Light Weight Image Super-Resolution with Adaptive Deep Residual Network

Shruthi S.
Assistant Professor,
Department of CSE, R R Institute of Technology, Bengaluru, Karnataka, India

Jyothi R.
Assistant Professor,
Department of CSE, R R Institute of Technology, Bengaluru, Karnataka, India

ABSTRACT

The propose work is a single image super-resolution model based on Adaptive Deep Residual named as ADR-SR, which uses the Input Output Same Size (IOSS) structure and releases the dependence of up sampling layers compared with the existing SR methods. Specifically, the key element of our model is the Adaptive Residual Block (ARB), which replaces the commonly used constant factor with an adaptive residual factor. The experiments prove the effectiveness of our ADR-SR model, which can not only reconstruct images with better visual effects, but also get better objective performances.

Keywords: Single image super-resolution (SISR), AD residual network, Deep learning

INTRODUCTION:

Mobile Ad Hoc Networks (MANETs) consists of a collection of mobile nodes which are not bounded in any infrastructure. Nodes in MANET can communicate with each other and can move anywhere without restriction. This non-restricted mobility and easy deployment characteristics of MANETs make them very popular and highly suitable for emergencies, natural disaster and military operations .Nodes in MANET have limited battery power and these batteries cannot be replaced or recharged in complex scenarios. To prolong or maximize the network lifetime these batteries should be used efficiently. The energy consumption of each node varies according to its communication state: transmitting, receiving, listening or sleeping modes. Researchers and industries both are working on the mechanism to prolong the lifetime of the node's battery. But routing algorithms plays an important role in energy efficiency because routing algorithm will decide which node has to be selected for communication.

The main purpose of energy efficient algorithm is to maximize the network lifetime. These algorithms are not just related to maximize the total energy consumption of the route but also to maximize the life time of each node in the network to increase the network lifetime. Energy efficient algorithms can be based on the two metrics: i) Minimizing total transmission energy ii) maximizing network lifetime. The first metric focuses on the total transmission energy used to send the packets from source to destination by selecting the large number of hops criteria. Second metric focuses on the residual batter energy level of entire network or individual battery energy of a node.

Related Work:

In [2] authors used average residual battery level of the entire network and it was calculated by adding two fields to the RREQ packet header of a on-demand routing algorithm i) average residual battery energy of the nodes on the path ii) number of hops that the RREQ packet has passed through. According to their equation retransmission time is proportional to residual battery energy. Those nodes having more battery energy than the average energy will be selected because its retransmission time will be less. Small hop count is selected at the stage when most of the nodes have same retransmission time. Individual battery power of a node is considered as a metric to prolong the network lifetime in [3]. Authors used an optimization function which considers nature of the packet, size of the packet and distance between the nodes, number of hops and transmission time are also considered for optimization. In [4] initial population for Genetic Algorithm has been computed from the multicast group which has a set of paths from source to destination and the calculated lifetime of each path. Lifetime of the path is used as a fitness function. Fitness function will select the highest chromosomes which is having highest lifetime. Cross over and mutation operators are used to enhance the selection. In [5] authors improved AODV protocol by implementing a balanced energy consumption idea into route discovery process. RREQ message will be forwarded when the nodes have sufficient amount of energy to transmit the message otherwise message will be dropped. This condition will be checked with threshold value which is dynamically changing. It allows a node with over used battery to refuse to route the traffic in order to prolong the network life. In [6] Authors had modified the route table of AODV adding power factor field. Only active nodes can take part in rout selection and remaining nodes can be idle. The lifetime of a node is calculated and transmitted along with Hello packets. In [7] authors considered the individual battery power of the node and number of hops, as the large number of hops will help in reducing the range of the transmission power. Route discovery has been done in the same way as being done in on-demand routing algorithms. After packet has been reached to the destination, destination will wait for time δt and collects all the packets. After time δt it calls the optimization function to select the path and send RREP. Optimization function uses the individual node's battery energy; if node is having low energy level then optimization function will not use that node.

