Quality Assessment for Block-based Compressed Images and Videos with regard to Blockiness Artifacts*

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ABSTRACT

In this paper a novel quality metric for block-based compressed images and videos is proposed. The metric is designed to measure the "strength" of the blocking artifacts. The method is fast and robust. Experimental results show that there is a clear relationship between the strength of the detected blockiness and the compression ratio. The proposed algorithm is also able to distinguish between natural edges present in the original image, and blocking artifacts originated from compression.

1 INTRODUCTION

Lossy image/video compression algorithms introduce several types of distortions into an image, such as, blockiness, blurring, mosquito effects, ringing, etc. [1] For low to moderate compression rates, there are very few visible artifacts and for most purposes the output image is perceptually indistinguishable from the original image. On the other hand, artifacts caused by high compression ratios are visible and may become highly annoying.

Video communication is a very demanding application in terms of bit rate. State of the art video compression techniques enable the transmitted data rate to be reduced to few kilobits/second for low-resolution video conferencing making it affordable for a wireless system. These highly compressed video streams are consequently associated with the presence of highly annoying artifacts.

Among the artifacts found in compressed images, blockiness is one of the most annoying ones. Block distortion or tiling is defined in ANSI T1.801.02-1996 as "Distortion of the image characterized by the appearance of an underlying block encoding structure." Blockiness is a result of the DCT block-based compression technique used by some of the traditional compression algorithms, like for example JPEG or MPEG. These compression methods do not account for the correlation between neighbouring blocks, which causes the boundaries of each block to appear as discontinuities (edges) in the decompressed images. Figure 2 illustrates this type of artifact. Clearly, blockiness is not the only type of artifact present in this image.

Two frequently used measures of the quality of images/videos are the mean absolute error (MSE) and the mean square error (PSNR) [2]. These measures are simple to calculate, since they are based solely on the differences between the degraded image/video and the reference. Nevertheless, the outputs of these measures do not always correlate well with human judgments of quality [3]. Besides, in most communication applications the reference image or video is not available and such measures cannot be computed. In order to provide users of communication systems with a quality of measure for compressed images or video, a fast and efficient non-reference metric is definitely needed.

In this paper a new quality metric based on measure of the strength of the blocking artifacts [4] is proposed. It takes advantage of the fact that edges in blocking artifacts appear at regular intervals. Experimental results show that the proposed metric is fast and robust.

Figure 1: "Barbara".

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Figure 2: Detail of "Barbara" (Fig. 1) compressed 20:1 using JPEG, showing the severe and obvious blocking artifacts, particularly in regions of smoothly varying intensity.

In fact, it is able to differentiate between blockiness artifacts and the natural edges of the image, which is generally a big challenge for such measurements. The image "Barbara" shown in Figure 1 has been selected due to a significant number of regularly spaced edges within the image, which makes it a reliable measurement of blockiness more difficult.

The rest of the paper is organized as follows. In Section 2 the blockiness detection system is described. In Section 3 the algorithm is applied to several images at different compression ratios to evaluate and demonstrate the effectiveness of the new metric.

2 BLOCKINESS DETECTION

In DCT-based compression systems, such as JPEG and MPEG, the blocking artifacts appear exclusively on the edges of the DCT blocks. Therefore, they present a regular pattern, whereas the natural edges of an image are not expected to appear with any regularity. The proposed method has been designed based on this characteristic of the blocking artifacts.

The first step of the proposed method is to evaluate the square of the luminance differences of adjacent pixels in the horizontal and vertical directions. These values are then summed along the rows and columns of the image. This way, the edges at blocking boundaries are reinforced, whereas the natural edges of the image, which are likely to be more randomly located, are weakened. Successively, the row and column profiles are computed.

