STILL IMAGE AND VIDEO COMPRESSION WITH MATLAB

K. S. Thyagarajan

A JOHN WILEY & SONS, INC., PUBLICATION

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To my wife Vasu,
who is the inspiration behind this book

CONTENTS

PREFACE

The term "video compression" is now a common household name. The field of still image and video compression has matured to the point that it is possible to watch movies on a laptop computer. Such is the rapidity at which technology in various fields has advanced and is advancing. However, this creates a need for some to obtain at least a simple understanding behind all this. This book attempts to do just that, to explain the theory behind still image and video compression methods in an easily understandable manner. The readers are expected to have an introductory knowledge in college-level mathematics and systems theory.

The properties of a still image are similar to those of a video, yet different. A still image is a spatial distribution of light intensity, while a video consists of a sequence of such still images. Thus, a video has an additional dimension—the temporal dimension. These properties are exploited in several different ways to achieve data compression. A particular image compression method depends on how the image properties are manipulated.

Due to the availability of efficient, high-speed central processing units (CPUs), many Internet-based applications offer software solutions to displaying video in real time. However, decompressing and displaying high-resolution video in real time, such as high-definition television (HDTV), requires special hardware processors. Several such real-time video processors are currently available off the shelf. One can appreciate the availability of a variety of platforms that can decompress and display video in real time from the data received from a single source. This is possible because of the existence of video compression standards such as Moving Picture Experts Group (MPEG).

This book first describes the methodologies behind still image and video compression in a manner that is easy to comprehend and then describes the most popular standards such as Joint Photographic Experts Group (JPEG), MPEG, and advanced video coding. In explaining the basics of image compression, care has been taken to keep the mathematical derivations to a minimum so that students as well as practicing professionals can follow the theme easily. It is very important to use simpler mathematical notations so that the reader would not be lost in a maze. Therefore, a sincere attempt has been made to enable the reader to easily follow the steps in the book without losing sight of the goal. At the end of each chapter, problems are offered so that the readers can extend their knowledge further by solving them.

Whether one is a student, a professional, or an academician, it is not enough to just follow the mathematical derivations. For longer retention of the concepts learnt, one must have hands-on experience. The second goal of this book, therefore, is to work out real-world examples through computer software. Although many computer programming languages such as C, C++, Java, and so on are available, I chose MATLAB as the tool to develop the codes in this book. Using MATLAB to develop source code in order to solve a compression problem is very simple, yet it covers all grounds. Readers do not have to be experts in writing cleaver codes. MATLAB has many built-in functions especially for image and video processing that one can employ wherever needed. Another advantage of MATLAB is that it is similar to the C language. Furthermore, MATLAB SIMULINK is a very useful tool for actual simulation of different video compression algorithms, including JPEG and MPEG.

The organization of the book is as follows.

Chapter 1 makes an argument in favor of compression and goes on to introduce the terminologies of still image and video compression.

However, one cannot process an image or a video before acquiring data that is dealt within Chapter 2. Chapter 2 explains the image sampling theory, which relates pixel density to the power to resolve the smallest detail in an image. It further elucidates the design of uniform and nonuniform quantizers used in image acquisition devices. The topic of sampling using nonrectangular grids—such as hexagonal sampling grids—is not found in most textbooks on image or video compression. The hexagonal sampling grids are used in machine vision and biomedicine. Chapter 2 also briefly demonstrates such a sampling technique with an example using MATLAB code to convert an image from rectangular to a hexagonal grid and vice versa.

Image transforms such as the discrete cosine transform and wavelet transform are the compression vehicles used in JPEG and MPEG standards. Therefore, unitary image transforms are introduced in Chapter 3. Chapter 3 illustrates the useful properties of such unitary transforms and explains their compression potential using several examples. Many of the examples presented also include analytical solutions.

The theory of wavelet transform has matured to such an extent that it is deemed necessary to devote a complete chapter to it. Thus, Chapter 4 describes the essentials of discrete wavelet transform (DWT), its type such as orthogonal and biorthogonal transforms, efficient implementation of the DWT via subband coding, and so on. The idea of decomposing an image into a multilevel DWT using octave-band splitting is developed in Chapter 4 along with examples using real images.

After introducing the useful compression vehicles, the method of achieving mathematically lossless image compression is discussed in Chapter 5. Actually the chapter starts with an introduction to information theory, which is essential to gauge the performance of the various lossless (and lossy) compression techniques. Both Huffman coding and arithmetic coding techniques are described with examples illustrating the methods of generating such codes. The reason for introducing lossless compression early on is that all lossy compression schemes employ lossless coding as a means to convert symbols into codes for transmission or storage as well as to gain additional compression.

The first type of lossy compression, namely, the predictive coding, is introduced in Chapter 6. It explains both one-dimensional and two-dimensional predictive coding methods followed by the calculation of the predictor performance gain with examples. This chapter also deals with the design of both nonadaptive and adaptive differential pulse code modulations, again with several examples.

Transform coding technique and its performance are next discussed in Chapter 7. It also explains the compression part of the JPEG standard with an example using MATLAB.

