Using The Super Resolution Convolutional Neural Network for Image Restoration

In super-resolution (SR) project, we will recover a high resolution image from a low resolution input.

To accomplish this goal, we will be deploying the super-resolution convolution neural network (SRCNN) using Keras. This network was published in the paper, "Image Super-Resolution Using Deep Convolutional Networks" by Chao Dong, et al. in 2014. You can read the full paper at https://arxiv.org/abs/1501.00092 (https://arxiv.org/abs/1501.00092).

The SRCNN is a deep convolutional neural network that learns end-to-end mapping of low resolution to high resolution images. As a result, we can use it to improve the image quality of low resolution images. To evaluate the performance of this network, we will be using three image quality metrics: peak signal to noise ratio (PSNR), mean squared error (MSE), and the structural similarity (SSIM) index.

We will be using OpenCV, the Open Source Computer Vision Library. OpenCV was originally developed by Intel and is used for many real-time computer vision applications. In this particular project, we will be using it to pre and post process our images. As you will see later, we will frequently be converting our images back and forth between the RGB, BGR, and YCrCb color spaces. This is necessary because the SRCNN network was trained on the luminance (Y) channel in the YCrCb color space.

During this project, we will learn how to:

- use the PSNR, MSE, and SSIM image quality metrics,
- process images using OpenCV,
- convert between the RGB, BGR, and YCrCb color spaces,
- build deep neural networks in Keras,
- deploy and evaluate the SRCNN network

In [1]:

```
import sys
import keras
import numpy
import matplotlib
import cv2
import skimage

print('Python: {}'.format(sys.version))
print('Keras: {}'.format(keras.__version__))
print('OpenCV: {}'.format(cv2.__version__))
print('NumPy: {}'.format(numpy.__version__))
print('Matplotlib: {}'.format(matplotlib.__version__))
print('Scikit-Image: {}'.format(skimage.__version__))
```

```
Using Theano backend.

Python: 3.7.6 (default, Jan  8 2020, 20:23:39) [MSC v.1916 64 bit (AMD64)]
Keras: 2.3.1
OpenCV: 3.4.1
NumPy: 1.18.1
Matplotlib: 3.1.3
Scikit-Image: 0.16.2
```

In [9]:

```
# import the necessary packages
from keras.models import Sequential
from keras.layers import Conv2D
from keras.optimizers import Adam
from skimage.measure import compare_ssim as ssim
from matplotlib import pyplot as plt
import cv2
import numpy as np
import math
import os
```

In [10]:

```
# python magic function, displays pyplot figures in the notebook
%matplotlib inline
```

Image Quality Metrics

Functions required:

- PSNR
- MSE
- SSIM

SSIM imported from the scikit-image library; however, we will have to define our own functions for the PSNR and MSE. Furthermore, we will wrap all three of these metrics into a single function that we can call later.

In [11]:

```
# define a function for peak signal-to-noise ratio (PSNR)
def psnr(target,ref):
    target_data=target.astype(float)
    ref_data=ref.astype(float)
    diff=ref_data-target_data
    diff=diff.flatten('C')
    rmse=math.sqrt(np.mean(diff ** 2.))
    return 20 * math.log10(255. / rmse)

# define function for mean squared error (MSE)
def mse(target, ref):
    # the MSE between the two images is the sum of the squared difference between the two i
    err = np.sum((target.astype('float') - ref.astype('float')) ** 2)
    err /= float(target.shape[0] * target.shape[1])
    return err

# define function that combines all three image quality metrics
def compare_images(target, ref):
    scores = []
    scores.append(psnr(target, ref))
    scores.append(mse(target, ref))
    scores.append(ssim(target, ref, multichannel =True))
    return scores
```

Preparing Images

For this project, we will be using the same images that were used in the original SRCNN paper. We can download these images from http://mmlab.ie.cuhk.edu.hk/projects/SRCNN.html (http://mmlab.ie.cuhk.edu.hk/projects/SRCNN.html). The .zip file identified as the MATLAB code contains the images we want. Copy both the Set5 and Set14 datasets into a new folder called 'source'.

Now that we have some images, we want to produce low resolution versions of these same images. We can accomplish this by resizing the images, both downwards and upwards, using OpeCV. There are several interpolation methods that can be used to resize images; however, we will be using bilinear interpolation.

Once we produce these low resolution images, we can save them in a new folder.