Let $I[x, y]$ be the pixel value at position (x, y) within an image. The row and column difference profiles are defined as follows:

Row Difference Profile:

$$RP[y] = \sum_{x} \left(I[x,y] - I[x+1,y] \right)^2 \qquad (1)$$

Column Difference Profile:

$$CP[x] = \sum_{y} \left(I[x,y] - I[x,y+1] \right)^2 \qquad (2)$$

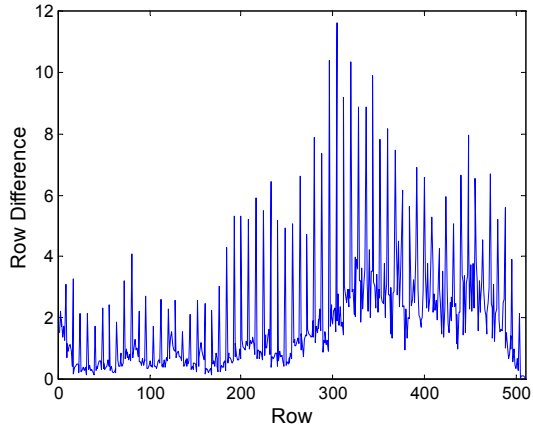


Figure 3: Row difference profile of the image in Figure 2.

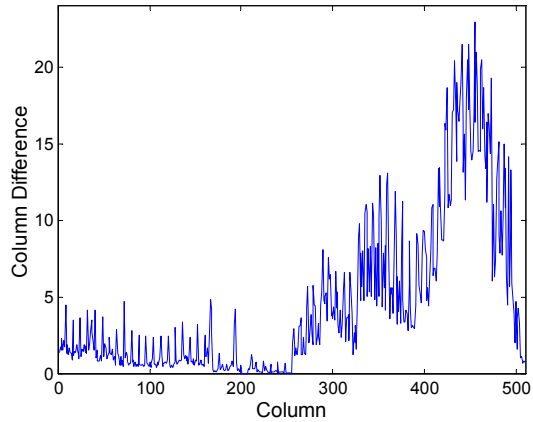


Figure 4: Column difference profile of the image in Figure 2.

The row and column profiles, corresponding to the image in Figure 2 are plotted in Figure 3 and 4 respectively. The regular pattern corresponding to the block edges appears superimposed over the pattern associated with the original edges within the image. As can be seen in the Figure 4, the column difference profile values for natural edges can often be stronger than for blocking artefact edges even when blockiness is evident.

The distribution of column difference values is shown in Figure 5. As depicted, the distribution is not normal, with the natural edges within the image having a significant effect on the overall distribution. When strong natural edges are present within a block, the mean value can be significantly skewed because of such outliers. In such circumstances, the difference between the mean within the block and the mean between the blocks is not statistically significant.

To measure the blockiness, it is important to detect the exact initial position of the blocks of size $b_S \times b_S$ used during compression. The blockiness detector algorithm has to take into account the fact that the block boundaries may not necessarily be on top and left edges of the image. For example, if the image is cropped after compression, the first block boundary may be anywhere within the first b_S pixels of the image. Filtering and other transformations can also cause shifts in the image. To detect the position of the first block, both the row

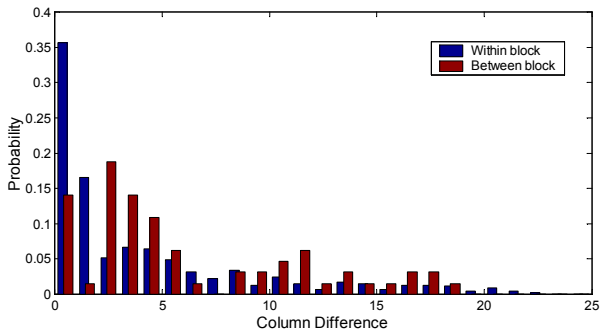


Figure 5: Probability density of the column difference values.

and column differences are divided into b_S partitions. The first partition consists of the differences from rows (or columns) 1, 9, 17, …, $(1+k \cdot b_S)$ corresponding to a block offset of 1 pixel. The next partition consists of the differences from rows (columns) 2, 10, 18, …, $(2+k \cdot b_S)$ and so on. For DCT-based compression (JPEG, MPEG) $b_S = 8$.

