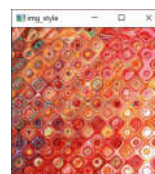
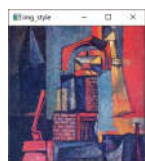


Python编程与人工智能实践

应用篇：基于tflite的图像风格迁移



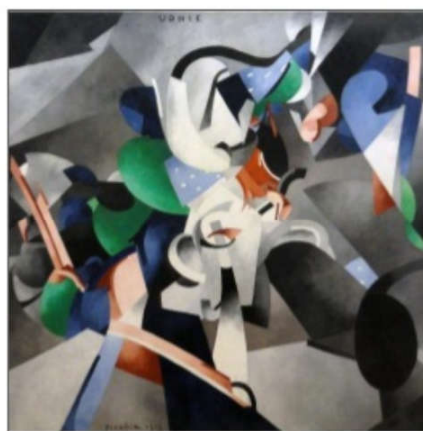
于泓
鲁东大学
信息与电气工程学院
2021.5.22

风格迁移

图像风格迁移是近年来深度神经网络技术发展的一个有趣的新方向，利用深度神经网络可以将一张图像的风格转换成另外一种风格，即所谓的模仿混合画（**pastiche**）。



Content



Style



Pastiche

风格迁移的过程

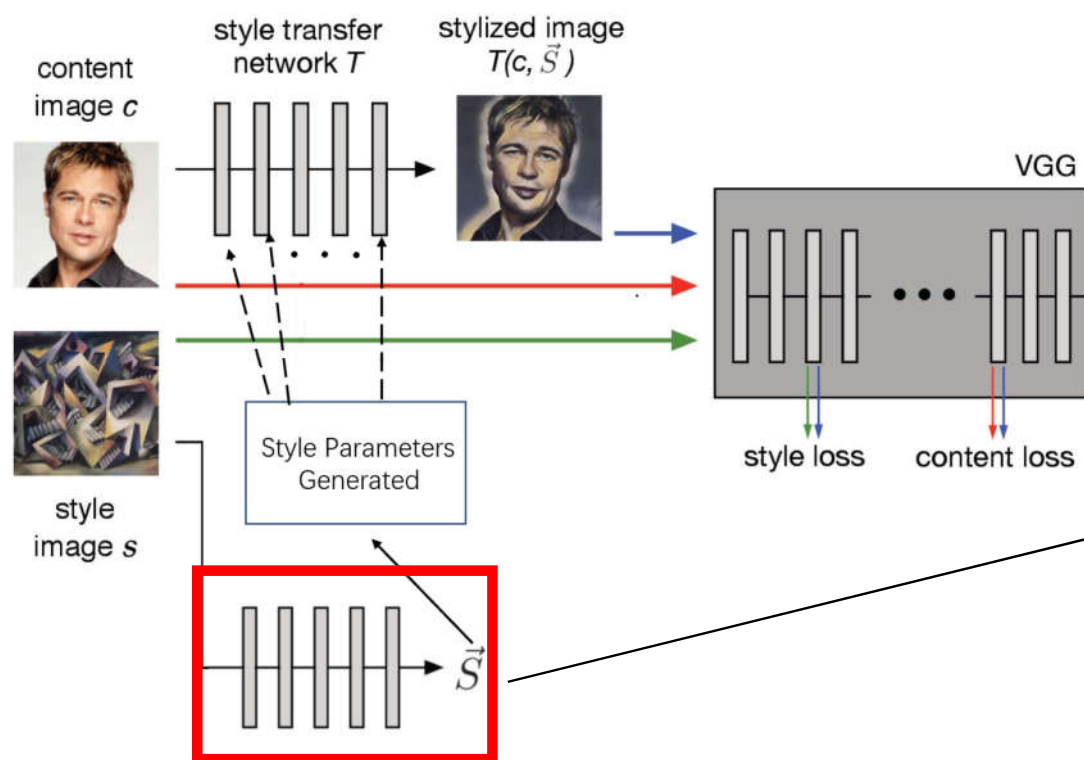


不同风格迁移的效果

风格迁移的基本原理

参考文献: Exploring the structure of a real-time, arbitrary neural artistic stylization network

