BÉZIER BLENDING MODEL FOR ENHANCEMENT OF JPEG (DCT AND LS) COMPRESSED IMAGES

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Abstract

A novel non-iterative post-processing enhancement technique is proposed for images degraded by either the JPEG-DCT or the JPEG-LS lossy coding algorithm. A degraded image is classified into active and smooth regions by modeling the quantization noise generated by these lossy coding algorithms. A distance transform is applied to the resulting classification, and is used to determine the size and order of a Bézier surface patch. These Bézier blending surfaces, built with Bernstein polynomials, provide an interesting representation for the image, which mitigates the quantization noise while preserving strong edges and textures. Results illustrate the significant visual improvement achieved with a computational complexity of $O(n)$.

1 Introduction

In this paper, we propose a novel post-processing technique to mitigate image artifacts generated by lossy image coding algorithms. Restoring an image degraded by a lossy coding algorithm is difficult due to the non-linearity of the coding process and the non-stationarity of image data [15]. Moreover, it turns out that the problem is ill-posed due to the many-to-one mapping quantization [1]. This ambiguity makes the problem of enhancement or restoration of compressed images ill-posed [1]. In general, the loss of information prevents us from completely restoring the original image. Nevertheless, many regularization techniques achieve a partial restoration by enforcing smoothness and making assumptions about the data distribution [6].

Another approach is to introduce pseudo-random noise to the original image before quantization. Robert randomization and dithering techniques [7] are based on this pre-processing approach. Unfortunately, these techniques increase the image entropy by increasing randomness in the original image [7]. Although these techniques yield some perceptual improvement, they usually increase the bit-rate as well.

These issues have challenged many researchers, resulting in a variety of approaches for the problem. Many of these approaches are applied to the block-based JPEG-DCT standard algorithm [8] for still image compression. Interest in enhancing JPEG-DCT images is due to their widespread popularity.

Some proposed techniques are applied in the sample domain, like those based on adaptive filtering, morphological operations, edge detection [12] and dithering. Other techniques are applied in the frequency domain by changing the DCT coefficients [4]. Some iterative techniques exploit interesting models such as Markov Random Fields (MRF) [17], Projection onto Convex Sets (POCS) [18, 5] and constrained linear optimization assuming some probability distribution for the image data [13]. Iterative solutions are usually computationally demanding and are not appealing for real-time applications such as image browsing.

In this paper, we propose a non-iterative image enhancement technique applied in the sample domain. The technique is based on surface modeling using Bernstein polynomials [3]. This technique can be applied to both the block based JPEG-DCT algorithm and the prediction based JPEG-LS (LOCO) still-image coding algorithm [14]. The perceptual quality is significantly improved while the required time and memory resources are very low when compared to iterative techniques. The algorithm has an $O(n)$ time complexity.

2 Estimating Active Regions

Our image enhancement approach is anisotropic [12]: it mitigates quantization noise while avoiding smoothing strong edges and textures. The first step is to classify the image into smooth regions and active regions (edges, noise and textures). The decoded image has quantization noise that complicates the edge detection. Since our goal is to mitigate quantization noise, we do not need to detect edges, but to differentiate edges and textures from the introduced quantization noise. We assume that the image is corrupted by random additive quantization noise with amplitudes in the range $[-\frac{Q}{2}, +\frac{Q}{2}]$, where Q is the quantization step-size. No statistical distribution is assumed for this noise. Actually, this noise is deterministic in the sense that if we know the original image and the coding algorithm, we can exactly reproduce the noise component.

We propose to estimate this noise by observing pixel variations in the horizontal (x) and vertical (y) directions. The only knowledge assumed is the quantization step Q and the received degraded image $\tilde{I}$.

