Lightweight Bimodal Network for Single-Image Super-Resolution via Symmetric CNN and Recursive Transformer

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https://github.com/IVIPLab/LBNet
Outline

- Background & Related Works
- Motivation
- Lightweight Bimodal Network (LBNet)
- Experiments & Discussion
- Summary
Image Super-resolution

- The purpose of single-image super-resolution (SISR) is to reconstruct a high-resolution (HR) image from its degraded low-resolution (LR) counterpart.

Lightweight Image Super-resolution

- Lightweight SR models are widely concerned for saving memory resources and computing resources.
- In the case of fewer parameters and computation, a better performance is obtained.
How to reconstruct SR images?

CARN/IDN/IMDN/MSFIN…

Model

LR

DIV2K

SR
Background & Related Works

- **Ahn's CARN**

  N. Ahn, et al. Fast, accurate, and lightweight super-resolution with cascading residual network, in *ECCV*, 2018, pp. 252–268.

- **Hui's IDN**

  Z. Hui, et al. Fast and accurate single image super-resolution via information distillation network, in *CVPR*, 2018, pp. 723–731.
Background & Related Works

- **Hui's**

  Z. Hui, et al. Lightweight image super-resolution with information multi-distillation network, in *ACM MM*, 2019, pp. 2024–2032.

- **Li's s-LWSR**

  B. Li, et al. s-lwsr: Super lightweight super-resolution network, *IEEE TIP*, vol. 29, pp. 8368–8380, Aug. 2020.

- **Wang's MSFIN**

  B. Li, et al. s-lwsr: Super lightweight super-resolution network, *IEEE TIP*, vol. 29, pp. 8368–8380, Aug. 2020.
Background & Related Works

- Other Lightweight Methods

SRCNN

AWSRN

VDSR

RFDN

FSRCNN

LatticeNet
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Motivation

- Transformer Modules

\[ F_{\text{mid}} = F_{\text{in}} + f_{\text{MHA}}(f_{\text{norm}}(F_{\text{in}})) \]

\[ F_{\text{out}} = F_{\text{1}} + f_{\text{MLP}}(f_{\text{norm}}(F_{\text{mid}})) \]

\[ \text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V. \]

- Transformers can capture and model long-term image dependencies.
Motivation

- **Target**
  - We aim to explore an efficient lightweight SISR model with low complexity, low model size and low execution time.

- **Contributions**
  - To better apply Transformer to lightweight SISR tasks, we propose a Recursive Transformer to learn the long-term dependence of images. Transformer will bring a lot of parameter consumption, and the recursive mechanism helps to use it to fully learn dependency information without increasing additional parameter consumption. This is the first attempt of the recursive mechanism in Transformer, which can refine the texture details by global information with few parameters and GPU memory consumption.
  - To reduce the computational consumption caused by the repeated features extracted by CNN, the Feature Refinement Dual-Attention Block (FRDAB) are specially designed for feature extraction. Furthermore, a local feature fusion module (LFFM) is proposed for feature fusion.
Motivation

Contributions

• Considering that as the depth of the CNN network increases, the complexity and parameters of the model will increase. The symmetric CNN network increases the feature extraction and representation capabilities of the network through the top CNN network and the bottom shared parameter branch network, and does not bring additional parameter consumption.

• To make full use of the local features extracted by the symmetric CNN network and the global dependency information learned by the recursive Transformer network, we propose a novel Lightweight Bimodal Network (LBNet) for SISR. LBNet elegantly integrates CNN and Transformer, enabling it to achieve a better balance between the performance, size and execution time of the model.
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Symmetric CNN is specially designed for local feature extraction, which mainly consists of some paired parameter sharing LFFM and CA modules.

Recursive Transformer introduced the recursive mechanism to allow the Transformer to be fully trained without greatly increasing model parameters.
FRDAB is a dual-attention block, which specially designed to reduce the computational cost of repetitive features extracted by the CNN network.

