A Blind Reference-Free Blockiness Measure

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Abstract. Some image and video processing algorithms can have the unintended consequence of introducing blocking artifacts into the processed imagery. Measuring blockiness plays an important role in many applications. This paper presents a reference-free blockiness measurement method. For a given image, the absolute difference between horizontally adjacent pixels is computed, normalized, and averaged along each column. A one-dimensional discrete Fourier transform is thereafter employed and a vertical blockiness measure is derived. A horizontal blockiness measure is computed similarly. Finally, a blockiness measure for the given image is formulated by pooling those two directional blockiness measures. The proposed method can accurately assess the blockiness without any a priori knowledge of the block origin and block size; therefore it is a blind measure. Experimental results show the effectiveness of the proposed method. The robustness of the proposed method is also justified.

Keywords: Perceptual quality assessment, blockiness, reference-free, gradient image, discrete Fourier transform.

1 Introduction

Blocking artifacts present in images by the periodical appearance of block structure. Generally, blocking artifacts are introduced by compression techniques based on the block discrete cosine transform (BDCT), which has been widely used in traditional image and video coding standards. In those standards, the BDCT is often followed by a quantization process in which each block is processed independently without accounting for the correlation between neighboring blocks. This can cause the block boundaries, also called block-edges, to appear as discontinuities in the reconstructed image or video frame.

An uncompressed image from [1], its JPEG compressed version, and its MPEG-2 compressed version, are given in Fig. 1. To highlight the blocking artifacts in the compressed images, a partially magnified image (within the white rectangle) of each of those three images is also shown. This figure shows how compression can introduce blocking artifacts.

Blocking artifacts have strong influence on the overall perceptual quality. To eliminate blocking artifacts, a number of techniques have been developed.

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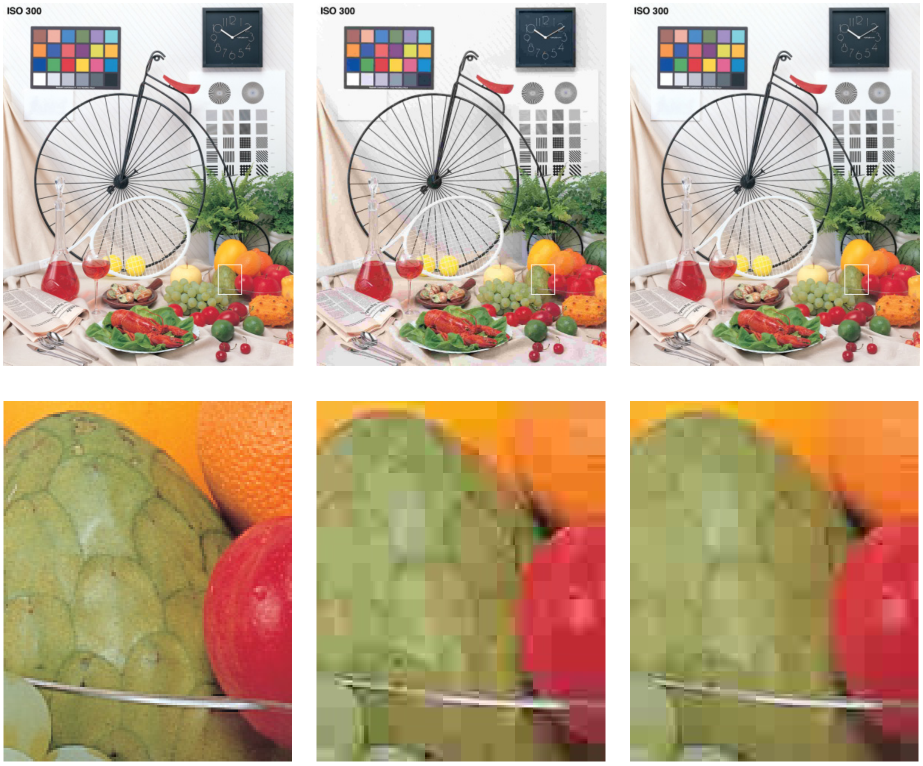