The wavelet domain image compression topic is treated extensively in Chapter 8. Examples are provided to show the effectiveness of both orthogonal and biorthogonal DWTs in compressing an image. The chapter also discusses the JPEG2000 standard, which is based on wavelet transform.

Moving on to video, Chapter 9 introduces the philosophy behind compressing video sequences. The idea of motion estimation and compensation is explained along with subpixel accurate motion estimation and compensation. Efficient techniques such as hierarchical and pyramidal search procedures to estimate block motion are introduced along with MATLAB codes to implement them. Chapter 9 also introduces stereo image compression. The two images of a stereo image pair are similar yet different. By using motion compensated prediction, the correlation between the stereo image pair is reduced and hence compression achieved. A MATLAB-based example illustrates this idea clearly.

The concluding chapter, Chapter 10, describes the video compression part of the MPEG-1, -2, -4, and H.264 standards. It also includes examples using MATLAB codes to illustrate the standards' compression mechanism. Each chapter includes problems of increasing difficulty to help the students grasp the ideas discussed.

I thank Dr. Kesh Bakhru and Mr. Steve Morley for reviewing the initial book proposal and giving me continued support. My special thanks to Dr. Vinay Sathe of Multirate Systems for reviewing the manuscript and providing me with valuable comments and suggestions. I also thank Mr. Arjun Jain of Micro USA, Inc., for providing me encouragement in writing this book. I wish to acknowledge the generous and continued support provided by The MathWorks in the form of MATLAB software. This book would not have materialized but for my wife Vasu, who is solely responsible for motivating me and persuading me to write this book. My heart-felt gratitude goes to her for patiently being there during the whole period of writing this book. She is truly the inspiration behind this work.

K. S. THYAGARAJAN

San Diego, CA

1

INTRODUCTION

This book is all about image and video compression. Chapter 1 simply introduces the overall ideas behind data compression by way of pictorial and graphical examples to motivate the readers. Detailed discussions on various compression schemes appear in subsequent chapters. One of the goals of this book is to present the basic principles behind image and video compression in a clear and concise manner and develop the necessary mathematical equations for a better understanding of the ideas. A further goal is to introduce the popular video compression standards such as Joint Photographic Experts Group (JPEG) and Moving Picture Experts Group (MPEG) and explain the compression tools used by these standards. Discussions on semantics and data transportation aspects of the standards will be kept to a minimum. Although the readers are expected to have an introductory knowledge in college-level mathematics and systems theory, clear explanations of the mathematical equations will be given where necessary for easy understanding. At the end of each chapter, problems are given in an increasing order of difficulty to make the understanding firm and lasting.

In order for the readers of this book to benefit further, MATLAB codes for several examples are included. To run the M-files on your computers, you should install MATLAB software. Although there are other software tools such as C++ and Python to use, MATLAB appears to be more readily usable because it has a lot of built-in functions in various areas such as signal processing, image and video processing, wavelet transform, and so on, as well as simulation tools such as MATLAB Simulink. Moreover, the main purpose of this book is to motivate the readers to learn and get hands on experience in video compression techniques with easy-to-use software tools, which does not require a whole lot of programming skills. In the

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remainder of the chapter, we will briefly describe various compression techniques with some examples.

1.1 WHAT IS SOURCE CODING?

Images and videos are moved around the World Wide Web by millions of users almost in a nonstop fashion, and then, there is television (TV) transmission round the clock. Analog TV has been phased out since February 2009 and digital TV has taken over. Now we have the cell phone era. As the proverb *a picture is worth a thousand words* goes, the transmission of these visual media in digital form alone will require far more bandwidth than what is available for the Internet, TV, or wireless networks. Therefore, one must find ways to format the visual media data in such a way that it can be transmitted over the bandwidth-limited TV, Internet, and wireless channels in real time. This process of reducing the image and video data so that it fits into the available limited bandwidth or storage space is termed *data compression*. It is also called *source coding* in the communications field. When compressed audio/video data is actually transmitted through a transmission channel, extra bits are added to it to counter the effect of noise in the channel so that errors in the received data, if present, could be detected and/or corrected. This process of adding additional data bits to the compressed data stream before transmission is called *channel coding*. Observe that the effect of reducing the original source data in source coding is offset to a small extent by the channel coding, which adds data rather than reducing it. However, the added bits by the channel coder are very small compared with the amount of data removed by source coding. Thus, there is a clear advantage of compressing data.

