## ***Report Writing***

*Single Image Super-resolution (SR) [3] focuses on recovering a high-resolution image from a single low-resolution image. It is a problem which has non-unique solutions. This paper has proposed a model Super-Resolution Convolutional Neural Network (SRCNN).The paper proposes that SRCNN provides superior accuracy and faster speed compared to all the state-of-the-art example-based methods used for Single Image Super Resolution.This is proven with the help of different evaluation metrics for example, PNSR, SSIM etc. Sparse-coding-based method is one of the representative methods for SR solution and SRCNN shows an improved performance compared to the aforementioned method.SRCNN proposes a convolutional neural network that directly learns an end-to-end mapping between low-and high-resolution images. The method differs fundamentally from existing external example-based approaches.It does not explicitly learn the dictionaries [4] or manifolds for modeling the patch space. These are implicitly achieved via hidden layers. Furthermore, the patch extraction and aggregation are also formulated as convolutional layers. In SRCNN, the entire SR pipeline is fully obtained through learning, with little pre/post-processing.*

*The paper adds significantly to the original work which was published first in 2014 [5]. Firstly, SRCNN is improved by introducing larger filter size in the non-linear mapping layers, and explore deeper structures by adding non-linear mapping layers.The majority of SR algorithms focus on gray-scale or single-channel image super-resolution. SRCNN is extended to process three color channels simultaneously. SRCNN is faster than a number of example-based methods, because it is fully feed-forward and does not need to solve any optimization problem on usage.Thirdly, considerable new analyses and intuitive explanations are added to the initial results.*

*There are certain problems of SRCNN that are to be dealt with. The results indicate that SRCNN performance may be further boosted using a larger training set, but the effect of big data is not as impressive as shown in high-level vision problems. In general, the performance would improve if we increase the network width , i.e., adding more filters, at the cost of running time.*

*However, as the non-linear mapping of SRCNN is operated in higher dimensional space, which is complex and time-consuming, FSRCNN (Fast Super Resolution Convolutional Neural Network) was introduced which solved this problem by adding a shrinking layer before the mapping operation to reduce the feature dimension [5]. Besides, an expanding layer after the mapping layer is also added for better generating the High Resolution image. The speed of FSRCNN is much faster than SRCNN, and the performance of FSRCNN is better as well.*

*Aiming at the problem that the existing SRCNN algorithm has too long training time, poor reconstruction performance and slow running speed, a new image super-resolution reconstruction algorithm based on convolutional neural network is proposed [6]. The algorithm* *uses low-resolution images as the network input, the higher-order representation of the image is learned using the convolution operation, the high-resolution image is up-sampling by the deconvolution operation, and the residual structure is added to the network, so that the entire network can converge better.*

*Additionally, VDSR(Very Deep Super-resolution Convolutional Networks) [1] explores the improvement of SR performance with the increase of the depth of the network. The model uses 20 layers with small filters to obtain larger receptive field. Convergence speed is greatly affected by network depth. Furthermore, DRCN (Deeply-Recursive Convolutional Networks) [5] introduces a very deep recursive layer into the field of SR reconstruction. It may perform better if the depth of recursive layers increases, but the numbers of parameters do not increase much since all recursions share the same parameters which is contrary to convolution layers. It is also the obvious significance of importing recursive layers.*

*However, the problem that is still unresolved even with introducing new methodologies is the problem of noise robustness [5]. All the methods trained by noise free data cannot process images with noise effectively. Generally, SRCNN has better noise robustness than the other models. If the image to be reconstructed contains strong noise, a feasible approach is to first denoise the image and then construct it.*

***References***


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