The dual attention mechanism is used to channel and spatially reweight the extracted features.
- Residual connections and dense connections are applied in LFFM to fully utilize the features extracted by FRDAB.
- Group convolutions are used for dimensionality reduction to reduce model parameters and computational cost.
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### Experiments & Discussion

**Quantitative comparisons**

| Method                  | Scale | Params | Multi-Adds | Set5 PSNR/SSIM | Set14 PSNR/SSIM | BSD100 PSNR/SSIM | Urban100 PSNR/SSIM | Manga109 PSNR/SSIM |
|-------------------------|-------|--------|------------|----------------|-----------------|-----------------|--------------------|-------------------|
| Bicubic                 |       |        |            | 33.66/0.9299  | 30.24/0.8688    | 29.56/0.8431    | 26.88/0.8403       | 30.80/0.9339       |
| SRCNN [Dong et al., 2014] | 57K   | 52.7G  |            | 36.66/0.9542  | 32.42/0.9063    | 31.36/0.8879    | 29.50/0.8946       | 35.60/0.9663       |
| FSRCNN [Dong et al., 2016] | 12K   | 6.0G   |            | 37.05/0.9560  | 32.66/0.9090    | 31.53/0.8920    | 29.88/0.9020       | 36.67/0.9710       |
| VDSR [Kim et al., 2016a]  | 665K  | 612.6G |            | 37.53/0.9587  | 33.03/0.9124    | 31.90/0.8960    | 30.76/0.9140       | 37.22/0.9750       |
| DRCN [Kim et al., 2016b]  | 1774K | 17974.3G |           | 37.63/0.9588  | 33.04/0.9118    | 31.85/0.8942    | 30.75/0.9133       | 37.55/0.9732       |
| LapSRN [Lai et al., 2018] | 813K  | 29.9G  |            | 37.52/0.9590  | 33.08/0.9130    | 31.80/0.8950    | 30.41/0.9100       | 37.27/0.9740       |
| DRRN [Tai et al., 2017]   | 297K  | 6796.9G|            | 37.74/0.9591  | 33.23/0.9136    | 32.05/0.8973    | 31.23/0.9188       | 37.88/0.9749       |
| IDN [Hui et al., 2018]    | 553K  | 124.6G |            | 37.83/0.9600  | 33.30/0.9148    | 32.08/0.8985    | 31.27/0.9196       | 38.01/0.9749       |
| CARN [Ahn et al., 2018]   | 1592K | 222.8G |            | 37.76/0.9590  | 33.52/0.9166    | 32.09/0.8978    | 31.92/0.9256       | 38.36/0.9765       |
| CBPN [Zhu and Zhao, 2019] | 1036K | 240.7G |            | 37.90/0.9590  | 33.60/0.9171    | 32.17/0.8989    | 31.24/0.9279       | -                 |
| CBPN-S [Zhu and Zhao, 2019]| 430K  | 101.5G |            | 37.69/0.9583  | 33.36/0.9147    | 32.02/0.8972    | 31.55/0.9217       | 38.88/0.9774       |
| IMDN [Hui et al., 2019]   | 694K  | 158.8G |            | 38.00/0.9605  | 33.63/0.9177    | 32.19/0.8996    | 32.17/0.9283       | 38.86/0.9772       |
| AWRSN-M [Wang et al., 2019]| 1063K | 244.1G |            | 38.04/0.9605  | 33.66/0.9181    | 32.21/0.9000    | 32.23/0.9294       | 38.58/0.9774       |
| MADNet [Lan et al., 2020] | 878K  | 187.1G |            | 37.85/0.9600  | 33.38/0.9161    | 32.04/0.8979    | 31.62/0.9233       | -                 |
| GLADSR [Zhang et al., 2020]| 812K  | 187.2G |            | 37.99/0.9608  | 33.63/0.9179    | 32.16/0.8996    | 32.16/0.9283       | -                 |
| LAI [Xiao et al., 2021]   | 237K  |        |            | 37.94/0.9604  | 33.52/0.9174    | 32.12/0.8991    | 31.67/0.9242       | -                 |
| DCDN [Li et al., 2021b]   | 756K  |        |            | 38.01/0.9606  | 33.52/0.9166    | 32.17/0.8996    | 32.16/0.9283       | 38.70/0.9773       |
| SMR [Wang et al., 2021]   | 985K  | 351.5G |            | 38.00/0.9601  | 33.64/0.9179    | 32.17/0.8990    | 32.19/0.9284       | 38.76/0.9771       |
| LAPAR-A [Li et al., 2021a] | 548K  | 171.0G |            | 38.01/0.9605  | 33.62/0.9183    | 32.19/0.8999    | 32.10/0.9283       | 38.67/0.9772       |
| ECBSR [Zhang et al., 2021]| 596K  | 137.3G |            | 37.90/0.9615  | 33.34/0.9178    | 32.10/0.9018    | 31.71/0.9250       | 38.59/0.9768       |
| LBNet-T (Ours)            | 404K  | 49.0G  |            | 37.95/0.9602  | 33.53/0.9168    | 32.07/0.8983    | 31.91/0.9253       | 38.59/0.9768       |
| LBNet (Ours)              | 731K  | 153.2G |            | 38.05/0.9607  | 33.65/0.9177    | 32.16/0.8994    | 32.30/0.9291       | 38.88/0.9775       |
Experiments & Discussion