The row and column partitions, RP_n and CP_n respectively, are given by:

$$RP_n[y] = RP[b_s \cdot y + n] \tag{3}$$

$$CP_n[x] = CP[b_s \cdot x + n] \tag{4}$$

where n is the partition number, and x and y are the vertical and horizontal spatial positions, respectively. One of the partitions corresponds to the block boundaries, and the remaining $(b_S - 1)$ partitions correspond to columns or rows within the block.

The *edge activity* is a measure of the edge strength associated with each partition. There are b_S row partitions and b_S column partitions corresponding to the vertical and horizontal offsets. The partition with the highest edge activity is assumed to be the one corresponding to the block edges. The median value of each partition is used to estimate the level of edge activity associated with that partition, as given by the following:

Row Edge Activity:

$$RE_n = \underset{y}{\text{median}}(RP_n[y]) \tag{5}$$

Column Edge Activity:

$$CE_n = \underset{x}{\text{median}}(CP_n[x]) \tag{6}$$

The median is used because it gives less weight to outlier values than the mean. It is assumed that the maximum value of the row and column edge activities correspond to the blocking edges. Therefore the value of n that gives the maximum edge activity corresponds to the offset of the blocking edges within the image.

The last step of the algorithm is to estimate the strength of blockiness. This is estimated by comparing the edge activity measure from the blocking artifacts edges with the edge activity within the blocks. It is this relative comparison that enables the metric to be evaluated without having access to an uncompressed image. While the mean or median of the edge activity measures within the block could be used to estimate the activity within the block, this will always provide a measure of blockiness even when it is not perceptually noticeable. This is due to the fact that the maximum edge activity value has been assumed to be associated with the block edges, so all of the other values are less than this.

One approach that gives good results is to rank the edge activity measures in a numerical order and fit a line to the ranked values (excluding the maximum of course). Extrapolating this line gives an estimate of what the maximum value would be if there were no block artifacts within the image. The extrapolation takes into account the natural variation in the edge activity measures, enabling the blockiness to be estimated independently of the original edge activity present within the image. This approach is shown in Figure 6 for the data from this image.

Looking at this mathematically, if row edge activities are sorted with the minimum denoted by $RE[1]$ and the maximum denoted by $RE[b_S]$, then the best-fit line may be represented as

$$RE[i] = m \cdot i + c\,. \tag{7}$$

The parameters m and c may be estimated using least squares by minimizing the error term

$$E = \sum_{i=1}^{b_S} (m \cdot i + c - RE[i])^2 \tag{8}$$

Differentiating with respect to m and c, and solving the corresponding pair of simultaneous equations give the parameters of the best fit line through the within block activity measures. This is then extrapolated to give the estimate of the maximum activity measure, which is what would be expected at the block edges if there were no artifacts present in the image:

$$\overline{RE}[b_s] = m \cdot b_s + c = \sum_{i=1}^{b_s - 1} \left(i - \left\lfloor \frac{b_s - 1}{2} \right\rfloor \right) \cdot RE[i] \tag{9}$$

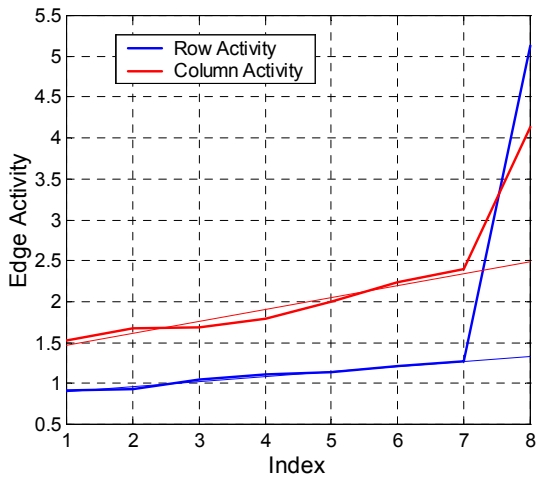


Figure 6: Ranked edge activity. The values other than the maximum are extrapolated to estimate what the maximum would be if there was no blockiness.