Proposed Algorithm:

Design Considerations:

- Super resolution model
- Network Architecture
- Adaptive weighted share-source module (AWSSM)
- Residual block and residual scale factor
- Squeeze and excitation module

Description of the Proposed Algorithm:

Aim of the proposed algorithm is to develop a residual squeeze and excitation block (RSEB) as a building block in DRSEN. The RSEB fuses the input and its internal features of current block, and models the interdependencies and relationships between channels to enhance the representation power. At the same time, we improve the up-sampling module and the global residual pathway in the network to reduce the parameters of the network. Experiments on two public remote sensing datasets (UC Merced and NWPU-RESISC45) show that our DRSEN achieves better accuracy and visual improvements against most state-of-the-art methods. The DRSEN is beneficial for the progress in the remote sensing images super-resolution field.

Here is the Overview of System:

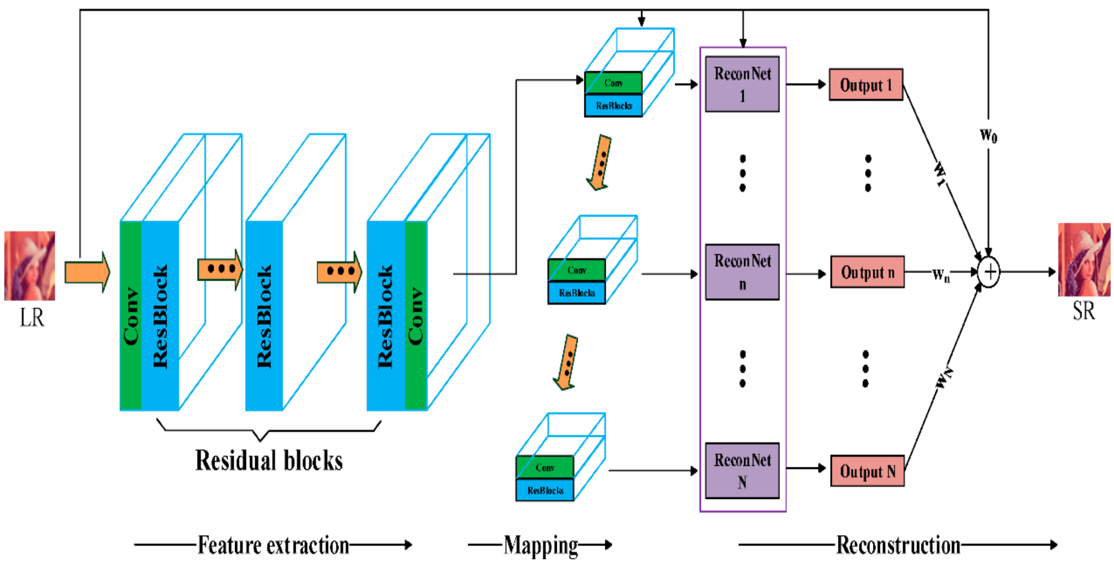

Figure 1: Block diagram of overview of the system

The architecture of the system SR network(MRSR),which consists of three parts:

- ➢ Feature extraction
- ➢ Mapping
- ➢ Reconstruction

The feature extraction is composed of multiple filters and residual blocks. The non-linear mapping between LR and SR adopt the multi-branch network structure and each branch is made up of residual blocks. In the reconstruction, the final output is restored from every branch output and the LR input with different weights.

Implementation:

Procedure for Single image super-resolution:

We use two sets of images as the ground truth to thoroughly evaluate the SISR algorithms from diverse sources. From the ground truth HR images, we generate LR test images using various settings of scaling factor and blur kernel width. We generate the SR images by the originally released code [27,17,46,5,43,36] or our implementation [16,30,11,9] if the code is not available. The generated SR image are used to evaluate the performance of SISR algorithms and quality assessment metrics. In order to evaluate the performance of metrics, we conduct human subject studies to generate perceptual scores of the SR images.

