BAM_SGP	GBIM[2]	S[3]	Q_Image[4]
Pearson Correlation	-0.941	-0.792	0.912	-0.901
Spearman Correlation	-0.925	-0.882	0.905	-0.885
Outlier Ratio	6.8%	30.4%	6.0%	12.1%

Table 1 shows the experimental results in LIVE database that consists of 233 JPEG images with subjective scores. It can be seen that the proposed BAM_SGP metric achieves much better *Pearson* and *Spearman* correlation coefficients, which means that BAM_SGP can achieve higher *prediction accuracy* and *monotonicity* between objective model and subjective assessment. Besides, the proposed metric and metric S can obtain nearly the same *prediction consistency*, better than metric GBIM and Q_Image in term of the *outlier ratio*.

Our own test set consists of about 12 classical images ("*Lena*", "*Barbara*", "*Baboon*" and so on) compressed at different ratios. Twenty observers were invited to perform an MOS test and the average scores were counted as subjective score. The proposed metric achieves the *Pearson* coefficient of **0.967** in the evaluation.

4 Conclusions

In this paper, a locally no-reference blocking artifacts metric using selective gradient and plainness measures has been presented. As a key feature, a boundary detection method is fused into the metric to distinguish the blocking artifacts boundaries from the true-edge boundaries, which ensures the most potential artifacts boundaries can be selected for the measurement. In our experiments the proposed metric outperforms the existing objective metrics and can keep well consistent with MOS.

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