Similarly the estimate of the column maximum is given by:

$$\overline{CE}[b_s] = m \cdot b_s + c = \sum_{i=1}^{b_s-1} \left(i - \left\lfloor \frac{b_s - 1}{2} \right\rfloor \right) \cdot CE[i] \quad (10)$$

Finally, the proposed measure of blockiness compares the measured edge activity with the estimated blockiness-free activity. This is given by:

$$B = \frac{RE[b_s] \cdot CE[b_s]}{\overline{RE}[b_s] \cdot \overline{CE}[b_s]} \quad (11)$$

Applying this algorithm to a range of images has shown that there is a clear relationship between the detected blockiness and the compression ratio, as shown in Figure 7 for a typical image. In fact blockiness can be measured even before it starts becoming noticeable to a human viewer. This interesting property can be used as a way of measuring the visibility threshold of blocking artifacts, i.e., the minimum strength of the distortion which humans are able to detect. Figure 7 also shows that for low compression ratios, negligible blockiness is detected, even in an image that has a number of strong regularly spaced edges. This indicates that the proposed algorithm is able to distinguish between natural edges present in the original image, and blocking artifacts originating from compression.

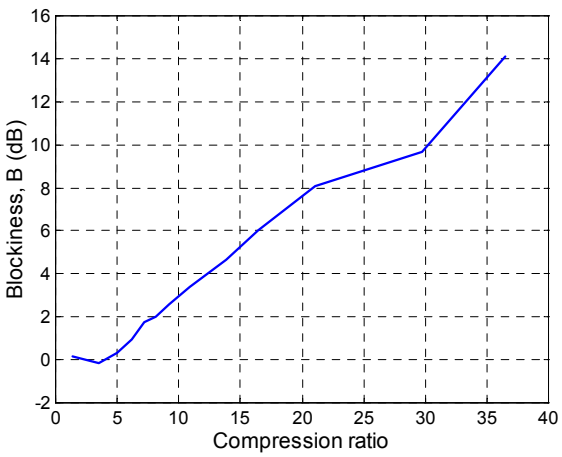


Figure 7: Blockiness measure as a function of compression ratio, using JPEG compression on the "Barbara" image of Figure 1.

3 SIMULATION RESULTS

The proposed algorithm has been tested on several images. All images have been compressed using a JPEG algorithm. Then, the blockiness strength has been measured for each of the compressed images at a range of compression ratios. We also measured the PSNR for these images. Figure 8 show the results obtained for the images "Barbara". Figure 9 shows six levels of JPEG compression for this image. Figure 10 shows the blockiness measure and PSNR for the image "Football".

The "football" image shows one limitation of the blockiness measure in assessing the quality of extremely highly compressed images. At the high compression

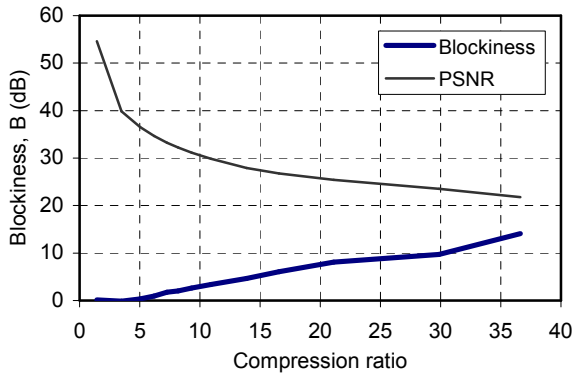


Figure 8: Blockiness and PSNR as a function of JPEG compression ratio on the "Barbara" image of Figure 1.