(a) (b) (c)

Fig. 1. An image and its compressed images (top), and partially magnified images (bottom): (a). original image, (b). JPEG compressed, and (c). MPEG-2 compressed

As an example, the video coding standard H.264/AVC employs an in-loop deblock filtering technique to improve image quality and coding efficiency. Measuring blockiness plays a significant role in assessing the perceptual quality of the reconstructed images or video sequences. Blockiness measure can be used to evaluate the perceptual quality degradation, to monitor the encoding process, or to assess the efficiency of image enhancement algorithms.

In this paper, we address the task of measuring blocking artifacts. Due to lack of access to a reference in many of the emerging video applications, reference-free (or no-reference, *NR*) blockiness measures are attracting increasing attention. After a brief review of the state of the art, we present a novel reference-free blockiness measurement method and its implementation details. Experimental results on still images and video sequences are then given to demonstrate the effectiveness of the proposed method. Thereafter, we justify the robustness of the proposed scheme on the issue of unknown block origin and unknown block size. Finally, we briefly discuss the future work.

2 Measuring Blocking Artifacts in Digital Images

Researchers have been working actively on reference-free blockiness measurement for years. Approaches in the literature can be classified into three categories. In the first category, the block information, which includes the knowledge of the *block origin* (sometimes called *block offset*) and the knowledge of the *block size*, is assumed to be known before the blockiness is measured. The knowledge of the block size is required while that of the block origin is not required in the second category. In the third category, neither the knowledge of the block origin nor that of the block size is needed, but approaches are designed to work together with block-edge detection techniques.

Most reference-free blockiness measurement approaches are in the first category. Wu and Yuen propose in [2] a blockiness measure without reference, termed the generalized block-edge impairment metric. The weighted L_2 norm of the differences between pixels at block boundaries is obtained. Weights are derived by taking into account luminance masking and texture masking effects. The weighted L_2 norm is further normalized by the average inter-pixel difference between pixels not at block boundaries to give the blockiness measure. Vlachos [3] uses the cross-correlation of subsample images to measure and detect blocking artifacts. Eight sub-images are chosen such that every sub-image contains one specific pixel from each of the 8×8 blocks. The summation of the phase correlations between some sets of sub-images, which measures the intra-block similarity, is divided by the summation of the phase correlations between some other sets of sub-images, which measures the inter-block similarity, to yield a measure of blockiness. Thereafter, researchers have developed quite many reference-free blockiness measurement methods in this category. In [4], the blockiness is translated into two-dimensional (2-D) discrete Fourier transform (DFT) harmonics, the amplitude and phase of which can provide vital information for quantifying the blockiness. Methods in [5] and [6] are specifically implemented in JPEG coefficient domain for JPEG images. The approach in [7] takes into account both the blockiness and the flatness, the approach in [8] uses Sobel operator, and the method in [9] integrates the blockiness measure and the flatness measure while using Sobel operator and utilizing masking effects of the human visual system (HVS). A novel blocking artifact cluster is introduced in [10]. The percentage of blocky blocks is calculated as a blockiness measure in [11].

Several techniques in the literature require not knowledge of the block origin but that of the block size. Wang at al. [12] model the blocky image as a non-blocky image interfered with a pure blocky signal. A 1-D DFT is applied to the difference between image pixels to estimate the average power spectra. Peaks in the spectra due to block structures are identified by their locations. The power spectra of the underlying non-blocky images are approximated by median-filtering the aforesaid average power spectra. The overall blockiness measure is then computed as the difference between these power spectra at the peak locations. Bailey et al. [13] propose a measure of blocking artifacts that can estimate the block offset. This method compares a measured edge activity with an estimated blockiness-free activity. Instead of using a traditional pixel discontinuity measure along block boundaries, Pan et al. [14] use edge directional information to measure blockiness. The edge direction histogram is constructed from the averaged gradient vector of each pixel. The edge direction histogram values at 0°, 90°, and 180°, together with the block size, are used to quantify the blockiness.

