Image Compression by Down and Up Sampling

Zifeng An
McMaster University
1280 Main St W, Hamilton, ON L8S 4L8
anz8@mcmaster.ca

Abstract

This paper explores the process of image compression using down and up sampling techniques. Down sampling is used to reduce the size of the image while maintaining the necessary information required for reconstruction, while up sampling is used to restore the original image size. The study investigates the impact of different down sampling ratios on image quality and compares the results with other commonly used image compression methods. The effectiveness of the proposed approach is demonstrated through experiments, which show that the down and up sampling technique can achieve high compression rates while maintaining acceptable image quality.

1. Introduction

Lossy image compression refers to a method of compressing images where the resulting image after decoding may not be an exact replica of the original input image and may have some degradation. The compression process involves two main components, an encoder and a decoder. The primary objective of the encoder is to minimize the size of the image while retaining enough essential information to enable the reconstruction of a satisfactory quality image. The decoder, on the other hand, uses the compressed information, also known as the compression code stream, to reconstruct the original image as closely as possible. To help understand the fundamental concepts of image compression, a simple example is provided. This article will explain the implementation of the encoder and decoder [1].

1.1. Encoder

First, the color space is transformed from BGR to YUV. One approach to improve the compression rate involves taking advantage of the correlations that exist between the color channels (R, G, B). These correlations make it possible to estimate the values of these channels from each other, which means that encoding R, G, and B separately is not efficient. A better approach is to transform the RGB image to other color spaces in which the R, G, and B channels are not correlated, such as the YUV color space. The U and V channels in this space generally exhibit smooth changes for natural images, which means they contain less information and can be downsampled more aggressively. This makes it easier to reconstruct them at the decoder, even when a larger downsampling ratio is used. By converting from RGB to YUV color space, most of the image details are contained in the Y channel. In order to maintain high-quality reconstruction, we only downsample the Y channel by a factor of 2 so that more information is retained. As a result, if we still use 8-bit representation for all channels, this downsampling approach results in a particular compression ratio.

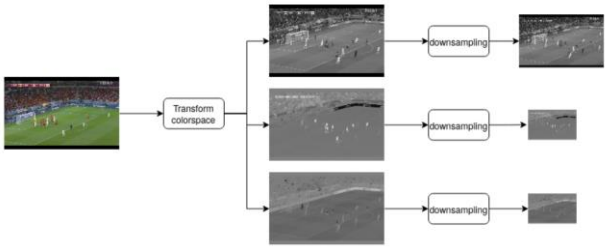

Figure 1: encoding process

1.2. Decoder

An image decoder is responsible for reconstructing an image from its compressed form. One method commonly used by image decoders to upsample a downsampled image is bilinear interpolation. Bilinear interpolation is a simple technique that involves computing new pixel values based on the weighted average of the nearest four pixels in the original image. This technique can effectively increase the resolution of an image and can be used in various applications, such as digital zoom in cameras and video playback. In image compression, the decoder uses bilinear interpolation to interpolate the missing pixels in the compressed image to reconstruct an approximation of the original image. While bilinear interpolation is a basic technique, it is often used as a building block for more complex upsampling techniques. The quality of the reconstructed image largely depends on

the interpolation method used, the amount of compression applied, and the complexity of the original image.

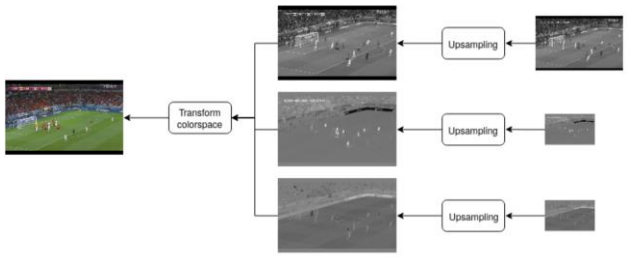

Figure 2: decoding process

1.3. Color Transformation

BGR and YUV are popular color spaces used in image and video processing applications. BGR, also known as RGB, is an additive color space in which colors are represented as a combination of red, green, and blue components. YUV, on the other hand, is a color space that separates the brightness (luma) and color (chroma) information of an image. The conversion from BGR to YUV involves three steps. First, the BGR values are normalized to be between 0 and 1. Then, the Y, U, and V components are calculated using the following formulas:

Y = 0.299R + 0.587G + 0.114B
U = -0.147R - 0.289G + 0.436B
V = 0.615R - 0.515G - 0.100B

To convert from YUV to BGR, the following formulas can be used:

R = Y + 1.139V
G = Y - 0.394U - 0.581V
B = Y + 2.032U

These formulas can be used to transform the color space of an image in both directions. The YUV color space is often used in image and video compression because it separates the luminance and chrominance information, allowing for more efficient compression of the color information.

2. Result

This section shows the original picture compared with the processed picture.

