Critical Analysis 1

Super Resolution And SRCNN:

The aim of Super-Resolution (SR) is to extract from a low-resolution input a high-resolution image. Super-resolution (SR) has applications in many areas, including surveillance videos for object facial recognition, scene detection, forensics, remote sensing images, astronomical images, and medical imaging.(Dong et al. 2016)

SRCNN is a deep convolutional neural network (CNN) that learns to map low-resolution to high-resolution images end-to-end. Therefore, to enhance the image quality of low-resolution files, we can use it. (Dong et al. 2016) SRCNN consists of operations as follows:

1. Pre-processing: Low-resolution (LR) image up-scaled to the desired high-resolution (HR) size.
2. Extraction of features: Extracts a collection of features maps from an upscaled LR image.
3. Non-linear mapping: Maps include maps that reflect patches from LR to HR.
4. Reconstruction: Produces from HR patches the HR image.

Main trends on the topic since the publication of the paper discussed:

With substantial real-life applications, super-resolution is a challenging research issue. In deep coevolutionary network-based techniques for image super-resolution, the remarkable success of deep learning approaches has led to rapid development. We note the following patterns in current art through thorough quantitative and qualitative comparisons:

(a) GAN-based solutions typically provide visually pleasing results, although Reconstruction error-based strategies retain spatial information in a picture more accurately, (b) the existing models usually generate sub-optimal results in the case of high magnification rates (8X or above), (c) top-performing methods are usually more complex in terms of computation and are deeper than their counterparts,(d) residual learning has been a significant contributing factor in enhancing output due to its decomposition of the signal, which supports the learning task. (Anwar et al. 2019)

Main problems solved or improvements over the original work

here are some improvements and approaches made after SRCNN was published:

FSRCNN has a relatively shallow network, making it easier for us to learn about each component's effect. It is much quicker than the previous SRCNN with improved reconstructed image quality. FSRCNN has a better PSNR (image quality) and a much shorter running time as compared to SRCNN and FSRCNN.(Change Loy & Tang 2016)

VDSR is a deep learning technique for a picture to be expanded. It has 20 layers of weight, which is much deeper compared to SRCNN, which only has 3 layers. With the least testing time, VDSR gets the best outcomes. The VDSR method can be used for image enlargement in real time and can even be extended to videos. (Kim et al. 2016)

Remaining problems from the published works so far:

From a high-resolution image to a low-resolution image, the process of degradation is very complicated and uncertain. Several variables, such as compression, blur, noise, data transfer, and other artefacts, may affect it. Some issues remain, as stated by (Wang et al. 2019) such as how SR can be done in cases where there are no corresponding HR images available. Since LR-HR images are considered by SR as pairs to learn a super-resolution mapping feature.

Furthermore, another significant problem is that existing SR models usually do not resolve extreme super-resolution that can be useful in crowd scenes for instances such as super-resolving faces. Very few operations aim SR rates higher than (8x). It becomes difficult to maintain precise local information in the picture in such intense up-sampling conditions. (Anwar et al. 2019)

Interesting problems to solve and why:

I would be personally interested in solving the extreme resolution problem because Image super-resolution is significantly limited in real-world scenarios, which if solved can be useful for cases such as super-resolving faces in crowd scenes. I am also interested on how to preserve high perceptual quality in these super-resolved images.

Bibliography:

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