Chapter VI

Compression of Still Images

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INTRODUCTION

Data compression, and in particular image compression, plays an important role in today's information age. Images take up over 90% of the data transfer volume on the Internet and bottlenecks like modems require heavy compression to satisfy the demands of a user. One can divide the subject of data compression into two categories: lossless compression for an exact reconstruction of the original data, and lossy compression for an approximate— as close as possible to the original—reconstruction. In this chapter we address lossless and lossy compression techniques for still images.

We first introduce fundamental transform techniques used by standard and nonstandard image compression algorithms, and standard lossless data compression techniques. We then outline current lossless and lossy image compression standards which are used as data exchange formats in the World Wide Web. State-of-the-art wavelet-based compression algorithms with focus on embedded codes are presented. The last section gives an introduction to fractal compression techniques and image quality metrics. The chapter closes with a comparison of lossy algorithms (in a subjective and objective way) and emphasizes their essential characteristics. Our reference image is the 256 x 256 pixel "Anne" with 256 grayscales (uncompressed size: 65,536 Bytes).

FUNDAMENTALS

Fourier Transform

A transform can be a process which takes information in one domain and expresses it in another one. For compression purposes, image signals are given in spatial domain and are

often transformed to the frequency domain. Image structures which repeat on small scales represent high frequencies, while extended structures represent low frequencies. A common way of entering the frequency domain is the *Fourier Transform* or its equivalent in sampled systems, the Discrete Fourier Transform (DFT). Fourier analysis holds that any periodic waveform can be reproduced by adding together an arbitrary number of sinusoidal functions of various frequencies, amplitudes and phases. The DFT is defined (Vetterli & Kovacevic, 1995) as

$$F(k) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} f(n) W_N^{nk}, \; k = 0,...,N-1 \quad (1)$$

and its inverse as

$$f(n) = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} F(k) W_N^{-nk}, \; n = 0,...,N-1 \quad (2)$$

where $W_N^{nk} = e^{-\frac{j2\pi nk}{N}}$, *F(k)* are the transform coefficients (frequency domain), *f(n)* are the samples in time domain, and *N* is the period of the discrete time sequence.

Discrete Cosine Transform

Aiming at obtaining the transform coefficients *F(k)* it is convenient to use the Karhunen-Loève Transform which concentrates as much energy (and information, likewise) as possible in as few coefficients as possible, and is thus good for compression. This means that this transform is the one that packs most energy into the first *k* coefficients, starting from low frequencies. Unfortunately, the Karhunen-Loève Transform is image dependent. Hence, various image-independent approximations of the Karhunen-Loève Transform have been developed. The most convenient variant is the *Discrete Cosine Transform* (DCT), which calculates the vector *F* from *f* as shown in (3) for the DC component and (4) for the AC components.

$$F(0) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} f(n) \quad (3)$$

$$F(k) = \sqrt{\frac{2}{N}} \sum_{n=0}^{N-1} f(n) \cos\left(\frac{2\pi(2n+1)k}{4N}\right) \text{ for } k = 1,\dots,N-1 \quad (4)$$

For compression purpose all coefficients *F(k)* are calculated, but only the first *N′ - N* coefficients are used. This results in a reconstructed image in which only the lower frequencies occur. Unfortunately, the absence of the high frequency coefficients influences the whole image, yielding typical artifacts (see section Joint Photographic Expert Group JPEG) at sharp edges.

Wavelet Transform

In order to spatially resolve image regions in which high frequencies occur, another approach has to be made. The most promising method is given by the *wavelet transform*. The basic idea is to represent the image in a hierarchical manner.

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