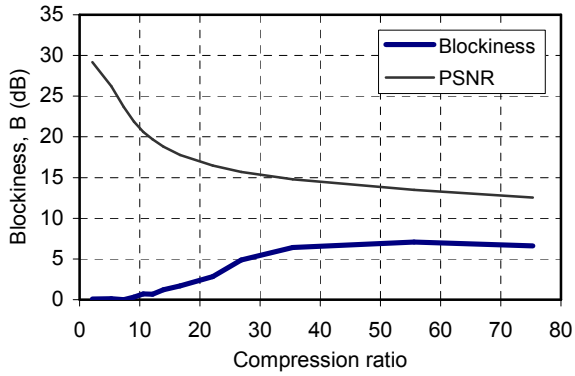


Figure 10: Blockiness and PSNR as a function of JPEG compression ratio on the "football" image.

ratios the blockiness measure stops increasing and actually decreases slightly, even though the image quality is visibly deteriorating. Looking at the images (see figure 11), the reason for this is readily apparent. At very high compression ratios, the detail within many of the blocks is completely lost, and each block is represented solely by the block's DC value. In this image, the DC value is constant over large regions of the image, reducing the between block edge activity. As a consequence, the blockiness factor decreases slightly at high compression ratios for this image.

This effect does not occur for all images, but appears to be related to the level of detail within the image. If there is significant fine detail within the image, this fine detail tends to be completely lost at high compression ratios. The blockiness measure continues to increase for images with less fine detail, or with large areas with a relatively slowly varying background.

4 CONCLUSIONS

In this work a new measure of blockiness is proposed. The proposed method, based on measures of the strength of blocking artifacts [4] is fast and robust. The algorithm effectively creates its own reference from the strength of the edges within a block. These provide an estimate of the image edge strength, against which the strength of the block edges is compared.

Experimental results show that there is a clear relationship between the blockiness measure and the compression ratio. This proposed algorithm has been shown to be able to distinguish between natural edges

(a) Uncompressed

(b) 37:1 compression

(c) 75:1 compression

Figure 11: The "football" image at high compression ratios, showing the increased uniformity between blocks at 75:1 compression ratio.

present in the original image, and blocking artifacts originating from compression.

REFERENCES

[1] M. Yuen, and H.R.Wu, "A survey of hybrid MC/DPCM/DCT video coding distortions," *Signal Processing,* vol. 70 (1998), pp. 247-278.

[2] C.J. Van den Branden Lambrecht and M. Kunt, "Characterization of human visual sensitivity for video imaging applications," *Signal Processing*, vol. 67, pp. 255-69, 1998.

[3] C.W. Brown and B.J. Shepherd, *Graphics File Formats: Reference and Guide*, Manning Publications Co., Greenwich, CT (1995)

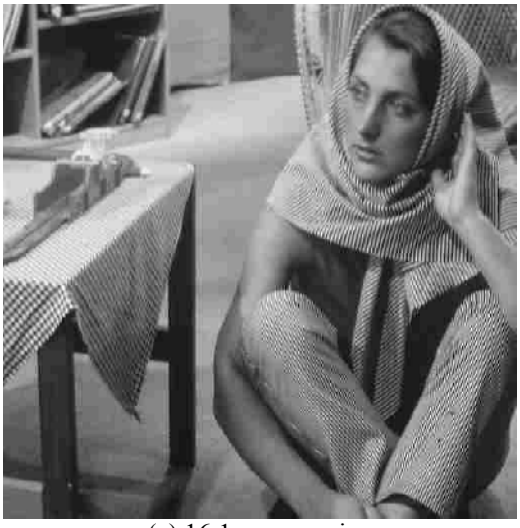
[4] K.T. Tan and M. Ghanbari, "A multi-metric objective picture-quality measurement model for MPEG video," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 10, pp. 1208-13, 2000.

(a) 5:1 compression

(d) 21:1 compression

(b) 11:1 compression

(e) 30:1 compression



(c) 16:1 compression

(f) 37:1 compression

Figure 9: The “Barbara” image compressed using JPEG compression at a range of compression ratios.