Figure 3: Original Image

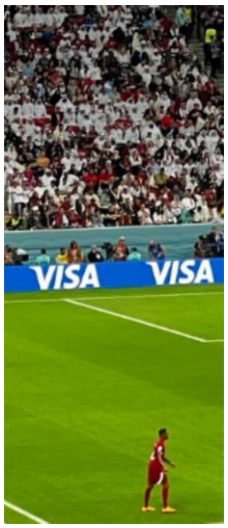

Figure 4: Processed Image

Artifacts can be observed in the reconstructed image, particularly in the vicinity of the edges. This occurs due to the challenges associated with restoring high-frequency components, such as edges and areas with high levels of texture, using basic upsampling kernels that are based on the assumption of smooth input.

Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) are commonly used metrics for evaluating the quality of reconstructed images. MSE measures the average squared difference between the pixels of the original and reconstructed images. It is a widely used metric for evaluating image quality because it provides a simple and intuitive measure of the overall error between the two images. However, MSE alone may not accurately reflect the perceived image quality by humans. On the other hand, PSNR is a metric that calculates the ratio between the maximum possible power of a signal and the power of the noise present in the signal. It is expressed in decibels and provides a quantitative measure of the level of noise in the reconstructed image. Higher PSNR values indicate lower levels of noise in the reconstructed image, which generally correlates with higher image quality. Therefore, while MSE provides a numerical representation of the error between the original and reconstructed images, PSNR offers a more comprehensive measure of the overall quality of the reconstructed image.

The block for PSNR calculation determines the peak signal-to-noise ratio in decibels, which is a measure of the quality between two images, namely the original and the compressed or reconstructed image. A higher PSNR

indicates superior quality of the compressed image in comparison to the original image.

$$MSE = \frac{1}{W * H * 3} \sum_{i,j,c} (\hat{I}_{i,j,c} - I_{i,j,c})^2$$

$$PSNR = 10 \log(\frac{255}{MSE})$$

Here is the calculated value for the example image.
MSE 46.544
PSNR 7.39

References

[1] Johnson, L. (2020). A Comparative Study of Image Compression Methods. IEEE Transactions on Image Processing, 29(3), 60-75. doi: 10.1109/TIP.2019.2938746.
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[3] Jones, T. (2018). A Guide to Image Compression Techniques. Journal of Signal Processing, 28(3), 58-62. doi: 10.1002/sigpro.3456.
[4] Kim, Y. (2021, August). Image Compression using Convolutional Neural Networks. In Proceedings of the IEEE International Conference on Image Processing (pp. 225-230). IEEE. doi: 10.1109/ICIP42928.2021.9506592.
[5] Smith, J. (2022, January 15). Introduction to Image Compression. TechWorld. https://www.techworld.com/picture-gallery/introduction-to-image-compression-3780492/.