We illustrate the processes of compressing and transmitting or storing a video source to a destination in Figure 1.1. The source of raw video may come from a video camera or from a previously stored video data. The source encoder compresses the raw data to a desired amount, which depends on the type of compression scheme chosen. There are essentially two categories of compression—*lossless* and *lossy*. In a lossless compression scheme, the original image or video data can be recovered exactly. In a lossy compression, there is always a loss of some information about the

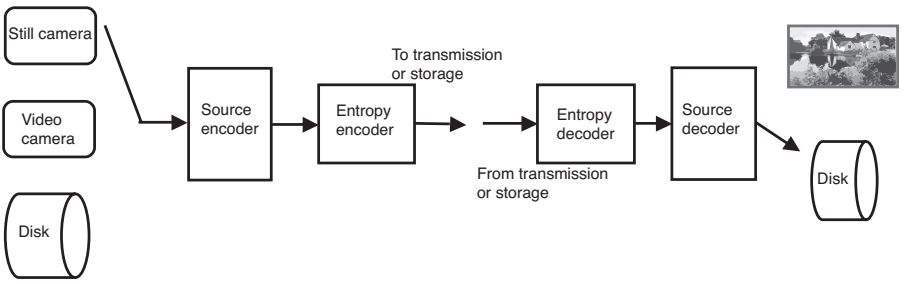


Figure 1.1 Source coding/decoding of video data for storage or transmission.

original data and so the recovered image or video data suffers from some form of distortion, which may or may not be noticeable depending on the type of compression used. After source encoding, the quantized data is encoded losslessly for transmission or storage. If the compressed data is to be transmitted, then channel encoder is used to add redundant or extra data bits and fed to the digital modulator. The digital modulator converts the input data into an RF signal suitable for transmission through a communications channel.

The communications receiver performs the operations of demodulation and channel decoding. The channel decoded data is fed to the entropy decoder followed by source decoder and is finally delivered to the sink or stored. If no transmission is used, then the stored compressed data is entropy decoded followed by source decoding as shown on the right-hand side of Figure 1.1.

1.2 WHY IS COMPRESSION NECESSARY?

An image or still image to be precise is represented in a computer as an array of numbers, integers to be more specific. An image stored in a computer is called a digital image. However, we will use the term image to mean a digital image. The image array is usually two dimensional (2D) if it is black and white (BW) and three dimensional (3D) if it is a color image. Each number in the array represents an intensity value at a particular location in the image and is called a picture element or pixel, for short. The pixel values are usually positive integers and can range between 0 and 255. This means that each pixel of a BW image occupies 1 byte in a computer memory. In other words, we say that the image has a grayscale resolution of 8 bits per pixel (bpp). On the other hand, a color image has a triplet of values for each pixel: one each for the red, green, and blue primary colors. Hence, it will need 3 bytes of storage space for each pixel. The captured images are rectangular in shape. The ratio of width to height of an image is called the aspect ratio. In standard-definition television (SDTV) the aspect ratio is 4:3, while it is 16:9 in a high-definition television (HDTV). The two aspect ratios are illustrated in Figure 1.2, where Figure 1.2a corresponds to an aspect ratio of 4:3 while Figure 1.2b corresponds to the same picture with an aspect ratio of 16:9. In both pictures, the height in inches remains the same,

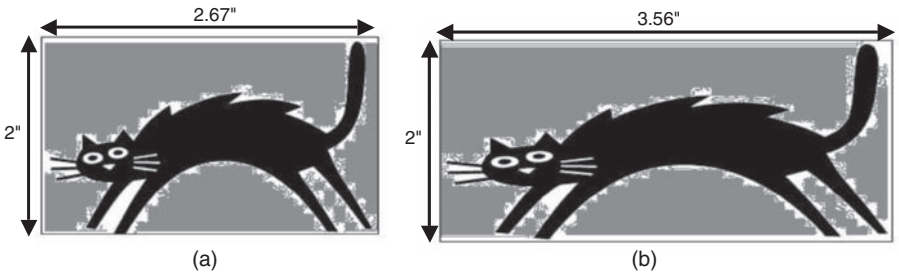


Figure 1.2 Aspect ratio: (a) 4:3 and (b) 16:9. The height is the same in both the pictures.

which means that the number of rows remains the same. So, if an image has 480 rows, then the number of pixels in each row will be $480 \times 4/3 = 640$ for an aspect ratio of 4:3. For HDTV, there are 1080 rows and so the number of pixels in each row will be $1080 \times 16/9 = 1920$. Thus, a single SD color image with 24 bpp will require $640 \times 480 \times 3 = 921{,}600$ bytes of memory space, while an HD color image with the same pixel depth will require $1920 \times 1080 \times 3 = 6{,}220{,}800$ bytes. A video source may produce 30 or more frames per second, in which case the raw data rate will be 221,184,000 bits per second for SDTV and 1,492,992,000 bits per second for HDTV. If this raw data has to be transmitted in real time through an ideal communications channel, which will require 1 Hz of bandwidth for every 2 bits of data, then the required bandwidth will be 110,592,000 Hz for SDTV and 746,496,000 Hz for HDTV. There are no such practical channels in existence that will allow for such a huge transmission bandwidth. Note that dedicated channels such as HDMI capable of transferring uncompressed data at this high rate over a short distance do exist, but we are only referring to long-distance transmission here. It is very clear that efficient data compression schemes are required to bring down the huge raw video data rates to manageable values so that practical communications channels may be employed to carry the data to the desired destinations in real time.