特点: 可以实现对未经训练的风格图像进行迁移, 并且可以人工的控制迁移的比重。

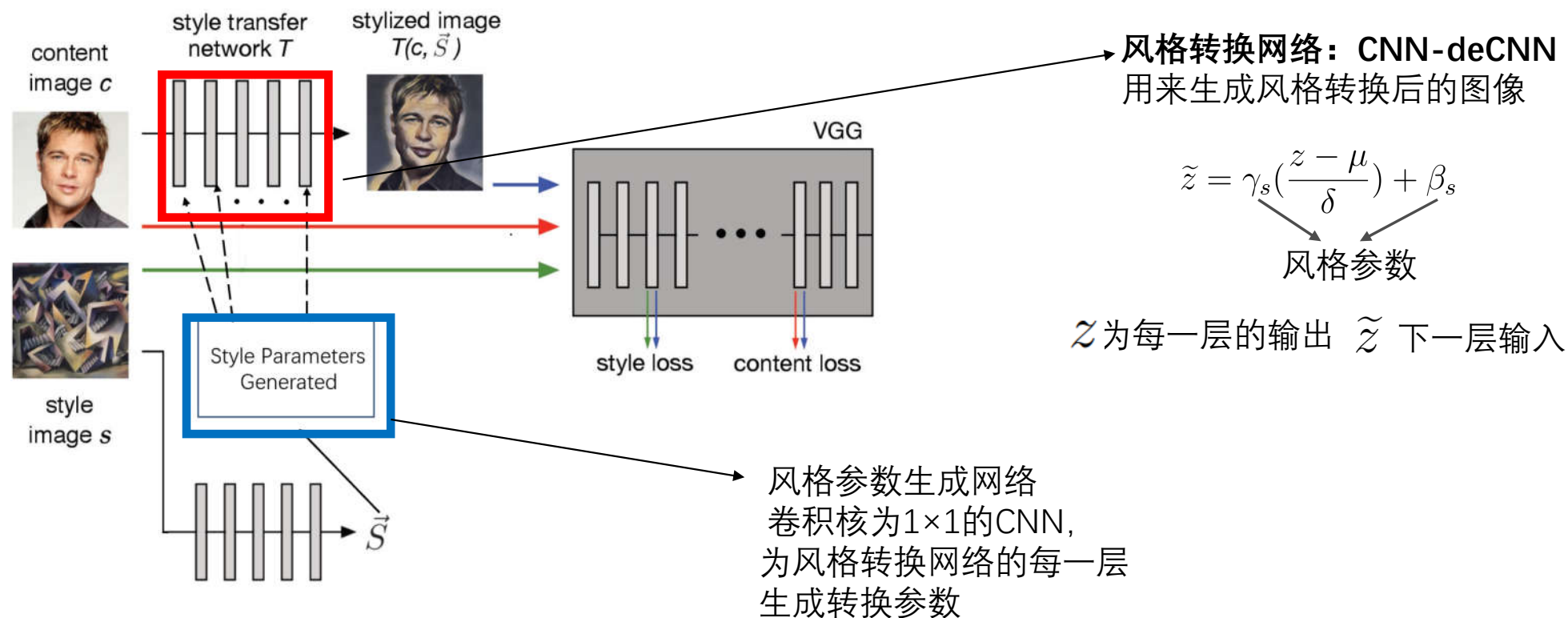


风格特征生成网络
用来生成风格特征矢量 \vec{S}

风格迁移的基本原理

参考文献: Exploring the structure of a real-time, arbitrary neural artistic stylization network