- Visual results of LBNet with other SR methods (x2)
### Experiments & Discussion

- Quantitative comparisons

| Method         | Scale | Params | Multi-Adds | Set5 PSNR/SSIM | Set14 PSNR/SSIM | BSD100 PSNR/SSIM | Urban100 PSNR/SSIM | Manga109 PSNR/SSIM |
|----------------|-------|--------|------------|----------------|------------------|-------------------|---------------------|-------------------|
| Bicubic        |       | -      | -          | 30.39/0.8682   | 27.55/0.7742     | 27.21/0.7385      | 24.46/0.7349        | 26.95/0.8556       |
| SRCNN [Dong et al., 2014] | 57K   | 52.7G  | -          | 27.25/0.9090   | 29.28/0.8209     | 28.41/0.7863      | 26.24/0.7989        | 30.59/0.9107       |
| FSRCNN [Dong et al., 2016] | 12K   | 5.0G   | -          | 33.16/0.9140   | 29.43/0.8242     | 28.53/0.7910      | 26.43/0.8080        | 31.10/0.9210       |
| VDSR [Kim et al., 2016a] | 665K  | 612.6G | -          | 33.66/0.9213   | 29.77/0.8314     | 28.82/0.7976      | 27.14/0.8279        | 32.01/0.9310       |
| DRCN [Kim et al., 2016b] | 1774K | 17974.3G | -          | 33.82/0.9226   | 29.76/0.8311     | 28.80/0.7963      | 27.15/0.8276        | 32.31/0.9328       |
| DRRN [Tai et al., 2017] | 297K  | 6796.9G | -          | 34.03/0.9244   | 29.96/0.8349     | 28.95/0.8004      | 27.53/0.8378        | 32.74/0.9390       |
| IDN [Hui et al., 2018] | 553K  | 56.3G  | -          | 34.11/0.9253   | 29.99/0.8354     | 28.95/0.8013      | 27.42/0.8359        | 32.71/0.9381       |
| CARN [Ahn et al., 2018] | 1592K | 118.8G | -          | 34.29/0.9255   | 30.29/0.8407     | 29.06/0.8034      | 28.06/0.8493        | 33.43/0.9427       |
| IMDN [Hui et al., 2019] | 703K  | 71.5G  | -          | 34.36/0.9270   | 30.32/0.8417     | 29.09/0.8046      | 28.17/0.8519        | 33.61/0.9445       |
| AWRSN-M [Wang et al., 2019] | 1143K | 116.6G | -          | 34.42/0.9275   | 30.32/0.8419     | 29.13/0.8059      | 28.26/0.8545        | 33.64/0.9450       |
| MADNet [Lan et al., 2020] | 930K  | 88.4G  | -          | 34.16/0.9253   | 30.21/0.8398     | 28.98/0.8023      | 27.77/0.8439        | -                 |
| GLADSR [Zhang et al., 2020] | 821K  | 88.2G  | -          | 34.41/0.9272   | 30.37/0.8418     | 29.08/0.8050      | 28.24/0.8537        | -                 |
| LAI1Net [Xiao et al., 2021] | 237K  | -      | -          | 34.26/0.9261   | 30.24/0.8404     | 29.04/0.8039      | 27.83/0.8453        | -                 |
| DCDN [Li et al., 2021b] | 765K  | -      | -          | 34.41/0.9273   | 30.31/0.8417     | 29.08/0.8045      | 28.17/0.8520        | 33.54/0.9441       |
| SMSR [Wang et al., 2021] | 993K  | 156.8G | -          | 34.40/0.9290   | 30.33/0.8412     | 29.10/0.8050      | 28.25/0.8536        | 33.68/0.9445       |
| LAPAR-A [Li et al., 2021a] | 594K  | 114.0G | -          | 34.36/0.9267   | 30.34/0.8421     | 29.11/0.8054      | 28.15/0.8523        | 33.51/0.9441       |
| EMASRN [Zhu et al., 2021] | 427K  | -      | -          | 34.36/0.9264   | 30.30/0.8411     | 29.05/0.8035      | 28.04/0.8493        | 33.43/0.9433       |
| LNet-T (Ours)    |       | 22.0G  | -          | 34.33/0.9264   | 30.25/0.8402     | 29.05/0.8042      | 28.06/0.8485        | 33.48/0.9433       |
| LNet (Ours)      |       | 68.4G  | -          | 34.47/0.9277   | 30.38/0.8417     | 29.13/0.8061      | 28.42/0.8559        | 33.82/0.9460       |
Experiments & Discussion