Step 1: Test Image Sets:

We use two image sets as the HR ground truth data for evaluation. The first set contains 200 images from the Berkeley segmentation dataset [20], which is widely used for SISR evaluations [11,9,32,12]. All images are of 321×481 pixels covering diverse contents acquired in a professional photographic style. The second set contains 29 undistorted high-quality images from the LIVE1 dataset [28], which is widely used for image quality assessment [26]. The resolution of these images' ranges from 480 × 720 to 512 × 768 pixels.

Step 2: Test Image Formation:

There are several ways to generate LR test images from the ground truth images [27,30,36] such that the generated LR test images may be numerically different. For clarity, we present an image formulation to address this problem. Given a ground truth HR image I_h, a scaling factor s, and a Gaussian blur kernel width σ, we generate a test LR image I_l by

$$I_l(x_l, y_l) = {}^{X}w\,(x - x_u, y - y_u)\, I_h(x, y) + \varepsilon, \qquad (1)$$

List of evaluated methods Language column, M: MATLAB, MC: Mixture of MATLAB and C/C++, E: Executable binary code. Learning column, N: No learning approach involved, E: External exemplar images are required, S: Self-similar exemplars are used. The execution time is measured on a machine with a 2.7 GHz Quad Core CPU with an image of 128 × 128 pixels (shown on the right).

Method	Language	Learning	Factors and Execution Time (sec.)					
			2x	3x	4x	5x	6x	8x
Bicubic Interpolation	MC	N	0.002	0.002	0.003	0.004	0.004	0.005
IP [16]	M	N	0.140	0.172	0.091	0.059	0.046	0.077
SLJT [27]	E	E	5.913	11.90	21.29	29.19	39.78	73.49
SSXS [30]	M	E	37.39	92.92	156.2	N.A.	N.A.	N.A.
GBI [11]	MC	S	364	807	3851	9028	21668	53762
KK [17]	MC	E	7.715	17.14	49.06	N.A.	N.A.	N.A.
YWHM [46]	M	E	321	598	1229	1956	2477	4795
FF [9]	M	S	1779	1513	2557	N.A.	N.A.	N.A.
DZSW [5]	M	E	266	568	887	1271	1721	2764
YY [43]	M	E	15.38	15.55	15.84	18.18	19.35	20.48
TSG [36]	M	E	0.948	1.126	1.405	1.873	2.093	3.189

Table 1. List of evaluated methods.

where $x_l \in \{1..., m\}$ and $y_l \in \{1..., n\}$ are indices of I_l; $x \in \{1...,s\times m\}$ and $y \in \{1...,s\times n\}$ are indices of I_h; and ε denotes noise. The noise term ε is introduced from discretization while storing I_l into an uncompressed 8-bit image. We compute the HR coordinates (x_u,y_u) from the and LR ones (x_l,y_l) by

$$x_u = s(x_l - 0.5) + 0.5,$$

$$y_u = s(y_l - 0.5) + 0.5. \quad (2)$$

The weight w is determined by σ as

$$w(\Delta x, \Delta y) = \frac{1}{Z} e^{-(\Delta x^2 + \Delta y^2)/2\sigma^2} \quad (3)$$

where Z is a normalization term. The formation is compatible with most SR methods [16,11,17,30,46,43,36] where the reconstructed images are well aligned with the ground truth images.

Step 3: Evaluated SISR Methods:

For fair comparisons, we evaluate the methods using the original binaries or source code [27,46,17,5,43,36]. In addition, we implement four state-of-the-art algorithms when the source or binary code is not available [16,30,11,9]. Table 1 lists the evaluated algorithms and their execution time under different scaling factors. We note these methods are implemented in different programming languages. For algorithms where the blur kernel width is an adjustable parameter [16,27,11,46,5,43], we set the same values as used in the LR image formation. We only evaluate the SSXS, KK, and FF methods [30, 17,9] under scaling factors 2, 3, and 4 because the released code or priors only support these scaling factors. When the training code and dataset are available [46,5,43,36], we re-train the priors for all 54 settings. For algorithms that require other parameter settings [27,30,46,5,9,43,36], the default values in the released code or manuscripts are used.