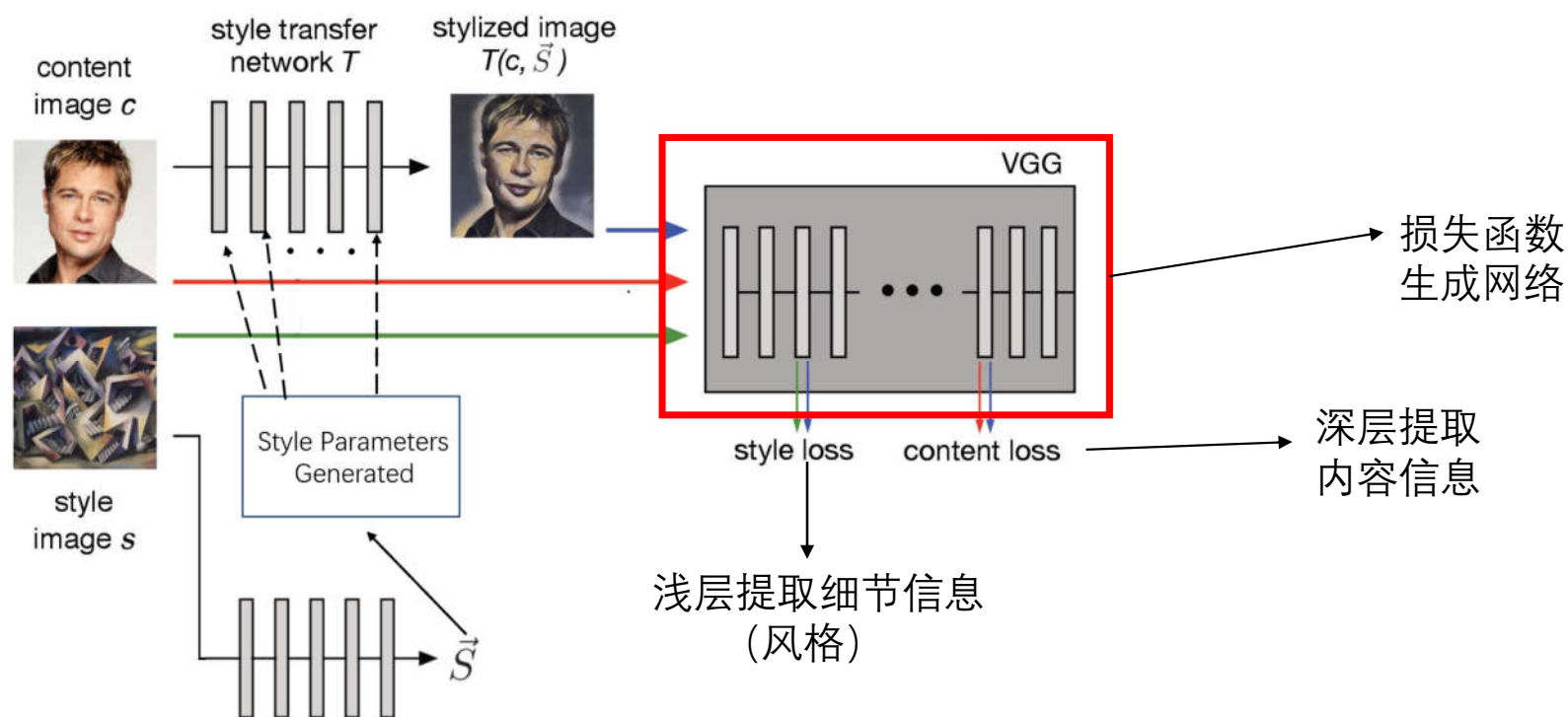
特点: 可以实现对未经训练的风格图像进行迁移, 并且可以人工的控制迁移的比重。



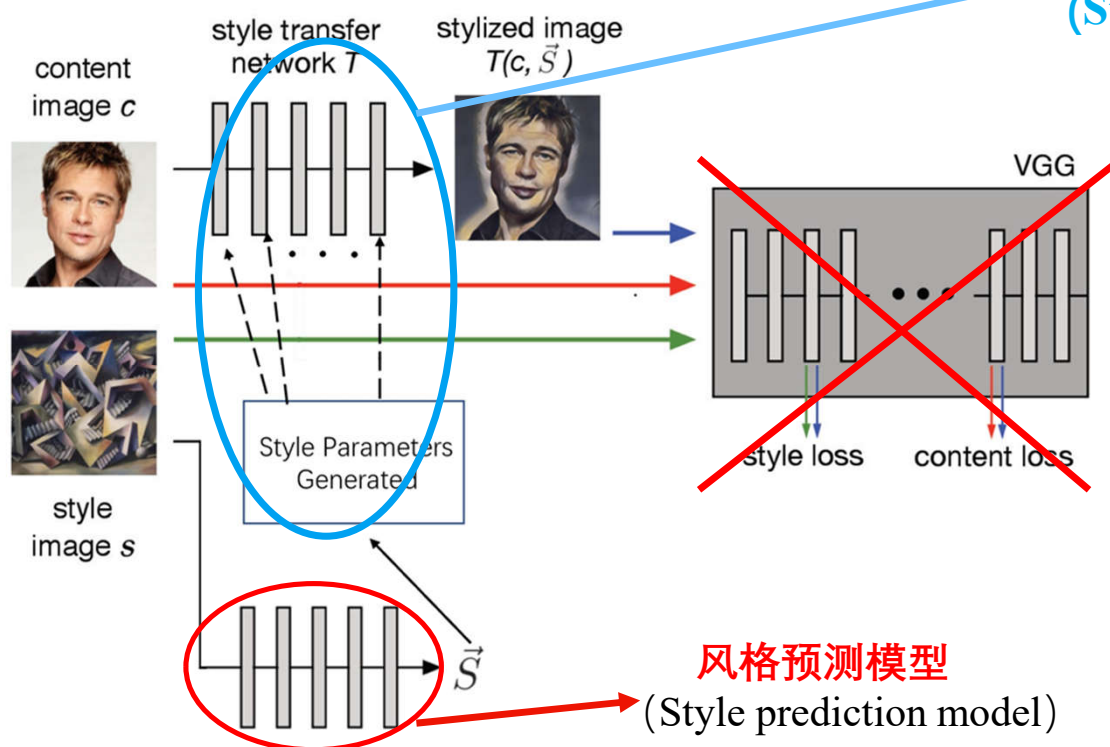
风格迁移的基本原理

参考文献: Exploring the structure of a real-time, arbitrary