IMAGE SUPER-RESOLUTION WITH DEEP LAPLACIAN PYRAMID NETWORKS

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ABSTRACT: *Convolutional Neural Networks have recently shown high quality reconstruction for single image super-resolution. But the existing methods require large number of network parameters and involve heavy computational loads at runtime for generating high-accuracy super-resolution results. In this paper we propose, the deep laplacian pyramid network for fast and accurate image super-resolution. The main objective of the project is to progressively reconstruct the sub-band residuals of high resolution images at multiple pyramid levels with low computational loads. To improve the Peak Signal to Noise Ratio and reduce the Normalized Mean Square Error for the obtained super resolution image.*

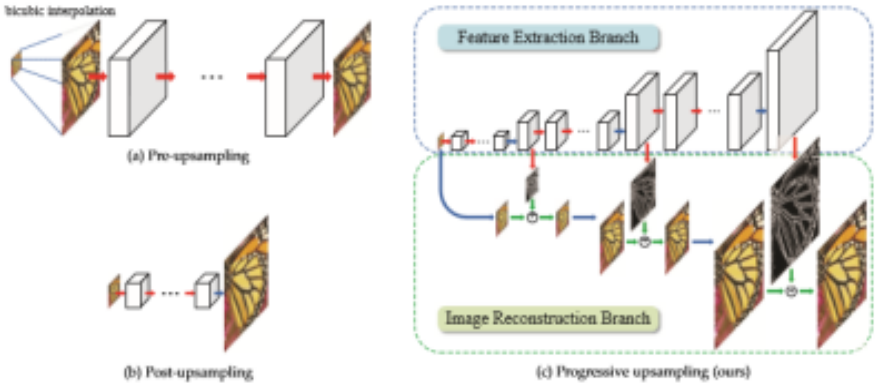
Key Words: *single-image super-resolution, sub-band residuals, laplacian pyramid.*

INTRODUCTION:

Super-resolution is the process of combining a sequence of low resolution images in order to produce high resolution image. Blurring of an image is smoothing of image which can remove the noise which is represented as noise in an image.

Convolutional Neural Networks have been widely used in vision tasks ranging from object recognition, segmentation, etc. While the existing models are able to generate high quality super-resolution images there are three issues in these methods. First, these methods use pre-scaled upsampling factor (eg.bicubic interpolation) improve an low-resolution to high-resolution image. Second, the existing methods have to optimize the networks with an mean-squared error loss. Third, the existing methods mainly reconstructs high-resolution in one upsampling step.

To overcome these issues we use deep laplacian pyramid networks to progressively reconstruct the high-resolution images. As shown in figure 1(c) our proposed model consists of a feature extraction branch and image reconstruction branch. The feature extraction branch uses a cascade of convolutional layers to extract non-linear feature from low-resolution images. The image reconstruction branch upsamples the low-resolution images and takes the sub-band residuals from the feature extraction branch to efficiently reconstruct high-resolution images through element-wise addition.

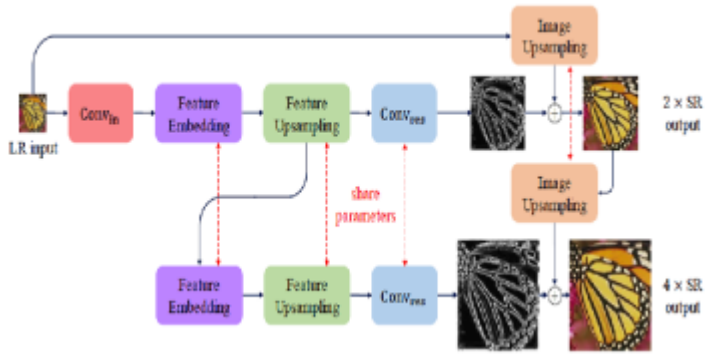


EXISTING MODEL:

The existing model is based on deep convolutional networks. The deep convolutional networks have shown that they have a significant reconstruction performance on single-image super-resolution. The recent trend is using deep convolutional neural network layers to improve the performance. But this model requires large number of network parameters and more computation time due to power consumption and real-time processing. Single-image super-resolution was mainly used in fields like security, video surveillance and medical imaging. But now single-image super-resolution images are widely needed in TV, video playing and websites as display resolution are getting higher and higher while the contents of the source remains between two and eight times lower resolution when compared to recent displays. Recent deep learning based techniques have achieved high performance in the problem of single-image super-resolution from low-resolution images to high-resolution images. In this method they propose a lighter network by optimizing the structure of the network by using recent deep learning techniques.

