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SUPER-RESOLUTION

Super-Resolution and it's need:

- The term super-resolution refers to the process of creating a high resolution image from a sequence of sampling limited low resolution observations. This is one of the major research area. Recovering a high-resolution image from a single low-resolution image is another different challenging problem dealt by various research scholars.
- In security and surveillance more information regarding particular scene details is required on demand; and in medical imaging where desire to reduce irradiation dosage is crucial, super-resolution technique is used. It is also used in various other fields.

Main Trends in Image Super-Resolution:

1. In SRCNN[1], an end-to-end mapping between low and high resolution images, with extra pre/post processing is proposed.

- The structure is simple, yet provides superior accuracy
- With moderate number of filters and layers, it achieves fast speed for practical online usage
- It can deal with three channels of color images simultaneously

2. How do we recover the finer texture details when we super-resolve at large upscaling factors? SR-GAN[2], deals with the above mentioned problem.

- It is the first framework capable of inferring photo-realistic natural images for 4× upscaling factors.
- Learning upscaling filters is beneficial in terms of accuracy and speed. SRGAN is an improvement over Dong et al. [1] where bicubic interpolation is used to upscale the Low resolution observation before feeding the image to the CNN.
- MSE loss is replaced by perceptual loss function which consists of adversarial loss and a content loss which are more invariant to changes in pixel space.

3. High computational cost of SRCNN[1] makes it unsuitable for practical usage that demands real-time performance, so the same authors have come up with the improvement of SRCNN (ie. FSRCNN[3])

- Without interpolation of LR image, a deconvolution layer is added at the end of the network and the mapping is learned directly from the original low-resolution image to the high-resolution one.
- Smaller filter sizes and more mapping layer.
- Input feature dimension is shrunk

4. Kim et al. [4] proposed an Increasing recursion depth network[DRCN] that improved performance without introducing new parameters for additional convolutions.

Key ideas of related published works:

- Yang et al.[5] investigated on prediction models, edge based models, image statistical models and patch based methods and found patch based models (example based) achieve state-of-the-art performance.

- Glasner[6] proposed first internal example based method where the search for example patches are from the input image itself and is based on the fact that patches often tend to recur within image or across different image scales.
- In [7], external example based method is used which uses a universal set of example patches to predict the missing information for the HR image.
- [1],[2],[3],[4] uses convolutional neural networks which is the present scope of image processing/computer vision

Problems solved:

[1] SR-CNN

- The network can cope with different color images and it can evaluate performance on difference channels.
- The model can be applied to other low level vision problems.

[2] SR-GAN

- Upscaling of images done with greater accuarcy
- MSE and PSNR is based on pixel wise image differences. The problem has been solved by introducing a new loss function proposed by Ledig et al.[2]

[3] FSRCNN

- Faster and cost efficient compared to [1]
- Computational complexity of SRCNN grows quadratically with the spatial size of the HR image because of the interpolation of LR image, this is overcome by introducing a deconvolutional layer.
- Costly nonlinear mapping in SRCNN, is avoided by shrinking and expanding layer at the beginning and the end of the mapping layer separately to restrict mapping in a low-dimensional feature space in FSRCNN[3]

[4]DRCN

- In SRCNN[1], the experiments indicate "deeper is not better" but in DRCN[4], Kim et al. designed a convolutional network that models long-range pixel dependencies with limited capacity and the network recursively widens the receptive field without increasing model capacity.

Unsolved Problems:

- Increasing the network width increases the performance but with a compromise in speed which is encountered as a problem in SRCNN[1].
- Larger filter size significantly improves the performance but however deployment speed also decreases(Dong et al.[1])
- Increasing the number of layers (going deeper) is still a probem in SRCNN[1] but Kim et al.[4] proposed DRCN upto 16 recursions. Having more than 16 recursions is still a challenge to be overcome to use image level context.

Interesting unresolved Problem:

Increasing the layers in neural network is the interesting challenge in my perspective since the more deeper we learn the more accurate the result is!

References:

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