Visual results of FDIWN with other SR methods (x3)

HR(Params,Mult-Adds)
PSNR/SSIM
24.52/0.6398

SRCNN(57K,52.7G)
27.27/0.7951

DRCN(1774K,17974.3G)
27.55/0.8048

IDN(553K,56.3G)
27.45/0.8013

CARN-M(412K,46.1G)
27.63/0.8071

CARN(1592K,118.8G)
27.68/0.8075

IMDN(703K,71.5G)
27.57/0.8039

MADNet(930K,88.4G)
27.79/0.8105

LBNet-T(407K,22.0G)
27.83/0.8128

LBNet(736K,68.4G)
## Experiments & Discussion

### Quantitative comparisons

| Method | Scale | Params | Mult-Adds | Set5 PSNR/SSIM | Set14 PSNR/SSIM | BSD100 PSNR/SSIM | Urban100 PSNR/SSIM | Manga109 PSNR/SSIM |
|--------|-------|--------|-----------|---------------|----------------|----------------------|----------------------|----------------------|
| Bicubic | -     | -      | -         | 28.42/0.8104  | 26.00/0.7027  | 25.96/0.6675  | 23.14/0.6577  | 24.89/0.7866  |
| SRCNN [Dong et al., 2014] | 57K   | 52.7G  | -         | 30.48/0.8628  | 27.49/0.7503  | 26.90/0.7101  | 24.52/0.7221  | 27.66/0.8505  |
| FSRCNN [Dong et al., 2016] | 12K   | 4.6G   | -         | 30.71/0.8657  | 27.59/0.7535  | 26.98/0.7150  | 24.62/0.7280  | 27.90/0.8610  |
| VDSR [Kim et al., 2016a] | 665K  | 0.61G  | -         | 31.35/0.8583  | 28.01/0.7674  | 27.29/0.7251  | 25.18/0.7524  | 28.83/0.8809  |
| DRCN [Kim et al., 2016b] | 1774K | 17974.3G | -       | 31.53/0.8854  | 28.02/0.7670  | 27.23/0.7233  | 25.14/0.7510  | 28.98/0.8816  |
| LapSRN [Lai et al., 2018] | 813K  | 149.4G | -         | 31.54/0.8850  | 28.19/0.7720  | 27.32/0.7280  | 25.21/0.7560  | 29.09/0.8900  |
| DRRN [Tai et al., 2017] | 297K  | 6796.9G | -       | 31.68/0.8888  | 28.21/0.7720  | 27.38/0.7284  | 25.44/0.7638  | 29.46/0.8960  |
| IDN [Hui et al., 2018] | 553K  | 32.3G  | -         | 31.82/0.8903  | 28.25/0.7730  | 27.41/0.7297  | 25.41/0.7632  | 29.41/0.8942  |
| CARN [Ahn et al., 2018] | 1592K | 90.9G  | -         | 32.13/0.8937  | 28.60/0.7806  | 27.58/0.7349  | 26.07/0.7837  | 30.42/0.9070  |
| CBPN [Zhu and Zhao, 2019] | 1197K | 97.9G  | -         | 32.21/0.8944  | 28.63/0.7813  | 27.58/0.7356  | 26.14/0.7869  | -                |
| CBPN-S [Zhu and Zhao, 2019] | 592K  | 63.1G  | -         | 31.93/0.8908  | 28.50/0.7785  | 27.50/0.7324  | 25.85/0.7772  | -                |
| IMDN [Hui et al., 2019] | 715K  | 40.9G  | -         | 32.21/0.8948  | 28.58/0.7811  | 27.56/0.7353  | 26.04/0.7838  | 30.45/0.9075  |