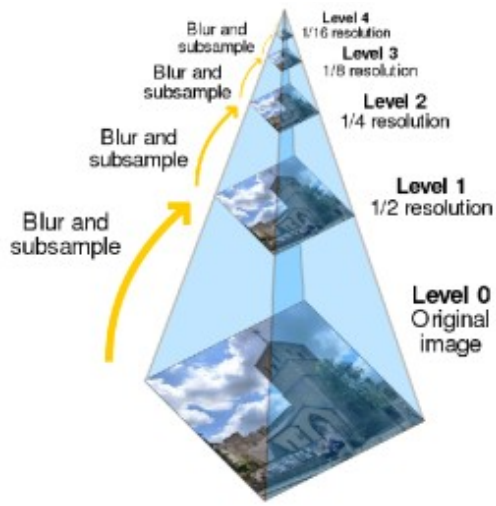
PROPOSED MODEL:

The proposed network progressively reconstructs the sub-band residuals of high-resolution images at multiple pyramid levels. The proposed method directly extracts features from the low-resolution input space and thereby results in low computational loads. The proposed model consists of feature extraction branch and image reconstruction branch. The feature extraction branch uses a cascade of convolutional layers to extract features from LR (Low Resolution) input images. The image reconstruction branch upsamples the LR images and takes the sub-band residuals from the feature extraction branch to efficiently reconstruct HR images through element-wise addition.



Our network architecture accommodates deep supervision (i.e., supervisory signals can be applied simultaneously at each level of pyramid) to guide reconstruction of images. Instead of using mean square error loss function, we propose to train the network other loss functions to better handle the noise and improve the performance. While both feature extraction branch and image reconstruction branch have multiple layers, we train the network in an end-to-end manner without stage-wise optimization.

- **LAPLACIAN PYRAMID:**



A laplacian pyramid saves the difference image of the blurred versions between each levels. Only the smallest level is not a difference image to enable reconstruction of the high resolution image using the difference images on high levels. This technique can be used in image compression. The general class of linear transform decomposes an image into an image into various components by multiplication with a set of transform functions. Some examples are discrete fourier transform and discrete cosine transform and finally the wavelet transform of which the laplacian pyramid and other subband transforms are simple ancestors.

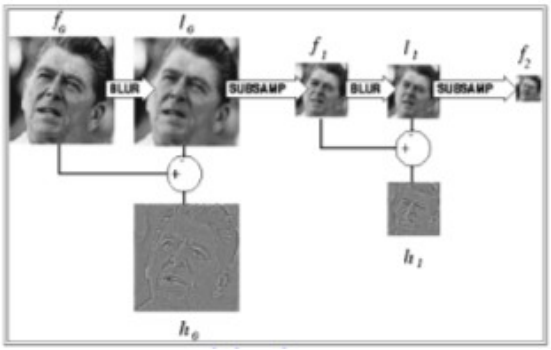


Figure 1 Decomposition step for two-level Laplacian Pyramid

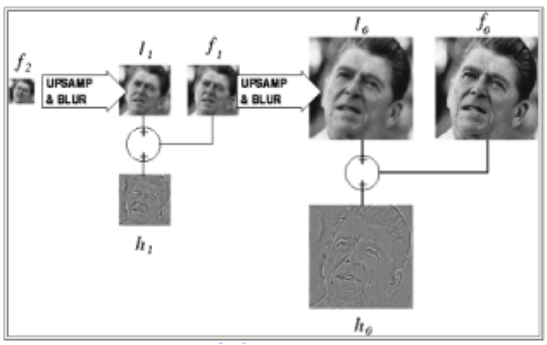


Figure 2 Reconstruction step for two-level Laplacian Pyramid.