Some reference-free blockiness measurement methods have adopted block-edge detection techniques. In [15], Muijs and Kirenko outline a reference-free blockiness measurement method that allows the block-edge locations and their visibility to be determined. The normalized pixel gradient is calculated and added horizontally or vertically. The presence of blocking artifacts results in pronounced peaks in the summation. The block size and block offset can be extracted by analyzing those peak locations. The blockiness measure is the ratio between the average value at the block-edge locations and the average value at the non-edge locations. Liu and Heynderickx [16] extend the measurement method in [15] by integrating the block-edge grid detecting method from [17] and some masking effects of the HVS. Meesters and Martens [18] present a blockiness estimation model that does not necessarily require any a priori information of the block size. The first stage is to transform the gray-scale image into a threshold step-edge visibility image. The second stage is to estimate the edge parameters based on vertical and horizontal 1-D Hermite transforms. The third stage is to collapse the estimated amplitudes into a single scalar blockiness measure.

In a word, all those aforesaid methods either assume knowledge of the block origin and/or the block size or use some techniques to determine the block origin and/or the block size before the blockiness is measured.

In this paper, a novel reference-free blockiness measurement method is proposed. This method is blind in that it can accurately assess the blockiness without any a priori knowledge of the block information.

As mentioned above, the DFT has been used in [12] and [4] in the process of blockiness measurement. The DFT is ideal to catch the periodicity of a periodic discrete signal. Thus, the DFT is used to estimate the power spectra in [12]. The DFT is also ideal for measuring the strength of the blockiness. Therefore in [4] a 2-D DFT is applied to the small blocks segmented from the gradient image and a blockiness measure is devised by examining both the amplitude information and the phase information of the harmonics.

The DFT is the Fourier representation of a finite-duration discrete sequence ([19], pp 559-561). Given a sequence $a[n]$ of finite length N, the N-point 1-D DFT, $A[k]$, of $a[n]$, is defined as

$$A[k] = \sum_{i=0}^{N-1} a[n] W_N^{kn}, \tag{1}$$

where $W_N = e^{-j(2\pi/N)}$, a complex constant related to the sequence length N.

In the proposed method, the DFT is applied differently than it is in the prior art. This method also incorporates masking effects of the HVS by normalizing a pixel difference by its neighbors, an idea derived from [15].

3 Proposed Method

Given an image or a video frame, we can process each component separately. As shown in Fig. 2, for each component, which is denoted as image pixel array, after calculating the absolute differences between horizontally adjacent pixels, normalizing the differences, and summating the differences to a 1-D signal, the DFT is applied to the 1-D signal and a vertical blockiness measure is then derived. A horizontal blockiness measure is computed in a similar fashion. Those two directional measures are finally pooled to formulate a blockiness measure for the whole component.

Denote the given pixel array as $I(x, y)$, where $0 \leq x \leq S_x - 1$, $0 \leq y \leq S_y - 1$, S_x is the width and S_y the height of the given image pixel array. We describe the process of computing the vertical blockiness BM_V here.

The absolute difference between horizontally adjacent pixels is firstly calculated. This operation results in a gradient image, $D_c(x, y)$, which is given by

$$D_c(x, y) = |I(x, y) - I(x + 1, y)|, \tag{2}$$

where $0 \leq x \leq S_x - 2$ and $0 \leq y \leq S_y - 1$.

Since the blockiness measurement approaches try to mimic the HVS, it is reasonable to normalize the gradient image, just as that described in [15]. In this method, each element in the gradient image is normalized as follows:

$$D_{cn}(x, y) = \frac{D_c(x, y)}{\sqrt{\frac{1}{2N} \sum_{i \in [-N, +N], i \neq 0} D_c^2(x + i, y)}}, \tag{3}$$

where totally $2N$ neighboring elements are involved in the normalization.