neural artistic stylization network

特点: 可以实现对未经训练的风格图像进行迁移, 并且可以人工的控制迁移的比重。



风格迁移模型 (Style transform model)

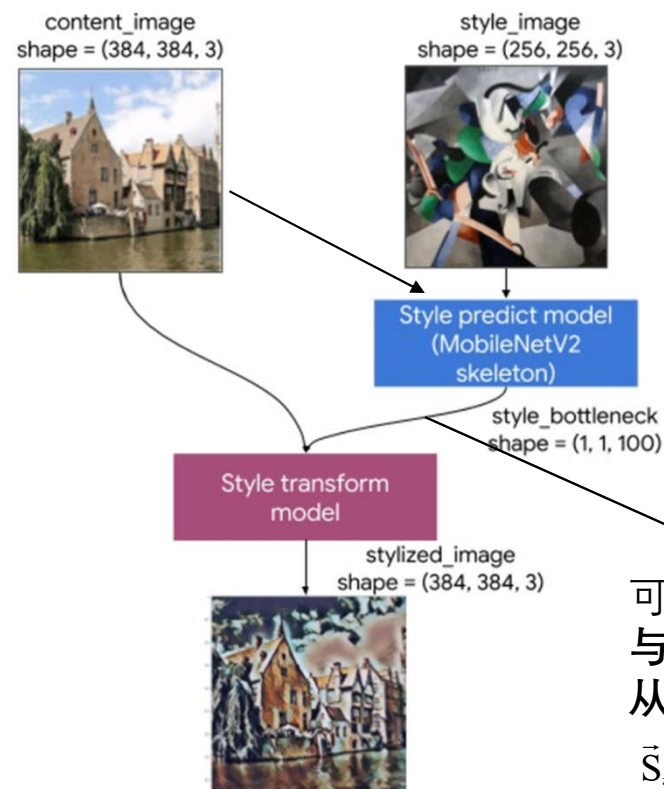
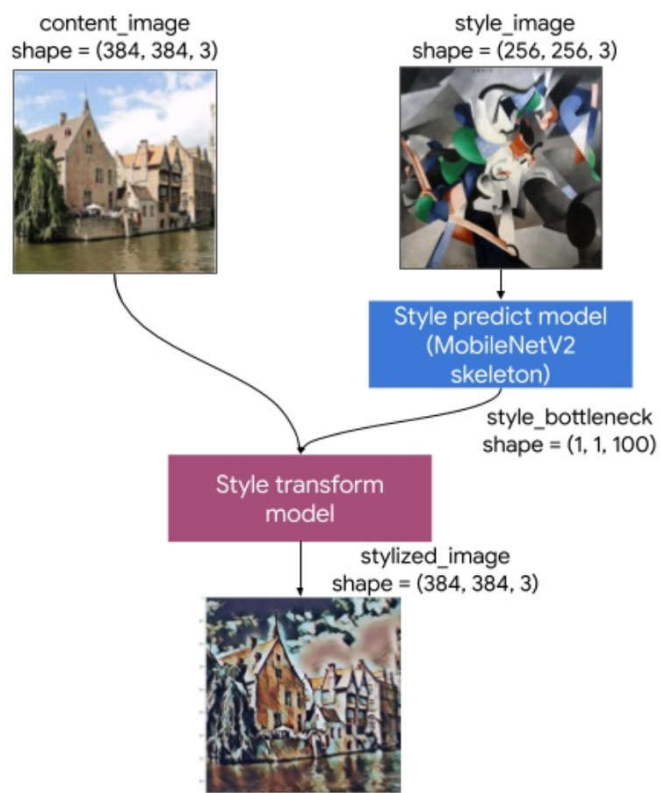


