International Journal For Technological Research In Engineering
Volume 3, Issue 7, March-2016 *ISSN (Online): 2347 - 4718*

UNADULTERATED IMAGE NOISES AND DISCREPANCY ESTIMATION

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ABSTRACT: In order to work well, many computer revelation algorithms require that their parameters be adjusted according to the image noise level, making it an important quantity to estimate. In this work, we present a statistical analysis of JPEG noises, including the quantization noise and the rounding noise during a JPEG compression cycle. We routinely encounter digital color images that were previously JPEG-compressed. En-route to the image's current representation, the previous JPEG compression's various settings—termed its JPEG compression history (CH)–are often discarded after the JPEG decompression step. We also learn the space of noise level functions– how noise level changes with respect to brightness–and use Bayesian MAP inference to infer the noise level function from a single image. We construct a sufficient statistic by exploiting the derived noise distributions, and justify that the statistic has several special properties to reveal the ground-truth quantization step. Experimental results demonstrate that the proposed estimator can uncover JPEG compression history with a satisfactory performance.

I. INTRODUCTION

Many computer vision algorithms can work well only if the parameters of the algorithm are hand-tweaked to account for characteristics of the particular images under study. One of the most common needs for algorithm parameter adjustment is to account for variations in noise level over input images. These variations can be caused by changes in the light level or acquisition modality, and the amount of variation can be severe.The following JPEG settings can be chosen by the user or an imaging device: (i) the color space used to compress the image's three color hydroplanes independently; (ii) the subsampling employed on each color hydroplane during compression and the complementary interpolation employed during decompression; and (iii) the quantization table used to compress each color hydroplane. We refer to these settings as the image's JPEG compression history (CH) .An image's CH is often not directly available from its current representation. For example, JPEG images are often imported into Microsoft Powerpoint or Word documents using graphics programs such as Microsoft Clip Gallery and then stored internally using a decompressed format. JPEG images are also routinely converted to lossless-compression formats such as Windows bitmap (BMP) format (say, to create a background image for Windows or to feed a print driver) or Tagged Image File Format (TIFF). In such cases, the JPEG compression settings are discarded after decompression. An image can be JPEG-compressed for multiple times. To our best knowledge, no study on JPEG noises has explored beyond the first JPEG compression cycle. In this paper, we derive the statistical properties of JPEG noises for higher compression cycles. The results indicate that the distributions of JPEG noises in a higher compression cycle are not always the same as those in the first cycle. Their distributions not only depend on the quantization steps used in the current compression cycle, but are also related to the quantization steps used in the previous compression cycles. The statistical analysis can be applied to JPEG quantization step estimation, where given a JPEG decompressed image stored in an uncompressed format, one attempts to estimate the set of quantization steps used for compression. To achieve the goal, we compute the quantization noise of the next compression cycle, called forward quantization noise.

II. RELATED WORK

There is a large literature on image denoising. Although very promising denoising results have been achieved using a variety of methods, such as wavelets [12], anisotropic diffusion [11] and bilateral filtering [17], the noise level is often assumed known and constant for varying brightness values. In contrast, the literature on noise estimation is very limited. Noise can be estimated from multiple images or a single image. Estimation from multiple image is an overconstrained problem, and was addressed in [7]. Estimation from a single image, however, is an under-constrained problem and further assumptions have to be made for the noise. In the image denoising literature, noise is often assumed to be additive white Gaussian noise (AWGN). A widely used estimation method is based on mean absolute deviation (MAD) [3]. In [15], the authors proposed three methods to estimate noise level based on training samples and the statistics (Laplacian) of natural images. However, real CCD camera noise is intensity-dependent. Color Spaces and Transforms Color perception is a sensation produced when light excites the receptors in the human retina. Color can be described by specifying the light's spectral power distribution. Such a description is highly redundant because the human retina has only three types of receptors that influence color perception.2 Consequently, three numerical components are sufficient to describe a color; this is termed the trichromatic theory [2]. Based on the trichromatic theory, digital color imaging devices use three parameters to specify any color; the three parameters can be viewed as a 3-D vector. The color space is the reference coordinate system with respect to which the 3-D vector describes color [1, 2]. There exist many different coordinate systems or color spaces according to which a color can be specified. For example, the Commission Internationale de L'Eclairage (CIE) defined the ´ CIE XYZ color space to specify all visible colors using positive X, Y, and Z values [1, 2]. Other examples include different varieties of RGB (Red R, Green G, and Blue B) and YCbCr (luminance Y, and chrominances Cb and Cr) color spaces. These color spaces are related to each other and to reference color spaces such as the CIE XYZ via linear or non-linear color transformations. For example, the popular Independent JPEG Group (IJG) JPEG implementation [9] converts the digital color image's $0 - 255$-valued R, G, B components to $0 - 255$-valued Y, Cb, Cr components using the following transformation.