Assume the following quantization process is applied to an image I, resulting in a degraded image $\tilde{I}$:

$$\tilde{I}(x,y) = \lfloor \frac{I(x,y) + \frac{Q}{2}}{Q} \rfloor \cdot Q \equiv I(x,y) + n(x,y) \quad (1)$$

The noise $n(x,y)$ complicates the task of differentiating among textures, edges and smooth regions. Consider the amplitude variation between two neighboring pixels due to a quantization noise of $\frac{Q}{2}$ as illustrated in Fig. 1. We observe that variations in the degraded image with amplitude of up to Q imply variations in the original image within a range of $(0, 2Q)$, as illustrated in Fig. 1 (a,b). Variations in the degraded image with amplitude of up to $2Q$ represent variations in the original image within a range of $(Q, 3Q)$, as illustrated in Fig. 1 (c,d). It indicates variations in the original image of at least Q. By classifying regions in the degraded image with variations less or equal to Q as smooth, we achieve an upper bound for the estimation error of $2Q$. In order to consider other noise sources with small amplitude not included in the general model expressed by (1), regions with variations less than $\frac{3}{2}Q$ will be classified as non-active and will be smoothed.

Based on the above analysis, in the following we propose an activity estimator. A region is classified as smooth with some quantization noise if the operator $dif(x,y)$ is *smaller* than $\frac{3}{2}Q$:

$$dif(x,y) = max(V_{dif}, H_{dif}) \quad (2)$$

where V_{dif} is the pixel transition in the vertical direction:

$$V_{dif} = |\tilde{I}(x,y) - \tilde{I}(x,y-1)| \quad (3)$$

and H_{dif} is the pixel transition in the horizontal direction:

$$H_{dif} = |\tilde{I}(x,y) - \tilde{I}(x-1,y)| \quad (4)$$

$\tilde{I}(x,y)$ represents the amplitude of the degraded image at position given by coordinates (x,y). The operator $dif(x,y)$ indicates the region activity in the neighborhood of (x,y). It is used to differentiate between smooth regions and regions with edges and textures, taking into account the quantization noise.

3 Modeling the Quantization Noise Generated by the JPEG Algorithms

Our proposed technique does not rely on a *priori* knowledge of the probability distribution for the image or the quantization noise. Instead, we use a local deterministic estimator to differentiate among smooth regions, edges and textures. This estimation is based on the quantization step used in the JPEG algorithms. In this way, we exploit the characteristics of the compression technique but avoid making assumptions about data distribution.

For the JPEG-LS using the LOCO (Low Complexity) algorithm, a prediction P is made based on a non-linear function of previous pixels in a scanning order [14]. This algorithm is very efficient for high bit rates (near lossless quality). The prediction error E, computed as the difference between the pixel amplitude X and the non-linear prediction P, is uniformly quantized using a fixed quantization step Q. The amount of banding artifacts in the degraded image depends on the amplitude of this quantization step.

In the JPEG-DCT [8] system, the coefficients resulting from the DCT (Discrete Cosine Transform) are quantized using a given quantization table. Each coefficient has its own quantization step. The first coefficient represents the average, or DC level, of the 8x8 block of pixels. When the DC coefficient is coarsely quantized, block artifacts are generated. Quantization of the other coefficients (AC) generates ringing artifacts and also degrades the block boundaries.

The resulting quantized DC coefficient is obtained by:

$$DC_{quantized} = \lfloor \frac{DC + \frac{Q}{2}}{Q} \rfloor \cdot Q \quad (5)$$

where Q is the quantization step used for the DC coefficient. We are considering enhancement only for the blockiness artifact. High-frequency ringing artifacts are not addressed.

Both JPEG algorithms generate artifacts in smooth regions of images. These artifacts can be understood as quantization noise with an amplitude of half the quantization step used, $\frac{Q}{2}$, added to the original image. These new transitions created in smooth regions are especially noticeable when the quantization is coarse. Our approach is to mitigate these undesirable transitions without blurring strong edges and textures.

The classification model proposed in the Section 2 is used to estimate noise generated by either JPEG-DCT or JPEG-LS. The quantization step information Q is obtained from the encoded bitstream and no side information is required. This activity estimation technique may also be applied to other algorithms based on either quantization of pixel predictions or quantization of average values of blocks of pixels.

4 Smoothing Quantization Noise Using Bernstein Polynomials

In this section, we define our smoothing operator for noise mitigation. Many techniques in the literature use low pass filters with fixed length to accomplish this task. Our approach is to use surface modeling based on Bézier blending patches. These surfaces are well known in graphics applications. We apply blending surface representation as a novel approach to image smoothing.

The Bézier patches provide the most popular parametric representation for curves and surfaces used in graphics applications [3]. These polynomials have two important properties: convex hull and affine invariance properties. These properties are very important for graphics applications [3] and will be exploited by our image enhancement technique. In the following, we describe the Bézier blending surfaces of degree n applied to image representation.

