Neural Architecture Search for Image Super-Resolution Using Densely Connected Search Space: DeCoNAS

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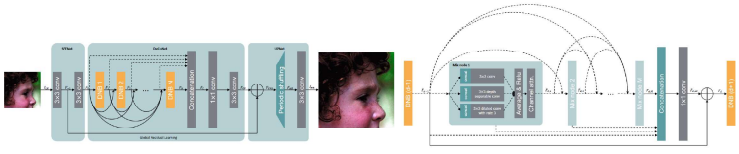
Abstract The recent progress of deep convolutional neural networks has enabled great success in single image super-resolution (SISR) and many other vision tasks. Their performances are also being increased by deepening the networks and developing more sophisticated network structures. However, finding an optimal structure for the given problem is a difficult task, even for human experts. For this reason, neural architecture search (NAS) methods have been introduced, which automate the procedure of constructing the structures. In this paper, we expand the NAS to the super-resolution domain and find a lightweight densely connected network named DeCoNASNet. We use a hierarchical search strategy to find the best connection with local and global features. In this process, we define a complexity-based penalty for solving image super-resolution, which can be considered a multi-objective problem. Experiments show that our DeCoNASNet outperforms the state-of-the-art lightweight super-resolution networks designed by handcraft methods and existing NAS-based design.

CONTRIBUTION

- ✓ We propose a new NAS-based SR network design, named DeCoNAS, which searches for networks with higher performance by combining hierarchical and local information efficiently.
- ✓ We design a complexity-based penalty and add it to the reward of the REINFORCE algorithm, which enables us to search for an efficient network that has high performance and fewer parameters

ALGORITHM



(a) (b)

Figure 1. The architecture of (a) the proposed DeCoNASNet system and (b) the Densely connected block (DNB).

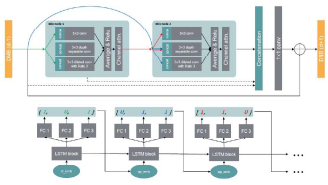


Figure 2. The example controller sequence and the constructed mix nodes.

$$\min_{\mathbf{w}} \mathop{\mathbb{E}}_{\mathbf{c}\sim\pi(\mathbf{c};\boldsymbol{\theta})}[L(\mathbf{c};\mathbf{w})] \tag{1}$$

$$\nabla_{\mathbf{w}} \mathop{\mathbb{E}}_{\mathbf{c}\sim\pi(\mathbf{c};\boldsymbol{\theta})}[L(\mathbf{c};\mathbf{w})] \approx \frac{1}{M}\sum_{i=1}^{M} \nabla_{\mathbf{w}} L(\mathbf{c}_i;\mathbf{w}) \tag{2}$$

Eq. 1. The loss function and gradient for child network

$$\max_{\boldsymbol{\theta}} E_{P(a_{1:T};\boldsymbol{\theta})}[R] \tag{3}$$

$$\nabla_{\boldsymbol{\theta}} \mathop{\mathbb{E}}_{P(a_{1:T};\boldsymbol{\theta})}[R] = \sum_{t=1}^{T}[\nabla_{\boldsymbol{\theta}} \log P(a_t|a_{t-1:1};\boldsymbol{\theta})(R-b)] \tag{4}$$

$$R = p(\mathbf{c},\mathbf{w}) - \alpha * cb(\mathbf{c}) \tag{5}$$

Eq. 2. The loss function and gradient for controller network

- ✓ We construct the densely connected search space for image super-resolution task as shown in fig. 1.
- ✓ We apply efficient neural architecture search method to find optimal and lightweight structure.
- ✓ We use REINFORCE algorithm to train controller network
- ✓ We design a complexity-based penalty to consider PSNR and parameter complexity together.

EXPERIMENTAL RESULTS

Table 1. Public benchmark test results (PSNR/SSIM) for ×2 SR.

Model	Params	Set 5	Set 14	B100	Uban100	Design time
Bicubic	-	33.66 / 0.9299	30.24 / 0.8688	29.56 / 0.8431	26.88 / 0.8403	-
SRCNN [6]	57K	36.66 / 0.9542	32.45 / 0.9067	31.36 / 0.8879	29.50 / 0.8946	-
VDSR [9]	665K	37.53 / 0.9587	33.03 / 0.9124	31.90 / 0.8960	30.76 / 0.9140	-
LapSRN [15]	813K	37.52 / 0.9591	33.08 / 0.9130	31.80 / 0.8950	30.41 / 0.9101	-
MemNet [12]	677K	37.78 / 0.9597	33.28 / 0.9142	32.08 / 0.8978	31.31 / 0.9195	-
SelNet [17]	970K	37.89 / 0.9598	33.61 / 0.9160	32.08 / 0.8984	- / -	-
CARN [14]	1,582K	37.76 / 0.9590	33.52 / 0.9166	32.09 / 0.8978	31.92 / 0.9256	-
MoreMNAS-A [29]	1,039K	37.63 / 0.9584	33.23 / 0.9138	31.95 / 0.8961	31.24 / 0.9187	56 GPU days
FALSR-A [30]	1,021K	37.82 / 0.9595	33.55 / 0.9168	32.12 / 0.8987	31.93 / 0.9256	24 GPU days
DeCoNASNet (ours)	1,713K	37.96 / 0.9594	33.63 / 0.9175	32.15 / 0.8986	32.03 / 0.9265	12 GPU hours

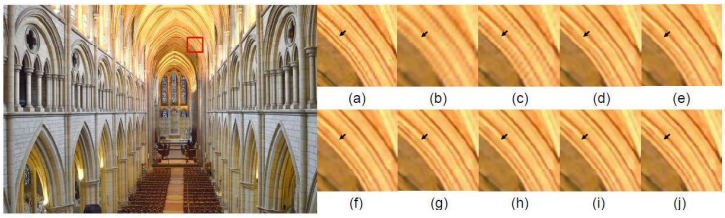


Figure 3. Qualitative comparison of the conventional methods and ours. (a) HR image, (b) bicubic LR image, (c) SRCNN, (d) VDSR, (e) LapSRN, (f) MemNet, (g) CARN, (h) MoreMNAS, (i) FALSR, (j) DeCoNASNet (ours).

- ✓ DeCoNASNet outperforms conventional state-of-the-art methods and existing NAS-based algorithms which have lower than 2M parameters.
- ✓ We achieve 32.03dB in PSNR for Urban100 test benchmark dataset.
- ✓ We find that DeCoNASNet successfully restores the details in images.

CONCLUSION

- ✓ We have proposed an RL-based neural architecture search algorithm for image SR, named as DeCoNAS.
- ✓ The proposed method can find a promising lightweight SR network (DeCoNASNet) within 16 hours, which is a lot faster than other NAS-based algorithms.
- ✓ Our complexity-based penalty to the reward could reduce the network complexity, which enabled lightweight network architecture.
- ✓ Experiments show that the resulted DeCoNASNet yields higher performance in terms of PSNR vs. complexity among the recent handcrafted lightweight SR networks and other NAS-based ones.