MEASUREMENT PARAMETERS:

In the existing methods in order to get high-resolution images the parameters like Peak Signal to Noise Ratio (PSNR) and Normalized Mean Square Error (NMSE) were calculated.

In the proposed method we are going to obtain the super-resolution images by measuring two parameters such as Structural Similairy Index (SSIM) and Improvement in Signal to Noise Ratio (ISNR).

- **STRUCTURAL SIMILARITY INDEX (SSIM):**

The Structural Similarity Index is a metric that quantifies the image quality degradation caused by processing such as data compression or by losses in data transmission. It is a full reference metric that requires two images from the same image capture – a reference image and a processed image. The processed image is typically compressed. SSIM is best known in video industry, but it has strong application in still photography.

SSIM actually measures the perceptual difference between two similar images. It cannot judge which of the two is better. Unlike PSNR, SSIM is based on visible structures in the image.

INFORMATION VALUE:

Image no	PSNR value				MSE value			
	Method 1	Method 2	Method 3	Method 4	Method 1	Method 2	Method 3	Method 4
11	13.17	13.34	13.44	13.56	3100.8	2700.8	2500.4	2100.6
12	15.10	15.23	15.35	15.45	1977.9	1777.1	1480.8	1200.8
13	11.23	11.34	11.45	11.56	4600.6	4460.5	4200.9	4098.8
14	11.45	12.04	12.15	12.27	4700.7	4400.9	4200.8	4056.9
15	11.70	11.88	11.92	11.96	4800.9	4500.7	4378.9	4180.9
16	13.88	13.90	13.94	13.98	3700.9	3500.5	3350.6	3167.1
17	12.56	12.67	12.76	12.84	3000.5	2880.7	2600.7	2456.9
18	15.74	15.82	15.88	15.92	2800.7	2560.7	2300.6	2190.8
19	8.78	8.82	8.88	8.92	8800.8	8580.9	8398.8	8190.9
110	11.34	11.43	11.54	11.62	4170.9	3980.8	3764.9	3500.9

Image no	RMSE value				SSIM value	
	Method 1	Method 2	Method 3	Method 4	Method 3	Method 4
11	56.78	55.88	55.45	55.32	0.837	0.936
12	44.90	44.56	44.35	44.16	0.856	0.954
13	66.65	66.45	66.32	66.14	0.864	0.967
14	60.56	60.34	60.24	60.09	0.876	0.976
15	70.72	70.63	70.45	70.32	0.882	0.982
16	54.86	54.69	54.45	54.32	0.885	0.987
17	61.89	61.77	61.56	61.47	0.888	0.989
18	45.78	45.53	45.35	45.23	0.892	0.991
19	94.86	94.57	94.38	94.22	0.895	0.994
110	64.64	64.36	64.28	64.18	0.899	0.998

CONCLUSION:

In this work we propose a deep convolutional network within a laplacian pyramid framework for fast and accurate image super-resolution. By sharing parameters across as well as within pyramid levels we use fewer parameters to achieve improved performance. Our network design is general and can potentially applied to other image transformation like SAR images. By sharing the parameters across as well as within the pyramid levels, we use 73% fewer parameters than our existing and preliminary methods and have improved the performance.

REFERNCES:

1. J. Yang, J. Wright, T. S. Huang, and Y. Ma, "Image super-resolution via sparse representation," IEEE Transactions on Image Processing, 2012.
2. C. Dong, C. C. Loy, K. He, and X. Tang, "Image super-resolution using deep convolutional networks," IEEE Transactions on Pattern Analysis and Machine Intelligence, 2014.
3. Assaf Shocher, Nadav Cohen and Michal Irani, "Zero-Shot Super-Resolution using Deep Internal Learning" in CVPR-Springer journal , 2015.
4. Xintao Wang, Ke Yu, Chao Dong and Chen Change Loy, "Recovering Resolution Texture in Image Super-resolution by Deep Spatial Feature Transform" in CVPR-Springer journal, 2016.
5. Yaniv Romano, John Isidoro and Peuman Milanfar, "RAISR: Rapid and Accuarte Image Super Resolution" in IEEE Transactions on Computational Imaging, 2017.