Let a rectangular region R in the image be represented by $M \times N$ pixels, $M, N > n$. Select $(n+1)^2$ pixel amplitudes $P_{s,t}$ uniformly distributed in this region, for $s \in \{0, \cdots, n\}$ and $t \in \{0, \cdots, n\}$. The s and t indexes are related to the coordinates of the image (x, y) according to the equations:

$$x = x_0 + \frac{M-1}{n} \cdot s \tag{6}$$

$$y = y_0 + \frac{N-1}{n} \cdot t \tag{7}$$

The x_0 and y_0 represent the image coordinates at bottom-left corner of the region R. The parameterized surface representation R' for the region R using a Bézier surface of degree n is given by:

$$R_n^{'}(u,v) = \sum_{s=0}^{n} \sum_{t=0}^{n} P_{s,t} B_n(s,u) B_n(t,v) \tag{8}$$

for u, v in $[0.0, 1.0]$. The u and v variables parameterize the coordinates in the rectangle R. For instance, the parameterized coordinates $(u = 0.0, v = 0.0)$ indicates the pixel located at bottom-left position. The parameterized coordinates $(u = 0.0, v = 0.5)$ indicate the pixel at left, half way to the top of the rectangle. This relationship is illustrated in Fig. 2. To generate the blending surface representation we need to vary both parameterized coordinates (u, v) from 0.0 to 1.0 in Eq. 8.

The $(n+1)$ Bernstein polynomials of degree n used in Eq. 8 are given by:

$$B_n(k, w) = C(k, n) w^k (1-w)^{n-k} \tag{9}$$

for $k \in \{0, \cdots, n\}$. The parameter w is a real value in the range $[0.0, 1.0]$, and $C(k, n)$ is the binomial coefficient:

$$C(k, n) = \frac{n!}{k!(n-k)!} \tag{10}$$

Our approach is to use Bézier patches for representing smooth regions found in an image. The Bézier blending representation has some interesting characteristics very appealing for image enhancement applications, see [9] for details: i) The coefficients are not computed, they are obtained directly from pixel amplitudes at known locations; ii) no clipping is generated when modeling the surface due to the convex hull property; iii) blockiness is reduced since some points at borders are shared among surface regions.

5 Enhancement Technique Using Variable Order Blending Surfaces and Distance Transform

This section describes a new technique using variable order parametric surfaces and the distance transform proposed by [2]. A summary of this novel enhancement approach was originally presented in [11]. This technique uses the quantization noise estimator discussed previously. The new proposed approach differs from [10] in some aspects. The degree of the surfaces is now variable and the blending is implemented on a pixel basis in order to avoid "patchy" artifacts.

The degree of the Bézier surface for each pixel is determined by using the distance transform proposed by Rosenfeld and Pfaltz [2]. Using the proposed operator (Eq. 2), a binary image (two levels) is obtained as follows: a pixel is set to 0 if it is active and set to 1 otherwise (low local activity). One example of the resulting binary image is illustrated in Fig. 3 for the image "Shuttle" in Fig. 6 encoded by the JPEG-LS algorithm. The original image "Shuttle" is illustrated in Fig. 4. The Rosenfeld-Pfaltz distance transform is then applied to this binary image. The resulting transformed image is illustrated in Fig. 5. The intensity represents the city-block distance [16] $D_{i,j}$ of each pixel to the nearest image boundary or active pixel. Using this transform, we obtain for each pixel $P_{i,j}$ the maximum allowable size $M \times M$ for a square region R centered at (i, j) that fits inside the low-activity region (no active pixel inside). The size is given by $M = 2 \times D_{i,j} + 1$. Computation of the distance transform requires only two passes over the image. The required processing has a very low complexity of time and space.