Step 4: Subject Studies:

We conduct human subject studies to evaluate the effectiveness of existing metrics for performance evaluation of SR algorithms. We select 10 images from the BSD200 dataset [20] as the ground truth data. The selected images cover a wide range of high-frequency levels in order to generate a representative subset of the entire BSD200 dataset. (See the supplementary material for their high-frequency levels). From each ground truth image, 9 LR images are generated using Eq. 1 under different settings (the scaling factors of 2, 3, and 4, and the Gaussian kernel width of 0.4, 1.2, and 2.0). From each LR image, we use 6 state-of-the-art methods to generate the SR images, and in total we generate 540 SR images. We collect 16,200 perceptual scores from 30 participants evaluating the 540 SR images without knowing the ground truth images or the method names. The SR images are displayed in a random order to avoid bias to favor certain methods. Subjects are asked to give scores between 0 to 10 to assess the image quality based on their visual perception.

SIMULATION RESULTS:

The super-resolution is broken down into two categories; super-resolution using a single image and super-resolution using multiple images. In this paper, a method for increasing image quality, based on the Dong method has been proposed. In the proposed method, which is based on only one image, tries to improve the quality of image, based on the Dong method and optimizing it using a compatible selection of a vocabulary, which is based on the concept of inherent sparseness of images and appropriate adjustment statements. In this method, we have tried to present the best clustering procedure with the highest precision for selection of patches.

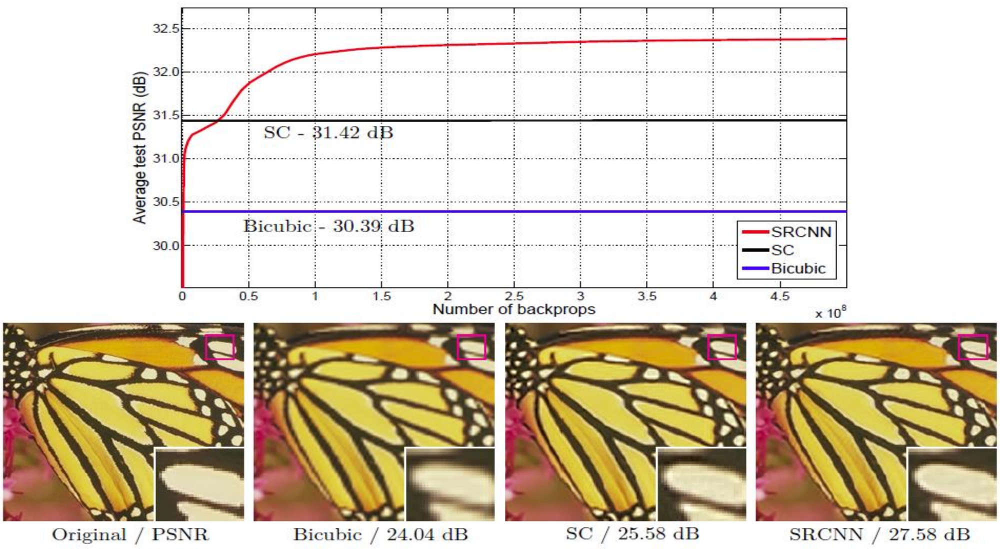

Figure 2: SRCNN (Super-resolution)