下载地址:

<https://tfhub.dev/google/lite-model/magenta/arbitrary-image-stylization-v1-256/int8/transfer/1?lite-format=tflite>

下载地址: <https://tfhub.dev/google/lite-model/magenta/arbitrary-image-stylization-v1-256/int8/prediction/1?lite-format=tflite>

风格转换过程



可以将**内容的风格矢量**
与**风格的风格矢量**融合
从而调整风格的比重

$$\vec{S}_{\text{输入}} = \alpha \vec{S}_{\text{风格}} + (1-\alpha) \vec{S}_{\text{内容}}$$

模型信息提取

```
# 风格特征提取模型
file_model_prediction = "model/magenta_arbitrary-image-stylization-v1-256_int8_prediction_1.tflite"

# 风格转换模型
file_model_transfer = "model/magenta_arbitrary-image-stylization-v1-256_int8_transfer_1.tflite"

# 加载模型
print("model_prediction")
interpreter = tf.lite.Interpreter(model_path=file_model_prediction)
interpreter.allocate_tensors()
# 获取输入信息
input_details = interpreter.get_input_details()
print("input_details",input_details)
output_details = interpreter.get_output_details()
print("output_details",output_details)

# 加载模型
print("model_transfer")
interpreter = tf.lite.Interpreter(model_path=file_model_transfer)
interpreter.allocate_tensors()
# 获取输入信息
input_details = interpreter.get_input_details()
print("input_details",input_details)
output_details = interpreter.get_output_details()
print("output_details",output_details)
```

model_prediction 风格特征提取网络

```
input_details
[{'name': 'style_image', 'index': 172, 'shape': array([ 1, 256, 256, 3]),
  'shape_signature': array([ 1, 256, 256, 3]), 'dtype': <class 'numpy.float32'>,
  'quantization': (0.0, 0), 'quantization_parameters': {'scales': array([], dtype=float32),
  'zero_points': array([], dtype=int32), 'quantized_dimension': 0}, 'sparsity_parameters': {}}]

outputdetails
[{'name': 'mobilenet_conv/Conv/BiasAdd', 'index': 173, 'shape': array([ 1, 1, 1, 100]),
  'shape_signature': array([ 1, 1, 1, 100]), 'dtype': <class 'numpy.float32'>,
  'quantization': (0.0, 0), 'quantization_parameters': {'scales': array([], dtype=float32),
  'zero_points': array([], dtype=int32), 'quantized_dimension': 0}, 'sparsity_parameters': {}}]
```