1.3 IMAGE AND VIDEO COMPRESSION TECHNIQUES

1.3.1 Still Image Compression

Let us first see the difference between *data compression* and *bandwidth compression*. Data compression refers to the process of reducing the digital source data to a desired level. On the other hand, bandwidth compression refers to the process of reducing the analog bandwidth of the analog source. What do we really mean by these terms? Here is an example. Consider the conventional wire line telephony. A subscriber's voice is filtered by a lowpass filter to limit the bandwidth to a nominal value of 4 kHz. So, the channel bandwidth is 4 kHz. Suppose that it is converted to digital data for long-distance transmission. As we will see later, in order to reconstruct the original analog signal that is band limited to 4 kHz exactly, sampling theory dictates that one should have at least 8000 samples per second. Additionally, for digital transmission each analog sample must be converted to a digital value. In telephony, each analog voice sample is converted to an 8-bit digital number using *pulse code modulation* (PCM). Therefore, the voice data rate that a subscriber originates is 64,000 bits per second. As we mentioned above, in an ideal case this digital source will require 32 kHz of bandwidth for transmission. Even if we employ some form of data compression to reduce the source rate to say, 16 kilobits per second, it will still require at least 8 kHz of channel bandwidth for real-time transmission. Hence, data compression does not necessarily reduce the analog bandwidth. Note that the original analog voice requires only 4 kHz of bandwidth. If we want to compress bandwidth, we can simply filter the analog signal by a suitable filter with a specified cutoff frequency to limit the bandwidth occupied by the analog signal.

Figure 1.3 Original cameraman picture.

Having clarified the terms data compression and bandwidth compression, let us look into some basic data compression techniques known to us. Henceforth, we will use the terms compression and data compression interchangeably. All image and video sources have redundancies. In a still image, each pixel in a row may have a value very nearly equal to a neighboring pixel value. As an example, consider the cameraman picture shown in Figure 1.3. Figure 1.4 shows the profile (top figure)

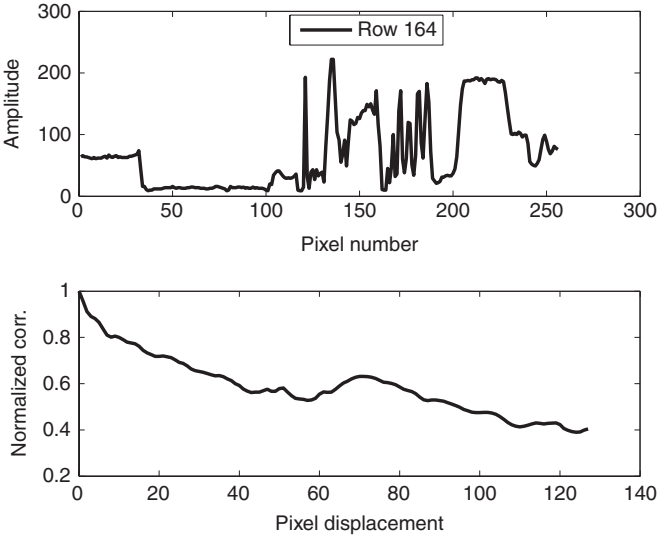


Figure 1.4 Profile of cameraman image along row number 164. The top graph shows pixel intensity, and the bottom graph shows corresponding normalized correlation over 128 pixel displacements.

and the corresponding correlation (bottom figure) of the cameraman picture along row 164. The MATLAB M-file for generating Figure 1.4 is listed below. Observe that the pixel values are very nearly the same over a large number of neighboring pixels and so is the pixel correlation. In other words, pixels in a row have a high correlation. Similarly, pixels may also have a high correlation along the columns. Thus, pixel redundancies translate to pixel correlation. The basic principle behind image data compression is to *decorrelate* the pixels and encode the resulting decorrelated image for transmission or storage. A specific compression scheme will depend on the method by which the pixel correlations are removed.

```
Figure1_4.m
%   Plots the image intensity profile and pixel correlation
%   along a specified row.
clear
close all
I = imread('cameraman.tif');
figure,imshow(I),title('Input image')
%
Row = 164; % row number of image profile
x = double(I(Row,:));
Col = size(I,2);
%
MaxN = 128; % number of correlation points to calculate
Cor = zeros(1,MaxN); % array to store correlation values
for k = 1:MaxN
    l = length(k:Col);
    Cor(k) = sum(x(k:Col) .* x(1:Col-k+1))/l;
end
MaxCor = max(Cor);
Cor = Cor/MaxCor;
figure,subplot(2,1,1),plot(1:Col,x,'k','LineWidth',2)
xlabel('Pixel number'), ylabel('Amplitude')
legend(['Row' ' ' num2str(Row)],0)
subplot(2,1,2),plot(0:MaxN-1,Cor,'k','LineWidth',2)
xlabel('Pixel displacement'), ylabel('Normalized corr.')
```