An average operation along each column is then applied, resulting in a 1-D array of length $S_x - 1$, called *horizontal profile* in this paper and denoted as P_H:

$$P_H(x) = \frac{1}{S_y} \sum_{y=0}^{S_y - 1} D_{cn}(x, y). \tag{4}$$

Take 1-D DFT to P_H and just consider the magnitude FP_H of the DFT coefficients. This is given by

$$FP_H(X) = |\sum_{x=0}^{S_x - 2} P_H(x) e^{-\frac{j2\pi xX}{S_x - 1}}|, \tag{5}$$

where $0 \leq X \leq S_x - 2$.

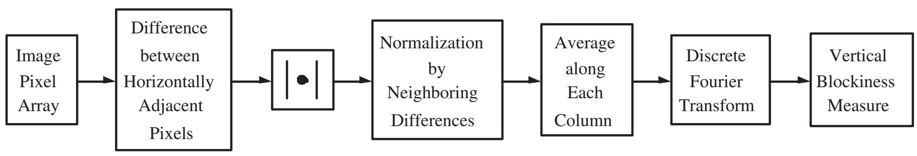

Fig. 2. Computing vertical blockiness measure

3.1 Computing Vertical Blockiness Measure with Given Block Size

The knowledge of the block origin and the block size is critical for most of the prior blockiness measurement algorithms. However, in a blind environment, the precise block information may not be readily available.

Since we use the DFT in the proposed scheme, we do not need information of the block origin. To accurately compute a blockiness measure, nevertheless, a block size is necessary. To simplify our description, we assume that the horizontal block size of the image is known as Kx. As a result, once the horizontal block size is given, we can compute a vertical blockiness measure for the given image.

Fig. 3 shows the horizontal profile P_H of the image in Fig. 1(b) and its DFT coefficients (magnitude) FP_H. Due to the nature of DFT, $FP_H(X)$ has peaks at $X = i\frac{S_x-1}{K_x} - 1$, for $i = 1, 2, ..., K_x - 1$. The heights of $FP_H(X)$ at those peak locations are closely related to the vertical blockiness of the image. These heights can thus be utilized for a vertical blockiness measure

$$BM_V = \frac{1}{FP_H(0)}\sqrt{\frac{1}{K_x - 1}\sum_{i=1}^{K_x-1} FP_H^2(i\frac{S_x - 1}{K_x} - 1)}, \qquad (6)$$

where $FP_H(0)$ is the DFT coefficient (magnitude) at $X = 0$, i.e., the direct current (DC) value.

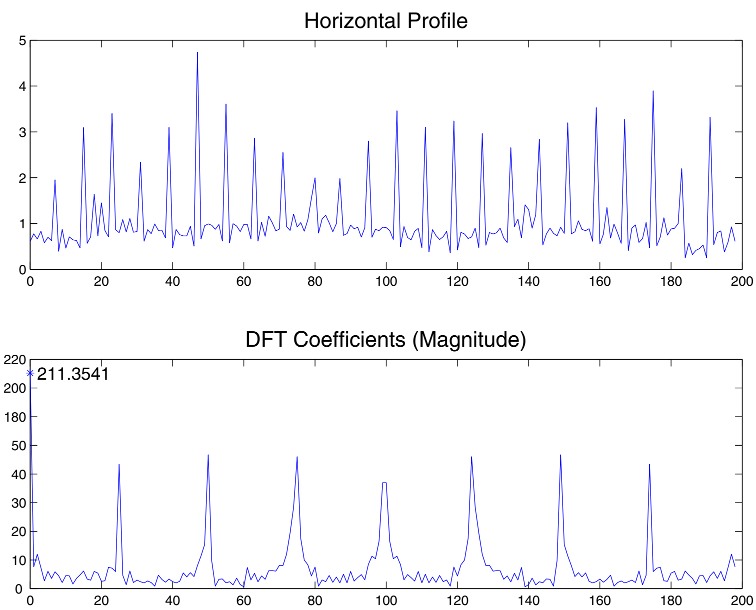

Fig. 3. The horizontal profile (top) and its DFT coefficients (bottom)