In [14]:

```
# prepare degraded images by introducing quality distortions via resizing

def prepare_images(path, factor):

    # loop through the files in the directory
    for file in os.listdir(path):

        # open the file
        img = cv2.imread(path + '/' + file)

        # find old and new image dimensions
        h, w, _ = img.shape
        new_height =int(h / factor)
        new_width =int(w / factor)

        # resize the image - down
        img = cv2.resize(img, (new_width, new_height), interpolation = cv2.INTER_LINEAR)

        # resize the image - up
        img = cv2.resize(img, (w, h), interpolation = cv2.INTER_LINEAR)

        # save the image
        print('Saving {}'.format(file))
        cv2.imwrite('images/{}'.format(file), img)
```

In [15]:

```
prepare_images('source/', 2)
```

```
Saving baboon.bmp
Saving baby_GT.bmp
Saving barbara.bmp
Saving bird_GT.bmp
Saving bridge.bmp
Saving butterfly_GT.bmp
Saving coastguard.bmp
Saving comic.bmp
Saving face.bmp
Saving flowers.bmp
Saving foreman.bmp
Saving head_GT.bmp
Saving lenna.bmp
Saving man.bmp
Saving monarch.bmp
Saving pepper.bmp
Saving ppt3.bmp
Saving woman_GT.bmp
Saving zebra.bmp
```

Testing Low Resolution Images

To ensure that our image quality metrics are being calculated correctly and that the images were effectively degraded, lets calculate the PSNR, MSE, and SSIM between our reference images and the degraded images that we just prepared.

In [16]:

```
# test the generated images using the image quality metrics

for file in os.listdir('images/'):

    # open target and reference images
    target = cv2.imread('images/{}'.format(file))
    ref = cv2.imread('source/{}'.format(file))

    # calculate score
    scores = compare_images(target, ref)

    # print all three scores with new line characters (\n)
    print('{}\nPSNR: {}\nMSE: {}\nSSIM: {}\n'.format(file, scores[0], scores[1], scores[2]))
```

```
C:\Users\balsh\anaconda3\lib\site-packages\ipykernel_launcher.py:22: UserWar
ning: DEPRECATED: skimage.measure.compare_ssim has been moved to skimage.met
rics.structural_similarity. It will be removed from skimage.measure in versi
on 0.18.

baboon.bmp
PSNR: 22.157084083442548
MSE: 1187.1161333333334
SSIM: 0.629277587900277

baby_GT.bmp
PSNR: 34.37180640966199
MSE: 71.28874588012695
SSIM: 0.9356987872724932

barbara.bmp
PSNR: 25.906629837568126
MSE: 500.65508535879627
SSIM: 0.8098632646406401

bird_GT.bmp
PSNR: 32.896644728720005
MSE: 100.12375819830247
SSIM: 0.9533644866026473

bridge.bmp
PSNR: 25.850528790115554
MSE: 507.1643714904785
SSIM: 0.7804245912255268

butterfly_GT.bmp
PSNR: 24.782076560337416
MSE: 648.6254119873047
SSIM: 0.8791344763843051

coastguard.bmp
PSNR: 27.161600663887082
MSE: 375.00887784090907
SSIM: 0.756950063354931

comic.bmp
PSNR: 23.799861502225532
MSE: 813.2338836565096
SSIM: 0.8347335416398209
```

```
face.bmp
PSNR: 30.99220650287191
MSE: 155.23189718546524
SSIM: 0.8008439492289884

flowers.bmp
PSNR: 27.454504805386147
MSE: 350.55093922651935
SSIM: 0.8697286286974628

foreman.bmp
PSNR: 30.14456532664372
MSE: 188.6883483270202
SSIM: 0.933268417388899

head_GT.bmp
PSNR: 31.020502848237534
MSE: 154.2237755102041
SSIM: 0.8011121330733371

lenna.bmp
PSNR: 31.47349297867539
MSE: 138.94800567626953
SSIM: 0.8460989200521499

man.bmp
PSNR: 27.22646369798821
MSE: 369.4496383666992
SSIM: 0.8214950645456561

monarch.bmp
PSNR: 30.196242365288896
MSE: 186.45643615722656
SSIM: 0.9439574293434104

pepper.bmp
PSNR: 29.88947161686106
MSE: 200.1033935546875
SSIM: 0.8357937568464359

ppt3.bmp
PSNR: 24.84926168950471
MSE: 638.6684263912582
SSIM: 0.9284023942315316

woman_GT.bmp
PSNR: 29.326236280817465
MSE: 227.812729498164
SSIM: 0.9335397280466592

zebra.bmp
PSNR: 27.909840639329513
MSE: 315.6585459528818
SSIM: 0.8911656209329116
```

Building the SRCNN Model

Now that we have our low resolution images and all three image quality metrics functioning properly, we can start building the SRCNN. In Keras, it's as simple as adding layers one after the other. The achitecture and hyper parameters of the SRCNN network can be obtained from the publication referenced above.