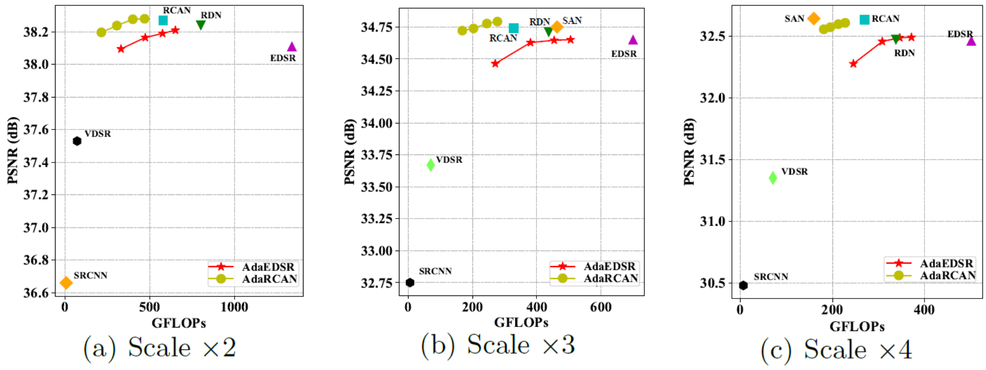

Figure 3: Frame-Recurrent video super-resolution

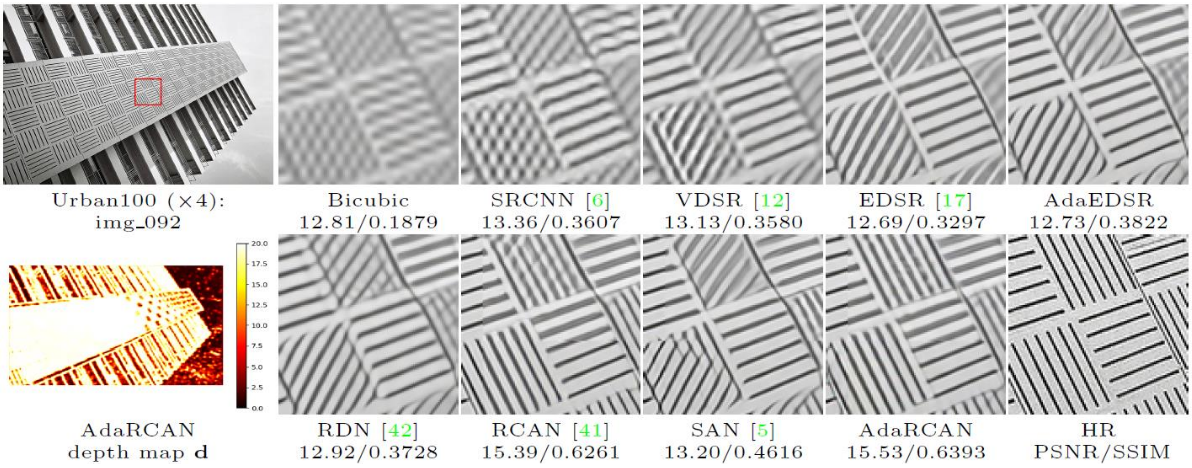

Figure 4: Deep Adaptive inference network for single image super resolution

CONCLUSION:

In summary, we propose a single image super-resolution model named ADR-SR based on adaptive deep residual, which can be used for super-resolution task with the same size of input and output image. The visual effects and objective performances of the experiment demonstrate the effectiveness of our ADR-SR.

- Input Output Same Size structure (IOSS) for same size super-resolution task.
- Adaptive Residual Block (ARB), the adaptive ability and convergence speed improve a lot.
- A new idea for super-resolution network design increases the width of the network instead of the depth to obtain additional performance improvements.

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Biography:

Prof. Shruthi S is an Assistant Professor in the Computer Science & Engineering Department,R.R Institute of Technology, Visvesvaraya Technological University. She Received Master of Technology degree in 2017 in computer Science branch from Visvesvaraya Technological University. Belgaum. Her area of interest are Machine Learning, Computer Network & Database management system.