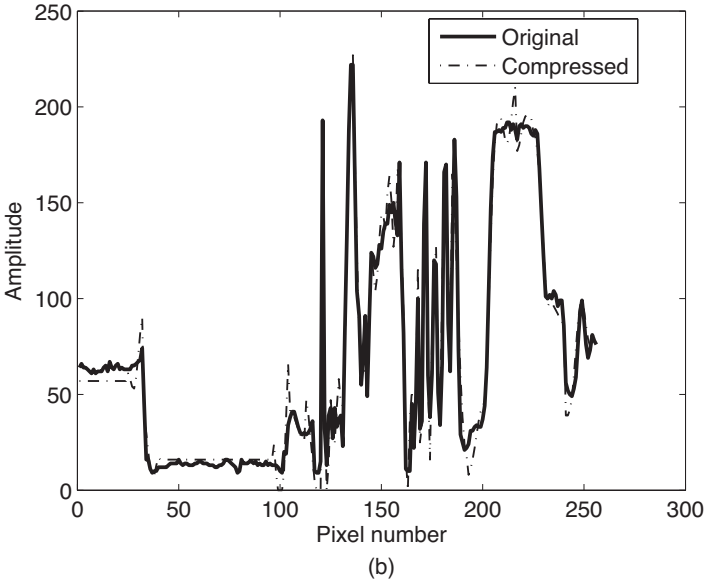
One of the earliest and basic image compression techniques is known as the *differential pulse code modulation* (DPCM) [1]. If the pixel correlation along only one dimension (row or column) is removed, then the DPCM is called one-dimensional (1D) DPCM or row-by-row DPCM. If the correlations along both dimensions are removed, then the resulting DPCM is known as 2D DPCM. A DPCM removes pixel correlation and requantizes the residual pixel values for storage or transmission. The residual image has a variance much smaller than that of the original image.

Further, the residual image has a probability density function, which is a double-sided exponential function. These give rise to compression.

The quantizer is fixed no matter how the decorrelated pixel values are. A variation on the theme is to use quantizers that adapt to changing input statistics, and therefore, the corresponding DPCM is called an adaptive DPCM. DPCM is very simple to implement, but the compression achievable is about 4:1. Due to limited bit width of the quantizer for the residual image, edges are not preserved well in the DPCM. It also exhibits occasional streaks across the image when channel error occurs. We will discuss DPCM in detail in a later chapter.

Another popular and more efficient compression scheme is known by the generic name *transform coding*. Remember that the idea is to reduce or remove pixel correlation to achieve compression. In transform coding, a block of image pixels is linearly transformed into another block of *transform coefficients* of the same size as the pixel block with the hope that only a few of the transform coefficients will be significant and the rest may be discarded. This implies that storage space is required to store only the significant transform coefficients, which are a fraction of the total number of coefficients and hence the compression. The original image can be reconstructed by performing the inverse transform of the reduced coefficient block. It must be pointed out that the inverse transform must exist for unique reconstruction. There are a number of such transforms available in the field to choose from, each having its own merits and demerits. The most efficient transform is one that uses the least number of transform coefficients to reconstruct the image for a given amount of distortion. Such a linear transform is known as the optimal transform where optimality is with respect to the minimum mean square error between the original and reconstructed images. This optimal image transform is known by the names *Karhunen–Loève transform* (KLT) or *Hotelling transform*. The disadvantage of the KLT is that the transform kernel depends on the actual image to be compressed, which requires a lot more side information for the receiver to reconstruct the original image from the compressed image than other *fixed* transforms. A highly popular fixed transform is the familiar *discrete cosine transform* (DCT). The DCT has very nearly the same *compression efficiency* as the KLT with the advantage that its *kernel* is fixed and so no side information is required by the receiver for the reconstruction. The DCT is used in the JPEG and MPEG video compression standards. The DCT is usually applied on nonoverlapping blocks of an image. Typical DCT blocks are of size 8×8 or 16×16. One of the disadvantages of image compression using the DCT is the *blocking* artifact. Because the DCT blocks are small compared with the image and because the average values of the blocks may be different, blocking artifacts appear when the zero-frequency (dc) DCT coefficients are quantized rather heavily. However, at low compression, blocking artifacts are almost unnoticeable. An example showing blocking artifacts due to compression using 8×8 DCT is shown in Figure 1.5a. Blockiness is clearly seen in flat areas—both low and high intensities as well as undershoot and overshoot along the sharp edges—see Figure 1.5b. A listing of M-file for Figures 1.5a,b is shown below.

(a)



(b)

Figure 1.5 (a) Cameraman image showing blocking artifacts due to quantization of the DCT coefficients. The DCT size is 8 × 8. (b) Intensity profile along row number 164 of the image in (a).

```
% Figure1_5.m
% Example to show blockiness in DCT compression
% Quantizes and dequantizes an intensity image using
% 8x8 DCT and JPEG quantization matrix
close all
clear
I = imread('cameraman.tif');
figure,imshow(I), title('Original Image')
%
fun = @dct2; % 2D DCT function
N = 8; % block size of 2D DCT
T = blkproc(I,[N N],fun);  % compute 2D DCT of image using NxN blocks
%
Scale = 4.0; % increasing Scale quntizes DCT coefficients heavily
% JPEG default quantization matrix
jpgQMat = [16 11 10 16  24  40  51  61;
           12 12 14 19  26  58  60  55;
           14 13 16 24  40  57  69  56;
           14 17 22 29  51  87  80  62;
           18 22 37 56  68 109 103  77;
           24 35 55 64  81 194 113  92;
           49 64 78 87 103 121 120 101;
           72 92 95 98 121 100 103  99];
Qstep = jpgQMat * Scale; % quantization step size
%   Quantize and dequantize the coefficients
for k = 1:N:size(I,1)
    for l = 1:N:size(I,2)
        T1(k:k+N-1,l:l+N-1) = round(T(k:k+N-1,l:l+N-1)./ Qstep).*Qstep;
    end
end
% do inverse 2D DCT
fun = @idct2;
y = blkproc(T1,[N N],fun);
y = uint8(round(y));
figure,imshow(y), title('DCT compressed Image')
% Plot image profiles before and after compression
ProfRow = 164;
figure,plot(1:size(I,2),I(ProfRow,:),'k','LineWidth',2)
hold on
plot(1:size(I,2),y(ProfRow,:),'-.k','LineWidth',1)
title(['Intensity profile of row ' num2str(ProfRow)])
xlabel('Pixel number'), ylabel('Amplitude')
%legend(['Row' ' ' num2str(ProfRow)],0)
legend('Original','Compressed',0)
```