输入图像大小

数据格式
取值范围 [0,1] data/255.0

输出特征 100维

model_transfer 风格转换网络

```
input_details
[{'name': 'content_image', 'index': 0, 'shape': array([ 1, 384, 384, 3]),
  'shape_signature': array([ 1, 384, 384, 3]), 'dtype': <class 'numpy.float32'>,
  'quantization': (0.0, 0), 'quantization_parameters': {'scales': array([], dtype=float32),
  'zero_points': array([], dtype=int32), 'quantized_dimension': 0}, 'sparsity_parameters': {}},

{'name': 'mobilenet_conv/Conv/BiasAdd', 'index': 428, 'shape': array([ 1, 1, 1, 100]),
  'shape_signature': array([ 1, 1, 1, 100]), 'dtype': <class 'numpy.float32'>,
  'quantization': (0.0, 0), 'quantization_parameters': {'scales': array([], dtype=float32),
  'zero_points': array([], dtype=int32), 'quantized_dimension': 0}, 'sparsity_parameters': {}}]

outputdetails
[{'name': 'transformer/expand/conv3/conv/Sigmoid',
  'index': 429, 'shape': array([ 1, 384, 384, 3]),
  'shape_signature': array([ 1, 384, 384, 3]), 'dtype': <class 'numpy.float32'>,
  'quantization': (0.0, 0), 'quantization_parameters': {'scales': array([], dtype=float32),
  'zero_points': array([], dtype=int32), 'quantized_dimension': 0}, 'sparsity_parameters': {}}]
```

输入图像大小

数据格式
取值范围 [0,1] data/255.0

风格特征矢量

输出图像大小

输出值的范围为[0,1]
*255转为像素值

一 风格特征提取

fea_style
img_style
model

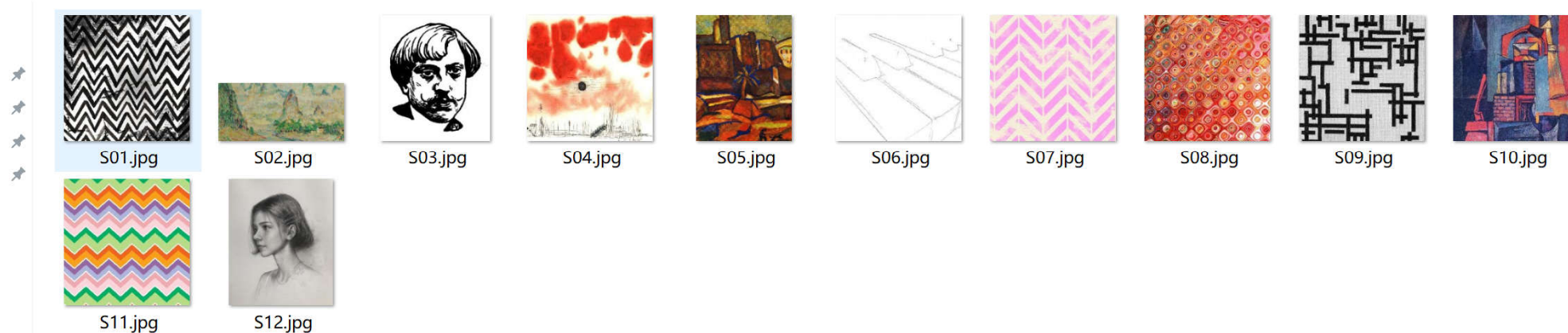


三个文件夹，分别用来存储，风格图片 (img_style)
风格特征 (fea_style)
下载模型 (model)

采集一些风格图片保存到img_style文件夹
(没有什么特别要求，可以到百度图片搜索纹理)

此电脑 > Data (D:) > 工作相关 > 我设计的课程 > python与人工智能课程设计 > 应用篇 > style_trans > img_style

搜索"img_style"



collect_fea_style.py

```
import numpy as np
import cv2
import tflite_runtime.interpreter as tflite
import os

# 风格特征提取模型
file_model_prediction = "model/magenta_arbitrary-image-stylization-v1-256_int8_prediction_1.tflite"
base_path = "img_style"

def img_preprocessing(img, size_output):
    # 获取图像的尺寸
    imH, imW, _ = np.shape(img)

    # BGR 转RGB
    img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

    # 尺寸缩放适应网络输入要求
    img_resized = cv2.resize(img_rgb, size_output)

    # 维度扩张适应网络输入要求
    input_data = np.expand_dims(img_resized, axis=0)

    # 正则化变为 0-1之间
    input_data = input_data/255.0

    return (imW, imH), np.float32(input_data)
```

