SmallSEOTools

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1.3 LITERATURE SURVEY
1.3.1 Image Colorization
1.3.1.1 Hint Based Colorization
[2] proposed using colorization hints from the user in a quadratic cost function which imposed that neighboring pixels in space-time with similar intensities should have similar colours. This was a simple but effective method but only had hints which were provided in form of imprecise colored scribbles on the grayscale input image. But with no additional information about the image, the method was able to efficiently generate high quality colorizations. [3] addressed the color bleeding issue faced in this approach and solved it using adaptive edge detection. [4] used luminescence based weighting for hints to boost efficiency. [5] extended the original cost function to apply color continuity over similar textures along with intensities.
[6] had proposed another approach that reduced the burden on the user by only requiring a full color example of an image with similar composition. It matched the texture and luminescence between the example and the target grayscale image and received realistic results as long as the example image was sufficiently similar.
Regardless of the scribble based or example based approach, the algorithms still needed sufficient human assistance in form of hand drawn or colorized images.
1.3.1.2 Deep Colorization
Owing to recent advances, the Convolutional Neural Networks are a de facto standard for solving image classification problems and their popularity continues to rise with continual improvements. CNNs are peculiar in their ability to learn and differentiate colors, patterns and shapes within an image and their ability to associate them with different classes.
[7] proposed a per pixel training for neural networks using DAISY [8], and semantic [9] features to predict the chrominance value for each pixel, that used bilateral filtering to smooth out accidental image artifacts. With a large enough dataset, this method proved to be superior to the example based techniques even with a simple Euclidean loss function against the ground truth values.
Finally, [10] successfully implemented a system to automatically colorize black & white images using several ImageNet-trained layers from VGG-16 [11] and integrating them with auto-encoders that contained residual connections. These residual connections merged the outputs produced by the encoding VGG16 layers and the decoding portion of the network in the later stages. [12] showed that deeper neural networks can be trained by reformulating layers to learn residual function with reference to layer inputs. Using this Residual Connections, [12] created the ResNets that went as deep as 152 layers and won the 2015 ImageNet Challenge.
1.3.1.3 Generative Adversarial Networks
[13] introduced the adversarial framework that provides an approach to training a neural network which uses the generative distribution of pg(x) over the input data

x.
Since it’s inception in 2015, many extended works of GAN have been proposed over years including DCGAN [14], Conditional-GAN [15], iGAN [16], Pix2Pix [17].
[14] applied the adversarial framework for training convolutional neural networks as generative models for images, demonstrating the viability of deep convolutional generative adversarial networks.
DCGAN is the standard architecture to generate images from random noise. Instead of generating images from random noise, Conditional-GAN [15] uses a condition to generate output image. For e.g. a grayscale image is the condition for colorization of image. Pix2Pix [17] is a Conditional-GAN with images as the conditions.
The network can learn a mapping from input image to output image and also learn a separate loss function to train this mapping. Pix2Pix is considered to be the state of the art architecture for image-image translation problems like colorization.
1.3.2 Image Upscaling
1.3.2.1 Frequency-domain-based SR image approach
[18] proposed the frequency domain SR method, where SR computation was considered for the noise free low resolution images. They transformed the low resolution images into Discrete Fourier transform (DFT) and further combined it as per the relationship between the aliased DFT coefficient of the observed low resolution image and that of unknown high resolution image. Then the output is transformed back into the spatial domain where a higher resolution is now achieved.
While Frequency-domain-based SR extrapolates high frequeny information from the low resolution images and is thus useful, however they fall short in real world applications.
1.3.2.2 The interpolation based SR image approach
The interpolation-based SR approach constructs a high resolution image by casting all the low resolution images to the reference image and then combining all the information available from every image available. The method consists of the following three stages (i) the registration stage for aligning the low-resolution input images, (ii) the interpolation stage for producing a higher-resolution image, and (iii) the deblurring stage which enhances the reconstructed high-resolution image produced in the step ii).
However, as each low resolution image adds a few new details before finally deblurring them, this method cannot be used if only a single reference image is available.
1.3.2.3 Regularization-based SR image approach
Most known Bayesian-based SR approaches are maximum likelihood (ML) estimation approach and maximum a posterior (MAP) estimation approach.
While [19] proposed the first ML estimation based SR approach with the aim to find the ML estimation of high resolution image, some proposed a MAP estimation approach. MAP SR tries to takes into consideration the prior image model to reflect the expectation of the unknown high resolution image.
1.3.2.4 Super Resolution - Generative Adversarial Networks (SR-GAN)
The Genrative Adversarial Network [13], has two neural networks, the Generator and the Discriminator. These networks compete with each other in a zero-sum game. [20] introduced SRGAN in 2017, which used a SRResNet to upscale images with an upscaling factor of 4x. SRGAN is currently the state of the art on public benchmark datasets

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