A third and relatively recent compression method is based on *wavelet transform*. As we will see in a later chapter, wavelet transform captures both long-term and short-term changes in an image and offers a highly efficient compression mechanism. As a result, it is used in the latest versions of the JPEG standards as a compression tool. It is also adopted by the SMPTE (Society of Motion Pictures and Television Engineers). Even though the wavelet transform may be applied on blocks of an image like the DCT, it is generally applied on the full image and the various wavelet

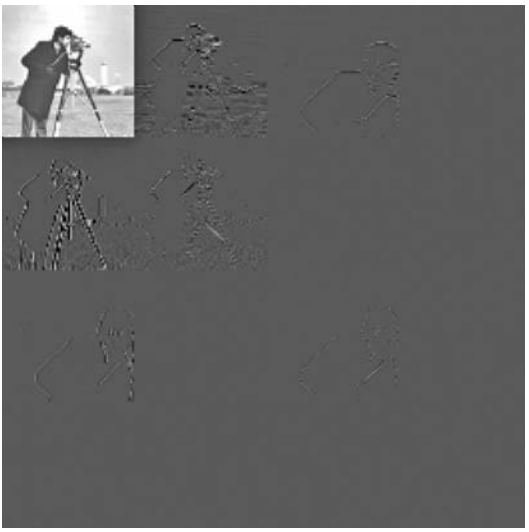
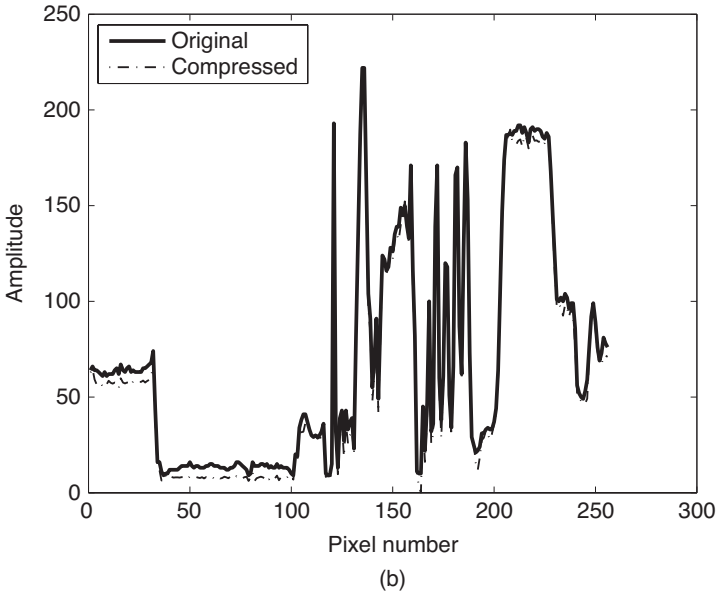


Figure 1.6 A two-level 2D DWT of cameraman image.

coefficients are quantized according to their types. A two-level discrete wavelet transform (DWT) of the cameraman image is shown in Figure 1.6 to illustrate how the 2D wavelet transform coefficients look like. Details pertaining to the levels and subbands of the DWT will be given in a later chapter. The M-file to implement multilevel 2D DWT that generates Figure 1.6 is listed below. As we will see in a later chapter, the 2D DWT decomposes an image into one approximation and many detail coefficients. The number of coefficient subimages corresponding to an L-level 2D DWT equals $3 \times L + 1$. Therefore, for a two-level 2D DWT, there are seven coefficient subimages. In the first level, there are three detail coefficient subimages, each of size $\frac{1}{4}$ the original image. The second level consists of four sets of DWT coefficients—one approximation and three details, each $\frac{1}{16}$ the original image. As the name implies the approximation coefficients are lower spatial resolution approximations to the original image. The detail coefficients capture the discontinuities or edges in the image with orientations in the horizontal, vertical, and diagonal directions. In order to compress, an image using 2D DWT we have to compute the 2D DWT of the image up to a given level and then quantize each coefficient subimage. The achievable quality and compression ratio depend on the chosen wavelets and quantization method. The visual effect of quantization distortion in DWT compression scheme is different from that in DCT-based scheme. Figure 1.7a is the cameraman image compressed using 2D DWT. The wavelet used is called Daubechies 2 (db2 in MATLAB) and the number of levels used is 1. We note that there are no blocking effects, but there are patches in the flat areas. We also see that the edges are reproduced faithfully as evidenced in the profile (Figure 1.7b). It must be pointed out that the amount of quantization applied in Figure 1.7a is not the same as that used for the DCT example and that the two examples are given only to show the differences in the artifacts introduced by the two schemes. An M-file listing to generate Figures 1.7a,b is shown below.