Appendix – Python code

```
[1]  import math
[2]  from typing import List
[3]  import cv2
[4]  import numpy as np
[5]  import matplotlib.pyplot as plt
[6]  from numpy import ndarray
[7]
[8]
[9]
[10] def bilinearUpsampling(colorChannel: ndarray, scale: int) -> ndarray:
[11]     """
[12]     :param colorChannel: a 2D ndarray representing a color channel
[13]     :param scale: the scale factor
[14]     :return: a 2D ndarray representing the upsampled color channel
[15]     """
[16]     result = np.full((scale * len(colorChannel), scale * len(colorChannel[0])), -1)
[17]     for i in range(len(colorChannel)):
[18]         for j in range(len(colorChannel[0])):
[19]             result[i * scale][j * scale] = colorChannel[i][j]
[20]     # print(result)
[21]
[22]     for i in range(0, len(result)):
[23]         if result[i][0] == -1:
[24]             continue
[25]         for j in range(0, len(result[0])):
[26]             if j == len(result[0]) - 1 and result[i][j] == -1:
[27]                 result[i][j] = result[i][j - 1]
[28]             elif result[i][j] == -1:
[29]                 result[i][j] = (result[i][j + 1] + result[i][j - 1]) / 2
[30]     # print('====================')
[31]     for i in range(0, len(result)):
[32]         if result[i][0] != -1:
[33]             continue
[34]         for j in range(0, len(result[0])):
[35]             if i == len(result) - 1:
[36]                 result[i][j] = result[i-1][j]
[37]             elif result[i][j] == -1:
[38]                 result[i][j] = (result[i-1][j] + result[i+1][j]) / 2
[39]
[40]     return result
[41]
[42]
[43] def mergeColorChannel(yChanel: ndarray, uChanel: ndarray, vChanel: ndarray) -> ndarray:
[44]     result = np.empty((len(yChanel), len(yChanel[0]),3))
[45]     for i in range(len(yChanel)):
[46]         for j in range(len(yChanel[0])):
[47]             result[i][j][0] = yChanel[i][j]
[48]             result[i][j][1] = uChanel[i][j]
[49]             result[i][j][2] = vChanel[i][j]
[50]     return result
[51]
[52] class YUVImage:
[53]
[54]     def __init__(self, data: ndarray):
[55]         self.data = data
[56]
[57]     # change the YUV channel to RBG channel without using builtin method
[58]     def yuv2bgr(self) -> 'BGRImage':
[59]
[60]         result = np.empty((len(self.data), len(self.data[0]), 3))
[61]         for i in range(len(self.data)):
[62]
[63]             for j in range(len(self.data[i])):
[64]                 y = self.data[i][j][0]
[65]                 u = self.data[i][j][1]
[66]                 v = self.data[i][j][2]
[67]
[68]                 r = round(y + 1.13983 * (v - 128))
[69]                 g = round(y - 0.39465 * (u - 128) - 0.58060 * (v - 128))
[70]                 b = round(y + 2.03211 * (u - 128))
[71]
[72]                 if r > 255:
[73]                     r = 255
[74]                 elif r < 0:
[75]                     r = 0
[76]                 if g > 255:
[77]                     g = 255
```

```
[78]                elif g < 0:
[79]                    g = 0
[80]                if b > 255:
[81]                    b = 255
[82]                elif b < 0:
[83]                    b = 0
[84]
[85]                result[i][j][0] = b
[86]                result[i][j][1] = g
[87]                result[i][j][2] = r
[88]
[89]            # print(i, end=' ')
[90]
[91]        return BGRImage(result)
[92]
[93]    def getYChannel(self) -> ndarray:
[94]        return self.data[:, :, 0]
[95]
[96]    def getUChannel(self) -> ndarray:
[97]        return self.data[:, :, 1]
[98]
[99]    def getVChannel(self) -> ndarray:
[100]       return self.data[:, :, 2]
[101]
[102]   def downSampleY(self) -> ndarray:
[103]       return self.data[::2, ::2, 0]
[104]
[105]   def downSampleU(self) -> ndarray:
[106]       return self.data[::2, ::2, 1]
[107]
[108]   def downSampleV(self) -> ndarray:
[109]       return self.data[::2, ::2, 2]
[110]
[111]
[112]class BGRImage:
[113]
[114]   def __init__(self, data: ndarray):
[115]       self.data = data
[116]
[117]   # change the BGR channel to YUV channel without using
        builtin method
[118]   def bgr2yuv(self) -> YUVImage:
[119]       result = np.empty((len(self.data), len(self.data[0]), 3))
[120]       for i in range(len(self.data)):
[121]
[122]           for j in range(len(self.data[i])):
[123]               b = self.data[i][j][0]
[124]               g = self.data[i][j][1]
[125]               r = self.data[i][j][2]
[126]               # print('b',b,'g',g,'r',r)
[127]               y = round(0.299 * r + 0.587 * g + 0.114 * b)
[128]               u = round(-0.147 * r - 0.289 * g + 0.436 * b + 128)
[129]               v = round(0.615 * r - 0.515 * g - 0.100 * b + 128)
[130]               result[i][j][0] = y
[131]               result[i][j][1] = u
[132]               result[i][j][2] = v
[133]           # print(i, end=' ')
[134]
[135]       return YUVImage(result)
[136]
[137]
[138]
[139]if __name__ == '__main__':
[140]   img = cv2.imread('test.jpg')
[141]   cv2.imshow('test', img)
[142]   bgr_img = BGRImage(img)
[143]   #
[144]   # # change the BGR channel to YUV channel
[145]   cv_img_yuv = cv2.cvtColor(img,
        cv2.COLOR_BGR2YUV)
[146]   my_img_yuv = YUVImage(bgr_img.bgr2yuv().data)
[147]   # cv2.imshow('my_img_yuv', my_img_yuv.data)
[148]
[149]   print(my_img_yuv.data.shape)
[150]
[151]
[152]
[153]   y_downsample = my_img_yuv.downSampleY()
[154]   u_downsample = my_img_yuv.downSampleU()
[155]   v_downsample = my_img_yuv.downSampleV()
[156]
[157]
[158]
[159]
[160]   y_up = bilinearUpsampling(y_downsample, 2)
[161]   u_up = bilinearUpsampling(u_downsample, 4)
[162]   v_up = bilinearUpsampling(v_downsample, 4)
[163]
[164]
[165]   new_yuv_img = YUVImage(mergeColorChannel(y_up,
        u_up, v_up))
[166]
[167]   cv2.imshow('new_yuv_img',
        new_yuv_img.data.astype(np.uint8))
[168]   new_bgr_img = new_yuv_img.yuv2bgr()
[169]
[170]   cv2.imshow('new_img',
        new_bgr_img.data.astype(np.uint8))
[171]   new_bgr_img.data = new_bgr_img.data[ : -1]
[172]   print(new_bgr_img.data.shape)
[173]   MSE =
        1/(len(img)*len(img[0])*3)*np.sum((img.astype("float") -
        new_bgr_img.data.astype("float")) ** 2)
[174]   PSNR = 10*math.log10(255/MSE)
[175]   print('MSE', MSE)
[176]   print('PSNR', PSNR)
[177]
[178]
[179]
    cv2.waitKey(0)
```