III. COMPRESSION

Wavelets have been particularly successful for image compression. Although many image coders do not incorporate an explicit probability model, a number of recent algorithms make use of joint statistical regularities between wavelet coefficients [19, 27, 22, 26, 15, 25, 6, 32, 16]. We have constructed two coders called EPWIC [4, 29, 3] based directly on the probability models described in sections 1 and 2. In both coders, subband coefficients are encoded one bitplane at a time using a non-adaptive arithmetic encoder that utilizes probabilities calculated from the corresponding model. Bitplanes are ordered using a greedy algorithm that considers the MSE reduction per encoded bit. The decoder uses the statistical model to predict coefficient values based on the bits it has received. Figure 4 shows a comparison of our coders to two wellknown coders: the JPEG coder2 , and the Embedded Zerotree Wavelet (EZW) coder [27]. Also shown in figure 4 is the relative encoding size as a function of target PSNR. This gives a sense of how long one would wait during a progressive transmission for an image of a given quality.

IV. RESTORATION

The classical solution to the noise removal problem is the Wiener filter, which assumes an image model of independent Gaussian-distributed coefficients in the Fourier domain. On the other hand, the non-Gaussian marginal statistics of filtered subbands have been utilized implicitly in a noise removal procedure known as "coring" [e.g., 23, 1, 5, 18], a simple version of which is used in consumer videocassette players. In this approach, the image is split into subbands, and the coefficients are thresholded to suppress low-amplitude values while retaining high-amplitude values. Recent work has provided statistical justification for such algorithms [e.g., 10]. As a simple example, a least-squares Bayesian estimator, assuming non-Gaussian marginal statistics of the type shown in figure 1, is a nonlinear function in the form of a softened coring function [28]. We've been developing a semi-blind noise-removal algorithm based on the joint statistical model of section 2. We use an overcomplete tight frame representation with four oriented subbands at each scale [30]. We use a causal neighborhood of size 18 and bootstrap to estimate model parameters.

V. DISCUSSION

We've described a parameterized model for the joint statistics of wavelet coefficient magnitudes, and demonstrated its use in applications of compression, restoration, and synthesis. The results are quite strong, considering the simplicity of the model. Many aspects of the model could be improved. The most obvious of these is to describe the signs of the coefficients, which exhibit significant statistical regularity.

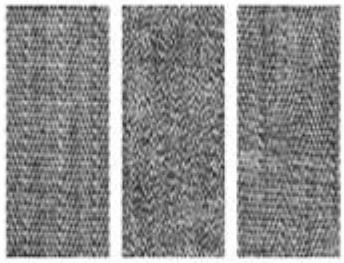

Figure 6. Texture synthesis examples. **Left**: Original texture example. **Center**: First-order model synthesis [13]. **Right**: Joint model synthesis

VI. CONCLUSION

This paper addressed the JPEG CHEst problem for color images and its potential applications. JPEG compression leaves its signature on an image by quantizing the image's DCT coefficients and forcing them to closely conform to near-periodic structures. The paper described two new approaches that exploit these structures to solve the CHEst problem. First, we formulated a statistical framework to characterize and exploit these JPEG-induced nearperiodic structures for gray-scale and color images. Essentially, the statistical approach chooses from a dictionary the best CH model that explains the regular structure of the observed image's DCT coefficients. Second, for cases when JPEG employs affine color transforms and no subsampling, we devised a blind CHEst scheme that does not rely on a finite dictionary.

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