We can choose the surface degree for each pixel $P_{i,j}$ in a region with low activity based on this computed distance. By choosing a degree $n = \lfloor \sqrt{D_{i,j}} \rfloor$ we achieve a good trade-off between quality and complexity. Once the degree n is determined for the pixel $P_{i,j}$, the blending operation is applied as follows: from the region R of size $M \times M$, select $(n+1)^2$ pixels $P_{s,t}$ uniformly distributed with $s \in \{0, \cdots, n\}$ and $t \in \{0, \cdots, n\}$. The new pixel value $P'_{i,j}$, at the center of the square region R, is computed by:

$$P'_{i,j} = \sum_{s=0}^{n} \sum_{t=0}^{n} P_{s,t} \cdot B_n(s, 0.5) \cdot B_n(t, 0.5) \tag{11}$$

The parametric coordinates are set to $(0.5, 0.5)$ in order to compute the surface amplitude at the center of the square patch. This procedure is repeated for all pixels. Pixels located in regions classified as smooth will have distance $D_{i,j} > 0$. Pixels in active regions will have distance $D_{i,j} = 0$ and smoothing will not be applied to these regions.

6 Results

In the following, we illustrate and discuss the image enhancement applied to images (8 bpp) degraded by lossy compression algorithms (JPEG-LS (LOCO) and JPEG-DCT).

In Fig. 7 we observe an impressive reduction of banding artifacts generated by JPEG-LS in the "Shuttle" image.

The method provides a considerable reduction of banding artifacts while avoiding blurring of edges. Despite the simplicity of our proposed classifier, we achieve excellent results. We notice in these experiments that better results are achieved for computer-generated images and images with well-defined edges, large smooth regions, and little noise.

We also present results for images compressed by JPEG-DCT. Fig. 8 and 9 illustrate the enhancement applied for the "Shuttle" image.

More examples are presented in [9]. In these examples, the blockiness artifacts are reduced and the perceived quality is considerably improved. A little blockiness in regions with noise, ringing and textures could not be properly classified by our simple approach. As a consequence, some blockiness remains in the enhanced image. We also observe that most ringing artifacts remain, especially those near strong edges. This method does not address this artifact. We also noticed little blurring in low contrast regions. Nevertheless, we noticed that the overall perceived quality is greatly improved, because the blockiness tends to be more annoying to the human visual system than ringing artifacts.

In average, the enhancement takes about 5 seconds per image (8-bits, 512 x 512 pixels) in a PC AMD-300 MHz. The algorithm is implemented in ANSI C and we achieve a significant speed performance by using look-up tables. We used one look-up table of 128 entries per blending surface degree (from 3 to 9).

7 Conclusions

By proposing a novel modeling of the quantization noise and exploiting a distance transform, we provide a very simple yet effective image classification. We use Bernstein polynomials to represent smooth regions in images as Bézier blending surfaces. This novel application of blending surfaces provides a very attractive approach to mitigate quantization noise. The proposed non-iterative technique achieves significant perceptual improvement for degraded images, as illustrated in the examples. It requires a very low complexity of $O(n)$. The proposed technique is appealing for on-line browsing of images compressed with JPEG-DCT and JPEG-LS algorithms. This new approach is especially efficient for computer-generated images and other images with large smooth areas, well-defined edges and little noise. The author would like to acknowledge the useful suggestions of Theodore Goodman and Brian Mealy (UCSC).

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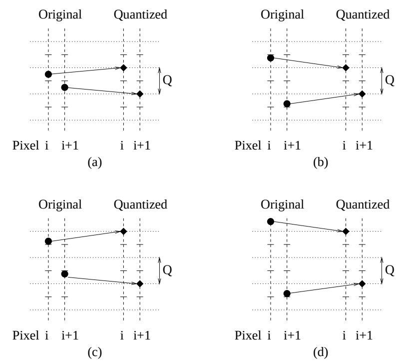

Figure 1. Four cases of resulting quantization levels for two neighboring pixels.

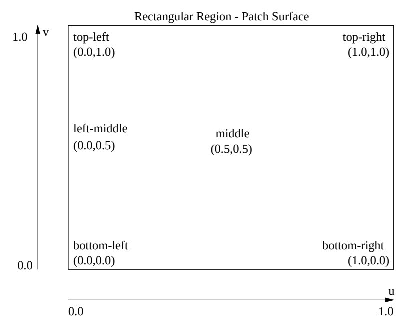

Figure 2. Examples of (u, v) parameterization for a rectangular region.