| AWSRN-M [Wang et al., 2019] | 1254K | 72.0G  | -         | 32.21/0.8954  | 28.65/0.7832  | 27.60/0.7368  | 26.15/0.7884  | 30.56/0.9093  |
| MADNet [Lan et al., 2020] | 1002K | 54.1G  | -         | 31.95/0.8917  | 28.44/0.7780  | 27.47/0.7327  | 25.76/0.7746  | -                |
| GLADSR [Zhang et al., 2020] | 826K  | 52.6G  | -         | 32.14/0.8940  | 28.62/0.7813  | 27.59/0.7361  | 26.12/0.7851  | -                |
| LAIINet [Xiao et al., 2021] | 263K  | -      | -         | 32.12/0.8942  | 28.59/0.7810  | 27.55/0.7351  | 25.92/0.7805  | -                |
| DCNN [Li et al., 2021b] | 777K  | -      | -         | 32.21/0.8949  | 28.57/0.7807  | 27.55/0.7356  | 26.09/0.7855  | 30.41/0.9072  |
| SMR [Wang et al., 2021] | 1006K | 89.1G  | -         | 32.12/0.8932  | 28.55/0.7808  | 27.55/0.7351  | 26.11/0.7868  | 30.54/0.9085  |
| LAPAR-A [Li et al., 2021a] | 659K  | 94.0G  | -         | 32.15/0.8944  | 28.61/0.7818  | 27.61/0.7366  | 26.14/0.7871  | 30.42/0.9074  |
| ECBSR [Zhang et al., 2021] | 603K  | 34.7G  | -         | 31.92/0.8946  | 28.34/0.7817  | 27.48/0.7393  | 25.81/0.7773  | -                |
| EMASRN [Zhu et al., 2021] | 546K  | -      | -         | 32.17/0.8948  | 28.57/0.7809  | 27.55/0.7351  | 26.01/0.7838  | 30.41/0.9076  |
| LBNet-T (Ours) | 410K  | 12.6G  | -         | 32.08/0.8933  | 28.54/0.7802  | 27.54/0.7358  | 26.00/0.7819  | 30.37/0.9059  |
| LBNet (Ours) | 742K  | 38.9G  | -         | 32.29/0.8960  | 28.68/0.7832  | 27.62/0.7382  | 26.27/0.7906  | 30.76/0.9111  |
Experiments & Discussion

- Visual results of LBNet with other SR methods (x4)
Experiments & Discussion

- Visual results of LBNet with other SR methods (x4)
Experiments & Discussion

- Visual results of FDIWN with other SR methods (x4)

| Method       | Params/Mul-Adds | PSNR | SSIM  |
|--------------|------------------|------|-------|
| HR           |                  |      |       |
| SRCNN (57K, 52.7G) | 23.22/0.6432    |      |       |
| DRCN (1774K, 17974.3G) | 23.71/0.6867    |      |       |
| IDN (553K, 32.3G) | 25.99/0.7900    |      |       |
| CARN-M (412K, 32.5G) | 25.05/0.7561    |      |       |
| CARN (1592K, 90.9G) | 25.81/0.7930    |      |       |
| IMDN (715K, 40.9G) | 25.78/0.7909    |      |       |
| MADNet (1002K, 54.1G) | 25.36/0.7736    |      |       |
| LBNnet-T (410K, 12.6G) | 25.43/0.7769    |      |       |
| LBNnet (742K, 38.9G) | 26.17/0.8036    |      |       |
Experiments & Discussion