In [17]:

```
# define the SRCNN model
def model():

    # define model type
    SRCNN = Sequential()

    # add model layers
    SRCNN.add(Conv2D(filters=128, kernel_size = (9, 9), kernel_initializer='glorot_uniform'
                     activation='relu', padding='valid', use_bias=True, input_shape=(None,
    SRCNN.add(Conv2D(filters=64, kernel_size = (3, 3), kernel_initializer='glorot_uniform',
                     activation='relu', padding='same', use_bias=True))
    SRCNN.add(Conv2D(filters=1, kernel_size = (5, 5), kernel_initializer='glorot_uniform',
                     activation='linear', padding='valid', use_bias=True))

    # define optimizer
    adam = Adam(lr=0.0003)

    # compile model
    SRCNN.compile(optimizer=adam, loss='mean_squared_error', metrics=['mean_squared_error']

    return SRCNN
```

Deploying the SRCNN

Now that we have defined our model, we can use it for single-image super-resolution. However, before we do this, we will need to define a couple of image processing functions. Furthermore, it will be necessary to preprocess the images extensively before using them as inputs to the network. This processing will include cropping and color space conversions.

Additionally, to save us the time it takes to train a deep neural network, we will be loading pre-trained weights for the SRCNN. These weights can be found at the following GitHub page: https://github.com/MarkPrecursor/SRCNN-keras (https://github.com/MarkPrecursor/SRCNN-keras)

Once we have tested our network, we can perform single-image super-resolution on all of our input images. Furthermore, after processing, we can calculate the PSNR, MSE, and SSIM on the images that we produce. We can save these images directly or create subplots to conveniently display the original, low resolution, and high resolution images side by side.

In [21]:

```
# define necessary image processing functions

def modcrop(img, scale):
    tmpsz = img.shape
    sz = tmpsz[0:2]
    sz = sz - np.mod(sz, scale)
    img = img[0:sz[0], 1:sz[1]]
    return img


def shave(image, border):
    img = image[border: -border, border: -border]
    return img
```

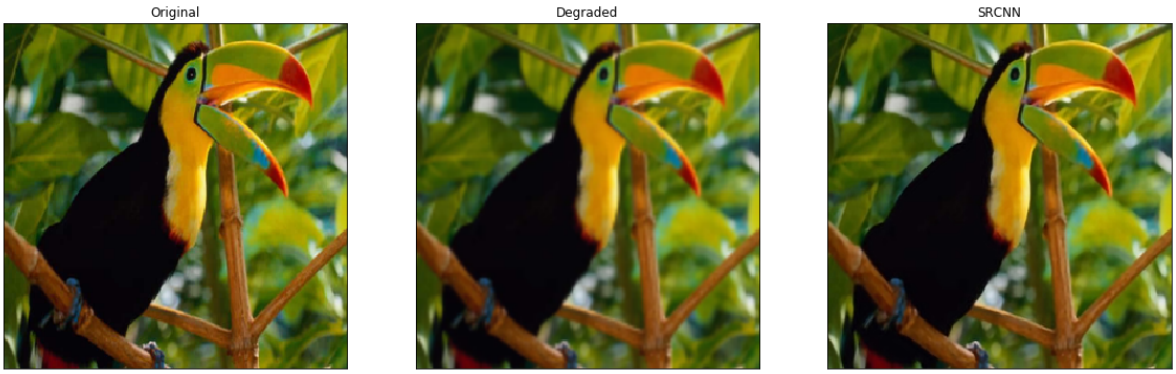
In [22]:

```
# define main prediction function

def predict(image_path):

    # load the srcnn model with weights
    srcnn = model()
    srcnn.load_weights('3051crop_weight_200.h5')

    # load the degraded and reference images
    path, file = os.path.split(image_path)
    degraded = cv2.imread(image_path)
    ref = cv2.imread('source/{}'.format(file))

    # preprocess the image with modcrop
    ref = modcrop(ref, 3)
    degraded = modcrop(degraded, 3)

    # convert the image to YCrCb - (srcnn trained on Y channel)
    temp = cv2.cvtColor(degraded, cv2.COLOR_BGR2YCrCb)

    # create image slice and normalize
    Y = numpy.zeros((1, temp.shape[0], temp.shape[1], 1), dtype=float)
    Y[0, :, :, 0] = temp[:, :, 0].astype(float) / 255

    # perform super-resolution with srcnn
    pre = srcnn.predict(Y, batch_size=1)

    # post-process output
    pre *= 255
    pre[pre[:] > 255] = 255
    pre[pre[:] < 0] = 0
    pre = pre.astype(np.uint8)

    # copy Y channel back to image and convert to BGR
    temp = shave(temp, 6)
    temp[:, :, 0] = pre[0, :, :, 0]
    output = cv2.cvtColor(temp, cv2.COLOR_YCrCb2BGR)

    # remove border from reference and degraged image
    ref = shave(ref.astype(np.uint8), 6)
    degraded = shave(degraded.astype(np.uint8), 6)

    # image quality calculations
    scores = []
    scores.append(compare_images(degraded, ref))
    scores.append(compare_images(output, ref))

    # return images and scores
    return ref, degraded, output, scores
```