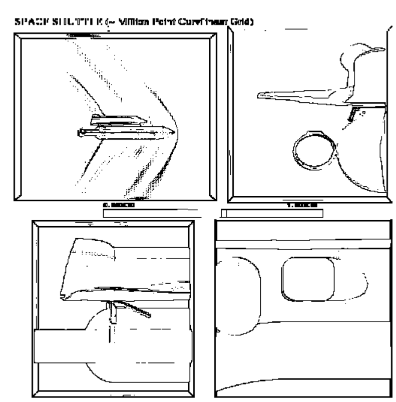

Figure 3. Edges and textures detection on the degraded image 6.

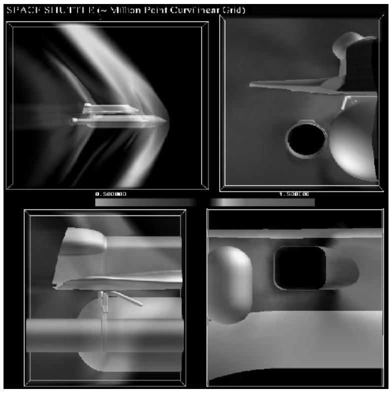

Figure 4. Original image “Shuttle”.

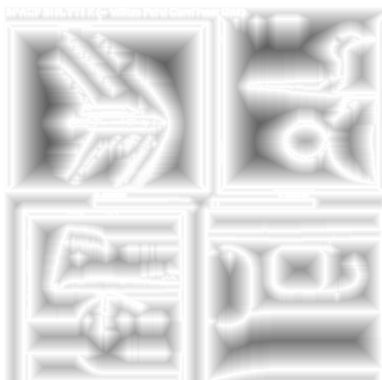

Figure 5. Distance transform applied to the estimation image 3.

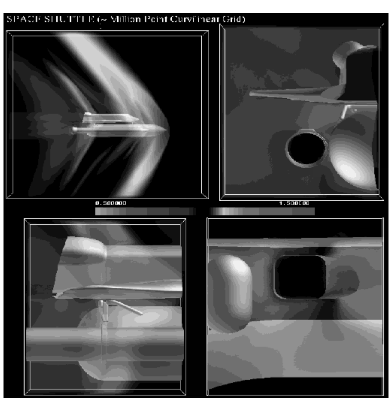

Figure 6. “Shuttle” compressed by JPEG-LS LOCO using $Q = 16$, bit rate = 0.292 bpp.

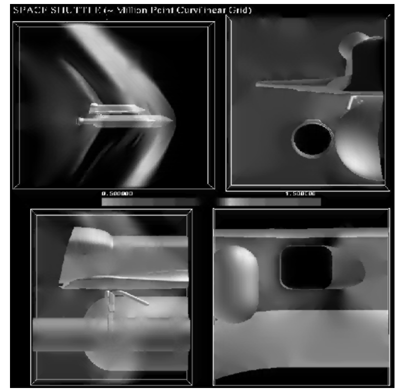

Figure 7. Enhancement applied to “Shuttle” image compressed by JPEG-LS LOCO (Fig. 6).

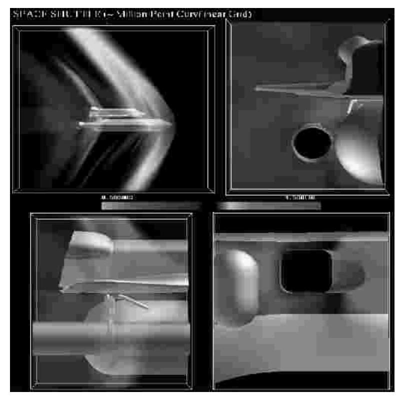

Figure 8. “Shuttle” compressed by JPEG-DCT using $Q_{DC} = 10$, bit rate = 0.340 bpp.

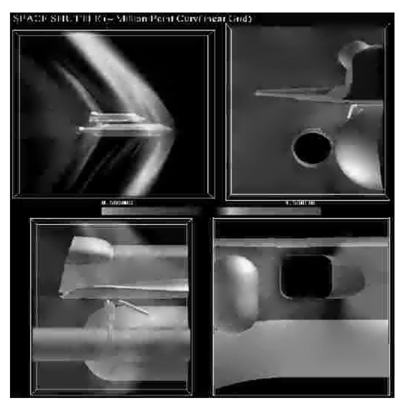

Figure 9. Enhancement applied to “Shuttle” image compressed by JPEG-DCT (Fig. 8).