- Model complexity analysis
Experiments & Discussion

- Investigations of the model size and performance
Experiments & Discussion

- Symmetric CNN Investigations

| Scale | FF | SA | CA | Params | Mult-Adds | PSNR/SSIM  |
|-------|----|----|----|--------|-----------|------------|
| ×4    | ✔  | ✗  | ✗  | 96.1K  | 10.01G    | 25.28/0.7601 |
| ×4    | ✗  | ✔  | ✗  | 96.3K  | 10.03G    | 25.31/0.7614 |
| ×4    | ✗  | ✗  | ✔  | 96.5K  | 10.01G    | **25.36/0.7622** |

- FRDAB Investigations

| Method                        | Params | Mult-Adds | PSNR/SSIM      |
|-------------------------------|--------|-----------|----------------|
| LBNet+RCAB                    | 228K   | 23.7G     | 29.94/0.9002   |
| LBNet+IMDB                    | 295K   | 31.3G     | 30.21/0.9043   |
| LBNet+FRDAB (Ours)            | 365K   | 38.9G     | **30.33/0.9059** |

| Scale | SA | CA | Params       | Mult-Adds       | PSNR/SSIM      |
|-------|----|----|--------------|-----------------|----------------|
| ×4    | ✗  | ✗  | 358.7K       | 38.80120G       | 30.18/0.9039   |
| ×4    | ✔  | ✗  | 359.6K       | 38.90281G       | 30.06/0.9025   |
| ×4    | ✗  | ✔  | 363.9K       | 38.80121G       | 30.30/0.9052   |
| ×4    | ✔  | ✔  | 364.8K       | 38.90282G       | **30.33/0.9059** |
Experiments & Discussion

- Recursive Transformer Investigations

| Method       | Params | Multi-Adds   | Running time | PSNR/SSIM   |
|--------------|--------|--------------|--------------|-------------|
| w/o RT       | 365K   | 38.9028G     | 0.0168s      | 32.07/0.8929|
| with RT      | 742K   | 38.9032G     | 0.0274s      | 32.23/0.8949|

| Method       | Params | Multi-Adds   | Running time | PSNR/SSIM   |
|--------------|--------|--------------|--------------|-------------|
| TM-0         | 741.7K | 38.9032G     | 0.0274s      | 32.23/0.8949|
| TM-1         | 741.7K | 38.9036G     | 0.0356s      | 32.27/0.8958|
| TM-2         | 741.7K | 38.9039G     | **0.0401s**  | **32.29/0.8960**|
| TM-3         | 741.7K | 38.9043G     | 0.0516s      | 32.30/0.8960|

| Method       | Params | Multi-Adds   | Set5         | Set14        | BSD100         | Urban100        | Manga109        | Average        |
|--------------|--------|--------------|--------------|--------------|----------------|-----------------|----------------|----------------|
| SwinIR       | 897K   | 49.6G        | 32.44/0.8976 | 28.77/0.7858 | 27.69/0.7406   | 26.47/0.7980    | 30.92/0.9151   | 29.26/0.8274   |
| ESRT         | 751K   | 67.7G        | 32.19/0.8947 | 28.69/0.7833 | 27.69/0.7379   | 26.39/0.7962    | 30.75/0.9100   | 29.14/0.8244   |
| LBNet (Ours) | **742K** | **38.9G**    | **32.29/0.8960** | **28.68/0.7832** | **27.62/0.7382** | **26.27/0.7906** | **30.76/0.9111** | **29.12/0.8238** |
Outline

- Background & Related Works
- Motivation
- Lightweight Bimodal Network (LBNet)
- Experiments & Discussion
- Summary
The Local Feature Fusion Module (LFFM) and Feature Refinement Dual-Attention Block (FRDAB) are specially designed for feature extraction and utilization.

The well designed Recursive Transformer can learn the long-term dependence of images. It is the first attempt of the recursive mechanism in Transformer, which can refine the texture details by global information with few parameters and GPU memory consumption.

The experiment show that our proposed LBNet achieved a good balance between model size, performance, and computational cost.
Thanks !