(a)



(b)

Figure 1.7 (a) Cameraman image compressed using one-level 2D DWT. (b) Intensity profile of image in Figure 1.8a along row number 164.

```
% Figure1_6.m
% 2D Discrete Wavelet Transform (DWT)
% Computes multi-level 2D DWT of an intensity image
close all
clear
I = imread('cameraman.tif');
figure,imshow(I), title('Original Image')
L = 2; % number of levels in DWT
[W,B] = wavedec2(I,L,'db2'); % do a 2-level DWT using db2 wavelet
% declare level-1 subimages
w11 = zeros(B(3,1),B(3,1));
w12 = zeros(B(3,1),B(3,1));
w13 = zeros(B(3,1),B(3,1));
% declare level-2 subimages
w21 = zeros(B(1,1),B(1,1));
w22 = zeros(B(1,1),B(1,1));
w23 = zeros(B(1,1),B(1,1));
w24 = zeros(B(1,1),B(1,1));
% extract level-1 2D DWT coefficients
offSet11 = 4*B(1,1)*B(1,2);
offSet12 = 4*B(1,1)*B(1,2)+B(3,1)*B(3,2);
offSet13 = 4*B(1,1)*B(1,2)+2*B(3,1)*B(3,2);
for c = 1:B(2,2)
    for r = 1:B(2,1)
        w11(r,c) = W(offSet11+(c-1)*B(3,1)+r);
        w12(r,c) = W(offSet12+(c-1)*B(3,1)+r);
        w13(r,c) = W(offSet13+(c-1)*B(3,1)+r);
    end
end
% extract level-2 2D DWT coefficients
offSet22 = B(1,1)*B(1,2);
offSet23 = 2*B(1,1)*B(1,2);
offSet24 = 3*B(1,1)*B(1,2);
for c = 1:B(1,2)
    for r = 1:B(1,1)
        w21(r,c) = W((c-1)*B(1,1)+r);
        w22(r,c) = W(offSet22+(c-1)*B(1,1)+r);
        w23(r,c) = W(offSet23+(c-1)*B(1,1)+r);
        w24(r,c) = W(offSet24+(c-1)*B(1,1)+r);
    end
end
% declare output array y to store all the DWT coefficients
%y = zeros(261,261);
y = zeros(2*B(1,1)+B(3,1),2*B(1,2)+B(3,2));
y(1:B(1,1),1:B(1,1))=w21;
y(1:B(1,1),B(1,1)+1:2*B(1,1))=w22;
y(B(1,1)+1:2*B(1,1),1:B(1,1))=w23;
y(B(1,1)+1:2*B(1,1),B(1,1)+1:2*B(1,1))=w24;
%
y(1:B(3,1),2*B(1,1)+1:261)=w11;
y(2*B(1,1)+1:261,1:129)=w12;
y(2*B(1,1)+1:261,2*B(1,1)+1:261)=w13;
figure,imshow(y,[]),title([num2str(L) '-level 2D DWT'])


% Figure1_7.m
% An example to show the effect of quantizing the 2D DWT
% coefficients of an intensity image along with intensity
% profile along a specified row
```

```
%
close all
clear
I = imread('cameraman.tif');
figure,imshow(I), title('Original Image')
% do a 1-level 2D DWT
[W,B] = wavedec2(I,1,'db2');
w11 = zeros(B(1,1),B(1,2));
w12 = zeros(B(1,1),B(1,2));
w13 = zeros(B(1,1),B(1,2));
w14 = zeros(B(1,1),B(1,2));
%
offSet12 = B(1,1)*B(1,2);
offSet13 = 2*B(1,1)*B(1,2);
offSet14 = 3*B(1,1)*B(1,2);
% quantize only the approximation coefficients
Qstep = 16;
for c = 1:B(1,2)
    for r = 1:B(1,1)
        W((c-1)*B(1,1)+r) = floor(W((c-1)*B(1,1)+r)/Qstep)*Qstep;
        %{
        W(offSet12+(c-1)*B(1,1)+r) = floor(W(offSet12+(c-1)*B(1,1)+r)/8)*8;
        W(offSet13+(c-1)*B(1,1)+r) = floor(W(offSet13+(c-1)*B(1,1)+r)/8)*8;
        W(offSet14+(c-1)*B(1,1)+r) = floor(W(offSet14+(c-1)*B(1,1)+r)/8)*8;
        %}
    end
end
% do inverse 2D DWT
y = waverec2(W,B,'db2');
figure,imshow(y,[])
% plot profile
ProfRow = 164;
figure,plot(1:size(I,2),I(ProfRow,:),'k','LineWidth',2)
hold on
plot(1:size(I,2),y(ProfRow,:),'-.k','LineWidth',1)
title(['Profile of row ' num2str(ProfRow)])
xlabel('Pixel number'), ylabel('Amplitude')
%legend(['Row' ' ' num2str(ProfRow)],0)
legend('Original','Compressed',0)
```

