Critical Analysis for Super-Resolution CNN

Deep Learning and Computer Vision

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Introduction

The purpose of the critical analysis report is to discuss the *Image Super-Resolution Using Deep Convolutional Networks* paper introducing into mapping between low/high resolution images. Discussion is based on SRCNN paper, its model's architecture, performance and limitation. Soon after, the discussion includes the techniques and algorithms such as FSRCNN and DSIRSR, which aiming to improve the model performance and image resolution. Finally, it concludes the three papers discussing its improvements into the model and limitations.

Super-Resolution Convolutional Neural Network (SRCNN)

The paper *Image Super-Resolution Using Deep Convolutional Networks* provides solution for image quality restoration, where the low-resolution image is given on the input and high-resolution image is an outcome of the putting image though the model.

In order to learn the mapping the following operations are performed by the algorithm:

- Patch extraction and representation which extracts patches from low resolution images [1]
- Non-linear mapping which maps high-dimensional vector into another high-dimensional vector [1]
- Reconstruction, which aggregates the patches and generate the final image [1]

Given algorithm archives good performance on end-to-end mapping within low and high resolution image.
The limitation of the model might be performance in real-time processing.

Fast Super-Resolution by CNN (FSRCNN)

The main issue for SRCNN discussed in previous paragraph is high computational cost and issues with real-time performance (24fps). The paper *Accelerating the Super-Resolution Convolutional Neural Network* aims to improve the SCNN and accelerate the model.

Proposed architecture in the paper introduces deconvolutional layer at the end of the network, where the mapping is learned from the original low-resolution image to high resolution without interpolation [2].
On the next stage, the input feature dimension is being shrunk before mapping and expanding back afterwards [2].
Finally, the smaller fillers are adopted.

Therefore, the architecture of the models looks as follow [5]:

- Feature Extraction
- Shrinking
- No-linear Mapping
- Expanding
- Deconvolution

This model achieves better performance and enables real-time operations on a generic CPU. The final acceleration claimed in the paper indicates being faster over 40 times. The outcome of the computer image through the model gives higher quality image and shorter in time [4].

Dense Skip Connections and Inception-ResNet (DSIRSR)

A paper *Single Image Super-Resolution Using Deep CNN with Dense Skip Connections and Inception-ResNet* focuses on improvement of Deep CNNs by increasing the calculation speed and reducing the feature loss.

The algorithm model uses CNN to provide end-to-end mapping model without preprocessing of the image [3]. The next step in the algorithm is to connect the local and global information on the image using skip connection [3]. Further steps use residual learning and in-depth network which reduces the training time [3]. The final step of the algorithm is to replace the SGD using ADAM which results on reducing the learning rate within the training proces which improves the performance of the model.

The use of skip connection within the model allows to obtain mode contextual informations. This is achieved by creating short paths from top to bottom level of the features [3].

The results claimed in the paper shows the model provides better reconstruction performance than previously mentioned models. Moreover, results shows faster and more efficient calculations in comparison with the state of the art methods [6].

Conclusion

The discussion on the papers shows that since the proposed model of SRCNN was shown, the trends goes towards improving the performance on real-time image processing or the resolution of the output image from the model. The main limitation of the SRCNN was the computation time and issues with real-time processing performance. The paper on FSRCNN improves the actual model and offers real-time image processing. The final paper examined shows that proposed model improves the reconstruction performance and provides high-res output image.

References

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