3.2 Measuring Vertical Blockiness with Unknown Block Size

When the block size is not given, we can still give an accurate blockiness measure. In this subsection, we propose a scheme to address this issue.

As mentioned in Subsection 3.1, due to the nature of DFT, $FP_H(X)$ has peaks at $X = i\frac{S_x-1}{K_x} - 1$, for $i = 1, 2, ..., K_x - 1$, where K_x is the actual but unknown block size. If we calculate the measure using Equation (6) with the block size K running from 2 to some large number, while K equals to the actual block size K_x, the blockiness measure should be the maxima.

This leads to a searching scheme described as follows.

Assume the maximum possible block size is BS. We run Equation (6) with $K = 2$, $K = 3$, up to $K = BS$. Then we have a vertical block measure BM_{V2} for $K = 2$, a vertical block measure BM_{V3} for $K = 3$, up to a vertical block measure BM_{VBS} for $K = BS$. We select the maximum value among all these BM_V's as the vertical blockiness measure for this given pixel array.

3.3 Pooling

Once we have the two directional blockiness measures BM_V and BM_H, we can apply a pooling operation to generate a blockiness measure BM for the whole pixel array. The pooling is expressed as

$$BM = \sqrt{rBM_V^2 + (1-r)BM_H^2}, \tag{7}$$

where r is the weight of the vertical blockiness measure to the image blockiness measure, which can be experimentally determined to maximize the correlation with subjective quality assessment scores.

4 Evaluation

The proposed blockiness measurement method can be applied to any image or video format. We present in this section the experimental results on JPEG images and MPEG-2 video sequences.

We use the Pearson's correlation coefficient (PCC, [20]), the Spearman's rank order correlation coefficient (SROCC, [21]), and the root mean square error (RMSE) between the objective score and the subjective score to quantify the accuracy of the proposed method. The PCC is computed both before and after performing a non-linear regression. For the former, the PCC is computed between the non-fitted objective score and the subjective score, denoted as PCC-nf. For the latter, we use a logistic function and follow the procedure described in [22] (pp 32) to perform the non-linear regression. Thereafter, the PCC is computed between the fitted objective score and the subjective score, denoted as PCC-f. The RMSE is calculated between the fitted objective score and the subjective score.

4.1 Dataset

The JPEG image dataset in the LIVE image quality assessment database release 2 ([23], [24], and [25]) and the MPEG-2 video dataset in the LIVE video quality database ([26] and [27]) are used. The JPEG image dataset includes 29 color reference images (typically 768×512 in size) and 204 JPEG distorted images. The MPEG-2 video dataset includes ten reference video sequences of 768×432 in size and four MPEG-2 compressed video sequences for each reference sequence. The subjective difference mean opinion score (DMOS) for each distorted image or video sequence is included in the corresponding dataset.

Please notice, only the luminance component of each image or video sequence is used for blockiness measurement.

4.2 Experimental Results on JPEG Images

Testing results of the proposed method on the JPEG image dataset, with both a known block size and an unknown block size, are given in Table 1. In order to select r, a set of values were considered and 10 trials were performed. For each trial, half of the images in the dataset were randomly chosen and each value in the set was used to calculate a blockiness measure for the unknown block size using the searching scheme presented in Subsection 3.2. The one that yielded the best PCC-f and SROCC was recorded. After all 10 trials, the 10 recorded values of r were averaged, yielding a final $r = 0.3472459$.