图像预处理

风格特征提取

```
# 从风格图片中提取风格特征矢量.
def run_style_predict(file_model_prediction,img):

    # 加载模型
    interpreter = tf.lite.Interpreter(model_path=file_model_prediction)
    interpreter.allocate_tensors()

    # 获取输入的数据的信息
    input_details = interpreter.get_input_details()

    # 获取输入图像的高和宽
    height = input_details[0]['shape'][1]
    width = input_details[0]['shape'][2]

    # 对图像进行预处理
    t,preprocessed_style_image = img_preprocessing(img,(width,height))

    # 特征输入网络
    interpreter.set_tensor(input_details[0]["index"], preprocessed_style_image)

    # 获取模型矢量.
    interpreter.invoke()

    style_bottleneck = interpreter.tensor(interpreter.get_output_details()[0]["index"])(0)

    return style_bottleneck
```

```
if __name__ == "__main__":
    # 遍历文件夹
    for f_img in os.listdir(base_path):
        # 遍历所有以.jpg为后缀的文件
        if os.path.splitext(f_img)[-1] == ".jpg":
            str_style = os.path.splitext(f_img)[0]
            print(str_style)
            f_img = os.path.join(base_path, f_img)

            # 提取风格特征
            style_bottleneck = run_style_predict(file_model_prediction, cv2.imread(f_img))

            # 特征保存
            print('save style feature of image %s as %s.npz'%(f_img, os.path.join('fea_style', str_style)))













            np.savez(os.path.join('fea_style', str_style), fea = style_bottleneck)
```

```
PS D:\工作相关\我设计的课程\python与人工智能课程设计\应用篇\style_trans> python collect_fea_style.py
S01
save style feature of image img_style\S01.jpg as fea_style\S01.npz
S02
save style feature of image img_style\S02.jpg as fea_style\S02.npz
S03
save style feature of image img_style\S03.jpg as fea_style\S03.npz
S04
save style feature of image img_style\S04.jpg as fea_style\S04.npz
S05
save style feature of image img_style\S05.jpg as fea_style\S05.npz
S06
save style feature of image img_style\S06.jpg as fea_style\S06.npz
S07
save style feature of image img_style\S07.jpg as fea_style\S07.npz
S08
save style feature of image img_style\S08.jpg as fea_style\S08.npz
S09
save style feature of image img_style\S09.jpg as fea_style\S09.npz
S10
save style feature of image img_style\S10.jpg as fea_style\S10.npz
S11
save style feature of image img_style\S11.jpg as fea_style\S11.npz
S12
save style feature of image img_style\S12.jpg as fea_style\S12.npz
```

父子 信息

此电脑 > Data (D:) > 工作

名称

-  S01.npz
-  S02.npz
-  S03.npz
-  S04.npz
-  S05.npz
-  S06.npz
-  S07.npz
-  S08.npz
-  S09.npz
-  S10.npz
-  S11.npz
-  S12.npz