In [27]:

```
ref, degraded, output, scores = predict('images/bird_GT.bmp')

# print all scores for all images
print('Degraded Image: \nPSNR: {}\nMSE: {}\nSSIM: {}\n'.format(scores[0][0], scores[0][1],
print('Reconstructed Image: \nPSNR: {}\nMSE: {}\nSSIM: {}\n'.format(scores[1][0], scores[1]


# display images as subplots
fig, axs = plt.subplots(1, 3, figsize=(20, 8))
axs[0].imshow(cv2.cvtColor(ref, cv2.COLOR_BGR2RGB))
axs[0].set_title('Original')
axs[1].imshow(cv2.cvtColor(degraded, cv2.COLOR_BGR2RGB))
axs[1].set_title('Degraded')
axs[2].imshow(cv2.cvtColor(output, cv2.COLOR_BGR2RGB))
axs[2].set_title('SRCNN')

# remove the x and y ticks
for ax in axs:
    ax.set_xticks([])
    ax.set_yticks([])
```

```
C:\Users\balsh\anaconda3\lib\site-packages\ipykernel_launcher.py:22: UserWar
ning: DEPRECATED: skimage.measure.compare_ssim has been moved to skimage.met
rics.structural_similarity. It will be removed from skimage.measure in versi
on 0.18.

Degraded Image:
PSNR: 32.9717779215716
MSE: 98.40650856389986
SSIM: 0.9532838164378017

Reconstructed Image:
PSNR: 36.541211848724025
MSE: 43.25939393939394
SSIM: 0.9692203832304317
```



In [24]:

```
for file in os.listdir('images'):

    # perform super-resolution
    ref, degraded, output, scores = predict('images/{}'.format(file))

    # display images as subplots
    fig, axs = plt.subplots(1, 3, figsize=(20, 8))
    axs[0].imshow(cv2.cvtColor(ref, cv2.COLOR_BGR2RGB))
    axs[0].set_title('Original')
    axs[1].imshow(cv2.cvtColor(degraded, cv2.COLOR_BGR2RGB))
    axs[1].set_title('Degraded')
    axs[1].set(xlabel = 'PSNR: {}\nMSE: {} \nSSIM: {}'.format(scores[0][0], scores[0][1], s
    axs[2].imshow(cv2.cvtColor(output, cv2.COLOR_BGR2RGB))
    axs[2].set_title('SRCNN')
    axs[2].set(xlabel = 'PSNR: {} \nMSE: {} \nSSIM: {}'.format(scores[1][0], scores[1][1],

    # remove the x and y ticks
    for ax in axs:
        ax.set_xticks([])
        ax.set_yticks([])

    print('Saving {}'.format(file))
    fig.savefig('output/{}.png'.format(os.path.splitext(file)[0]))
    plt.close()
```

```
C:\Users\balsh\anaconda3\lib\site-packages\ipykernel_launcher.py:22: UserWar
ning: DEPRECATED: skimage.measure.compare_ssim has been moved to skimage.met
rics.structural_similarity. It will be removed from skimage.measure in versi
on 0.18.

Saving baboon.bmp
Saving baby_GT.bmp
Saving barbara.bmp
Saving bird_GT.bmp
Saving bridge.bmp
Saving butterfly_GT.bmp
Saving coastguard.bmp
Saving comic.bmp
Saving face.bmp
Saving flowers.bmp
Saving foreman.bmp
Saving head_GT.bmp
Saving lenna.bmp
Saving man.bmp
Saving monarch.bmp
Saving pepper.bmp
Saving ppt3.bmp
Saving woman_GT.bmp
Saving zebra.bmp
```