For comparison, experimental results on the same image dataset using Wu and Yuen's [2], Vlachos' [3], Bovik and Liu's [5], Park et al.'s [6], Pan et al.'s [7], Perra et al.'s [8], Zhang et al.'s [9], Yang et al.'s [10], Hillestad et al.'s [11], Wang et al.'s [12], Bailey et al.'s [13], Pan et al.'s [14], Muijs and Kirenko's [15],

Table 1. Accuracy testing results on the JPEG image dataset

Approach	PCC-nf	PCC-f	SROCC	RMSE
Wu and Yuen's [2]	0.6162	0.9562	0.9522	7.1031
Vlachos' [3]	0.7046	0.9216	0.9151	9.4141
Bovik and Liu's [5]	0.6868	0.9353	0.9549	8.5866
Park et al.'s [6]	0.8214	0.9218	0.8661	9.4057
Pan et al.'s [7]	0.8341	0.9363	0.9243	8.5189
Perra et al.'s [8]	0.8703	0.8703	0.8834	11.9468
Zhang et al.'s [9]	0.7221	0.9284	0.9208	9.0125
Yang et al.'s [10]	0.7016	0.9044	0.8934	10.3526
Hillestad et al.'s [11]	0.8758	0.9247	0.9316	9.2369
Wang et al.'s [12]	0.7259	0.9311	0.9357	8.8473
Bailey et al.'s [13]	0.7509	0.9377	0.9269	8.4313
Pan et al.'s [14]	0.7987	0.9033	0.9015	10.4055
Muijs et al.'s [15]	0.8586	0.9613	0.9514	6.6877
Liu and Heynderickx's [16]	0.6774	0.9494	0.9334	7.6182
Proposed method (block size known)	0.8896	0.9628	0.9468	6.5553
Proposed method (block size unknown)	0.8910	0.9627	0.9442	6.5615

and Liu and Heynderickx's [16] are also given in Table 1. All these approaches give quite good performance and the proposed method is among the approaches giving the best accuracy. Besides, the proposed method gives comparable results for both the given block size and the unknown block size.

4.3 Experimental Results on MPEG-2 Video Sequences

The proposed approach can be applied to a video sequence on a frame-by-frame basis. The blockiness measure for a sequence is defined as the mean value of the blockiness measures over all the video frames in the sequence.

Testing results on the MPEG-2 video dataset are given in Table 2. The parameter r for the proposed method was set as 0.0101585. Experimental results on the same video dataset using Wu and Yuen's [2], Vlachos' [3], Pan et al.'s [7], Perra et al.'s [8], Zhang et al.'s [9], Yang et al.'s [10], Hillestad et al.'s [11], Bailey et al.'s [13], Pan et al.'s [14], Muijs and Kirenko's [15], and Liu and Heynderickx's [16] are also reported.

Table 2. Accuracy testing results on the MPEG-2 video dataset

Approach	PCC-nf	PCC-f	SROCC	RMSE
Wu and Yuen's [2]	0.6344	0.9402	0.7365	7.1869
Vlachos' [3]	0.5378	0.9430	0.7930	7.0183
Pan et al.'s [7]	0.6231	0.9163	0.6684	8.4497
Perra et al.'s [8]	0.6916	0.9166	0.6531	8.4357
Zhang et al.'s [9]	0.6400	0.9176	0.7115	8.3872
Yang et al.'s [10]	0.4088	0.5115	0.3892	18.1297
Hillestad et al.'s [11]	0.6323	0.9182	0.7965	8.3585
Bailey et al.'s [13]	0.5852	0.9357	0.7020	7.4439
Pan et al.'s [14]	0.5008	0.9214	0.6718	8.1979
Muijs et al.'s [15]	0.7875	0.9265	0.7301	7.9399
Liu and Heynderickx's [16]	0.6501	0.6883	0.6939	15.3043
Proposed method (block size known)	0.8564	0.9460	0.8521	6.8373
Proposed method (block size unknown)	0.8549	0.9483	0.8534	6.6938

We can observe that most of these methods give very satisfactory performance while the proposed outperforms the state of the arts. Again, the proposed method gives comparable results for both a given block size and an unknown block size. Together with testing results on the JPEG image dataset, testing results on the MPEG-2 video dataset have demonstrated the effectiveness of the searching scheme for the unknown block size.