二、风格转换

```
import numpy as np
import cv2
import tfLite_runtime.interpreter as tflite
import os
from collect_fea_style import img_preprocessing, run_style_predict

# 风格特征提取模型
file_model_prediction = "model/magenta_arbitrary-image-stylization-v1-256_int8_prediction_1.tflite"
# 风格转换模型
file_model_transfer = "model/magenta_arbitrary-image-stylization-v1-256_int8_transfer_1.tflite"
# 进行风格转换 输入风格矢量 、 风格转换模型 、

def run_style_transform(file_model_transfer, style_bottleneck, content_image):
    im_H, im_W, _ = np.shape(content_image)

    # 加载模型
    interpreter = tflite.Interpreter(model_path=file_model_transfer)
    interpreter.allocate_tensors()

    # 获取输入信息
    input_details = interpreter.get_input_details()

    # 获取输入图像的高和宽
    height = input_details[0]['shape'][1]
    width = input_details[0]['shape'][2]

    # 对内容图像进行预处理
    t, preprocessed_content_image = img_preprocessing(content_image, (width, height))

    # 将数据送入模型.
    interpreter.set_tensor(input_details[0]["index"], preprocessed_content_image)
    interpreter.set_tensor(input_details[1]["index"], style_bottleneck)
    interpreter.invoke()
```

```
# 得到风格变换后的图像.
stylized_image = interpreter.tensor(interpreter.get_output_details()[0]["index"]())

# 将输出从0-1 转为 0-255 浮点转uint8
stylized_image = np.uint8(stylized_image*255)
stylized_image = np.squeeze(stylized_image)
# RGB 转 BGR
stylized_image = cv2.cvtColor(stylized_image, cv2.COLOR_RGB2BGR)
stylized_image = cv2.resize(stylized_image, (im_W, im_H))
return stylized_image

if __name__ == "__main__":
    # 加载风格特征
    path_fea_style = 'fea_style'
    path_img_style = "img_style"
    str_style = 'S10'
    style_fea = np.load(os.path.join(path_fea_style, str_style+'.npz'))['fea']

    # 显示风格图片
    img_style = cv2.imread(os.path.join(path_img_style, str_style+'.jpg'))
    cv2.imshow("img_style", img_style)

    # 读取原始图像
    img = cv2.imread("test.jpg")
    # 获取图像帧的尺寸
    imH, imW, _ = np.shape(img)
    # 适当缩放
    img = cv2.resize(img, (int(imW*0.8), int(imH*0.8)))
    cv2.imshow("img", img)
```

显示风格图像

显示原始图像


```
# 获取内容图像的风格特征
content_fea = run_style_predict(file_model_prediction,img)

# 设置风格比例
ratio =20
mix_fea = ratio*0.01*style_fea +(1-ratio*0.01)*content_fea

print("start processing Style=%s ratio=%d%%"%(str_style,ratio))
stylized_image = run_style_transform(file_model_transfer,mix_fea, img)
print("processing end")
cv2.putText(stylized_image,'Style: %s ratio:%d'%(str_style,ratio),
            (5,30),cv2.FONT_HERSHEY_SIMPLEX,
            0.8,(255,255,0),1,cv2.LINE_AA)

cv2.imshow('style', stylized_image)
```

内容图片风格与
风格图片风格融合

显示风格化后的图像

```
flag = 0
while True:
    if flag:
        # 进行风格转换
        print("start processing Style=%s ratio=%d%%"%(str_style,ratio))
        stylized_image = run_style_transform(file_model_transfer,mix_fea, img)
        cv2.putText(stylized_image,'Style: %s ratio:%d'%(str_style,ratio),(5,30),
                    cv2.FONT_HERSHEY_SIMPLEX,0.8,(255,255,0),1,cv2.LINE_AA)
        print("processing end")
        flag =0

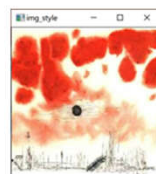
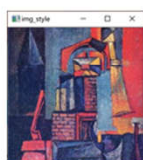
    # 显示结果
    cv2.imshow('style', stylized_image)
    # 获取按键
    key=cv2.waitKey(10) & 0xFF

    # 按s 切换风格
    if key == ord('s'):
        str_style = input('Enter your style name:')
        file_style = os.path.join(path_fea_style,str_style+'.npz')
        if not os.path.exists(file_style):
            print('Can not find ' + file_style)
        else:
            img_style = cv2.imread(os.path.join(path_img_style,str_style+'.jpg'))
            cv2.imshow("img_style",img_style)

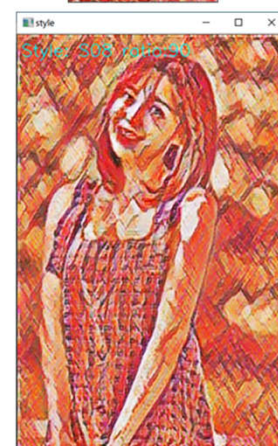
            style_fea = np.load(file_style)['fea']
            mix_fea = ratio*0.01*style_fea +(1-ratio*0.01)*content_fea
            flag = 1
            key =0
    elif key == ord('r'):
        str_ratio = input('Enter your style ratio:')
        ratio = float(str_ratio)
        mix_fea = ratio*0.01*style_fea +(1-ratio*0.01)*content_fea
        flag = 1
    elif key == ord('q'):
        break
```



原始图像



风格图像



风格转换
后图像