1.3.2 Video Compression

So far our discussion on compression has been on still images. These techniques try to exploit the *spatial correlation* that exists in a still image. When we want to compress video or sequence images we have an added dimension to exploit, namely, the temporal dimension. Generally, there is little or very little change in the spatial arrangement of objects between two or more consecutive *frames* in a video. Therefore, it is advantageous to send or store the differences between consecutive frames rather than sending or storing each frame. The difference frame is called the *residual* or *differential* frame and may contain far less details than the actual frame itself. Due to this reduction in the details in the differential frames, compression is achieved. To illustrate the idea, let us consider compressing two consecutive frames (frame 120 and frame 121) of a video sequence as shown in Figures 1.8a,b, respectively (see M-file listing shown below). The difference between frames 121 and 120 is shown

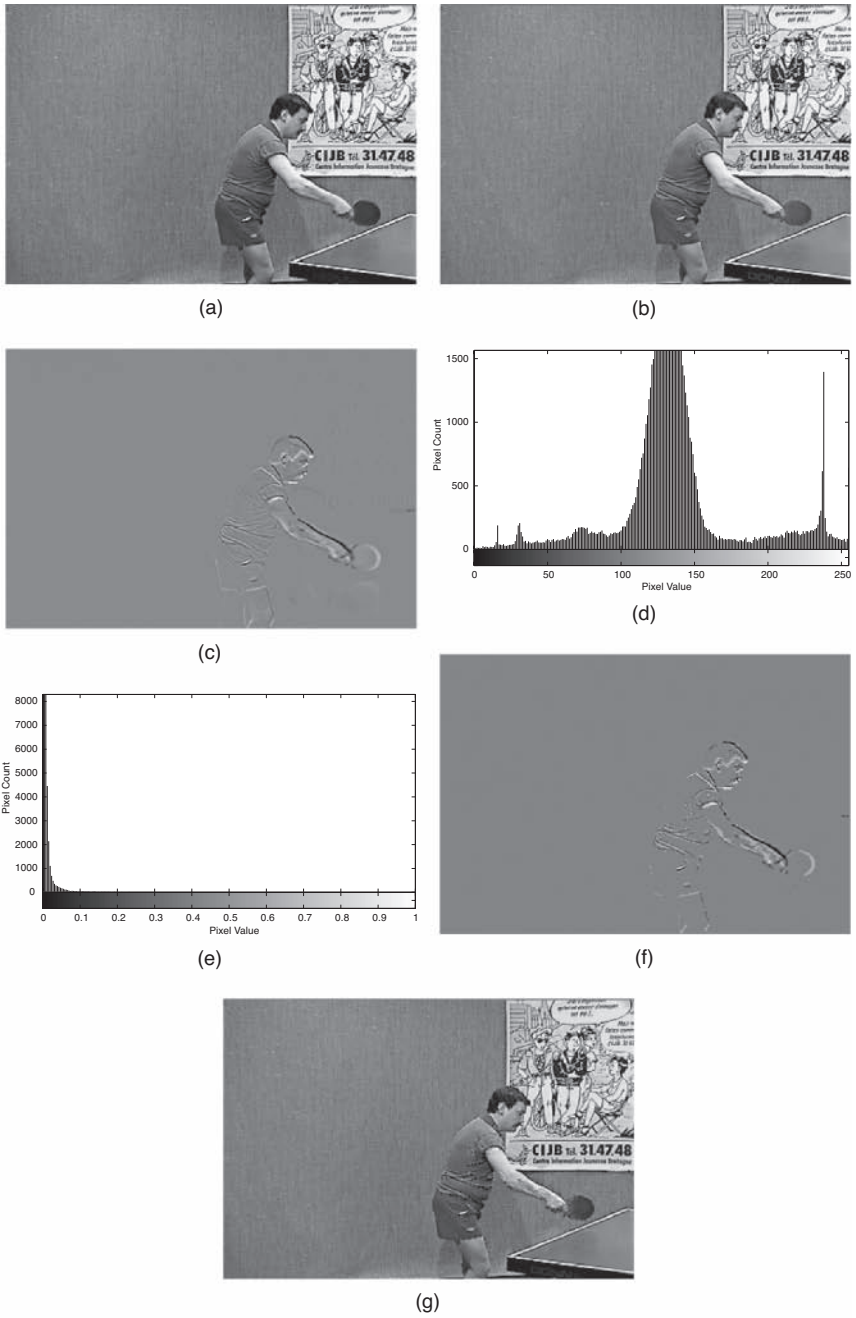


Figure 1.8 Compressing a video sequence: (a) frame 120 of a table tennis video sequence; (b) frame 121 of the video sequence; (c) difference between frames 121 and 120; (d) histogram of frame 121; (e) histogram of the difference of frames; (g) quantized difference frame; and (h) Reconstructed frame 121 by adding the quantized difference frame to frame 120.