Please note that we set $N = 1$ (see Equation (3)) for the proposed method and Muijs et al.'s [15] in all experiments reported in this paper.

5 Robustness

In this section, we further justify the robustness of the proposed method for the case of unknown block origin, thanks to the circular shift property of DFT.

The circular shift property of DFT is described in [19], pp 564-567. If

$$a[n] \longleftrightarrow A[k], \tag{8}$$

then

$$a[((n-m))_N] \longleftrightarrow e^{-\frac{j2\pi k}{N}m} A[k], \tag{9}$$

where $a[((n-m))_N]$ denotes circular shifting $a[n]$ by $|m|$ points to the right for a non-negative m or to the left for a negative m. Obviously, $e^{-\frac{j2\pi km}{N}}$ has no influence on the magnitude of DFT coefficients of the shifted signal.

In a blocky image, the blocking artifacts are dominant in the horizontal (or vertical) profile by the periodic presence of peaks, as seen in Fig. 3. Since we only use the magnitude of the DFT coefficients, shifting of those peaks in the profiles does not affect the blockiness measure.

We perform an experiment to test the proposed scheme with pixel shifting on the JPEG image dataset [23]. We first move the leftmost j column(s) to the rightmost and the top k row(s) to the bottom from the given image. Then we measure the blockiness of the shifted image using the scheme in Subsection 3.2 and calculate the accuracy of the measure. The testing results (PCC-f and SROCC) are given in Table 3 for $j = 0, 1, 2, 3, 4$ and $k = 0, 1, 2, 3, 4$ (except that for $j = 0$ and $k = 0$). In this table, the mean and the standard deviation of the PCC-f's are 0.9585 and 0.0007188, respectively, and the mean and the standard deviation of the SROCC's are 0.9389 and 0.0005474, respectively. Compared to the PCC-f 0.9627 and SROCC 0.9442 without pixel shifting, these results have witnessed the robustness of the proposed scheme.

Table 3. Accuracy testing results with pixel shifting

Vertical Shifting		Horizontal Shifting				
		0	1	2	3	4
0	PCC-f	—	0.9594	0.9593	0.9588	0.9593
	SROCC	—	0.9395	0.9396	0.9396	0.9396
1	PCC-f	0.9595	0.9595	0.9594	0.9594	0.9595
	SROCC	0.9392	0.9393	0.9398	0.9396	0.9398
2	PCC-f	0.9584	0.9584	0.9585	0.9576	0.9577
	SROCC	0.9384	0.9385	0.9387	0.9382	0.9385
3	PCC-f	0.9577	0.9582	0.9579	0.9579	0.9580
	SROCC	0.9385	0.9384	0.9388	0.9384	0.9386
4	PCC-f	0.9578	0.9583	0.9579	0.9579	0.9580
	SROCC	0.9385	0.9386	0.9387	0.9383	0.9385

6 Conclusion and Future Work

In this paper, a novel reference-free blockiness measurement method is presented. The main contribution of the proposed technique is to use the discrete Fourier transform in such a way that the blockiness can be measured without any a priori knowledge of the block origin and block size. This does not only save computational cost, but also does avoid inaccurate blockiness measure caused by imprecise block information. Experimental studies on publicly available datasets have shown that the proposed method outperforms the state of the art.

While calculating the mean square of DFT coefficients at the peak locations (see Equation (6)), we equally weigh those coefficients at different DFT frequencies. Further investigation into the response of the HVS to different DFT frequencies is under way.

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