DID: A Nested Dense in Dense Structure with Variable Local Dense Blocks for Super-Resolution Image Reconstruction

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January 15, 2021

ICPR 2020

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Outline

- Motivation And Contribution
- Variable Local Dense Block(VLDB) Structure
- Dense in Dense(DID)-Network Structure
- Experimental Results
- Conclusion

1. Motivation

Essential Task in SR methods: information missed VS feature mining

- An LDB with fixed depth： non-adaptive match with receptive fields(RFs),

  → Variable depth, increasing layers in LDBs gradually

- Lack of fully feature multiplexing： LDBs and Super LDBs

  → Connection

2. Contributions

- Suggest a VLDB， # of conv. layers in an LDB varies to match RFs efficiently at a pattern of an arithmetic series.
- a nested DID structure by VLDB output reusing & VLDB networking

3. Variable Local Dense Block(VLDB)

1) Non adaptive Local Dense Block

- **Fixed Depth, each LDB**

c^{th} layer output $F_{d,c} = \sigma(W_{d,c}[F'_{d-1}, F_{d,1}, \ldots, F_{d,c-1}] + B_{d,c})$

LFF output $F_{d,LF}$: $F_{d,LF} = H^{d}_{LFF}([F'_{d-1}, F_{d,1}, \ldots, F_{d,C_d}])$

output of d^{th} VLDB F_d: $F_d = F'_{d-1} + F_{d,LF}$

A fixed DB depth can not match the RF

2) Variable Local Dense Block

Layer numbers in d^{th} VLDB : $C_d = kd$

Advantages: small # of layers in early LDBs

matched RFs lead to rapid convergency

---- less gradient vanishing & exploding

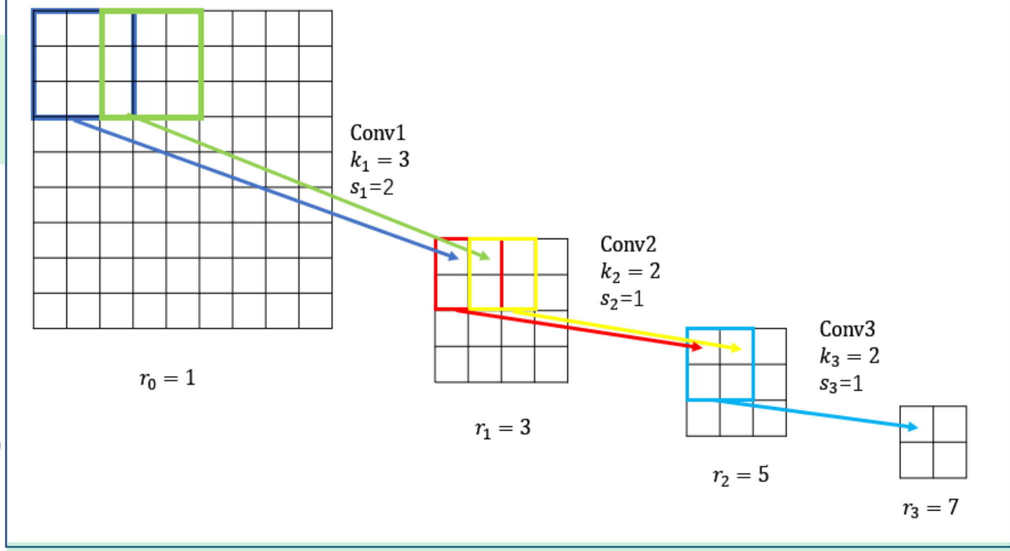


Fig.1. Relations of RFs ~ kernel sizes & strides

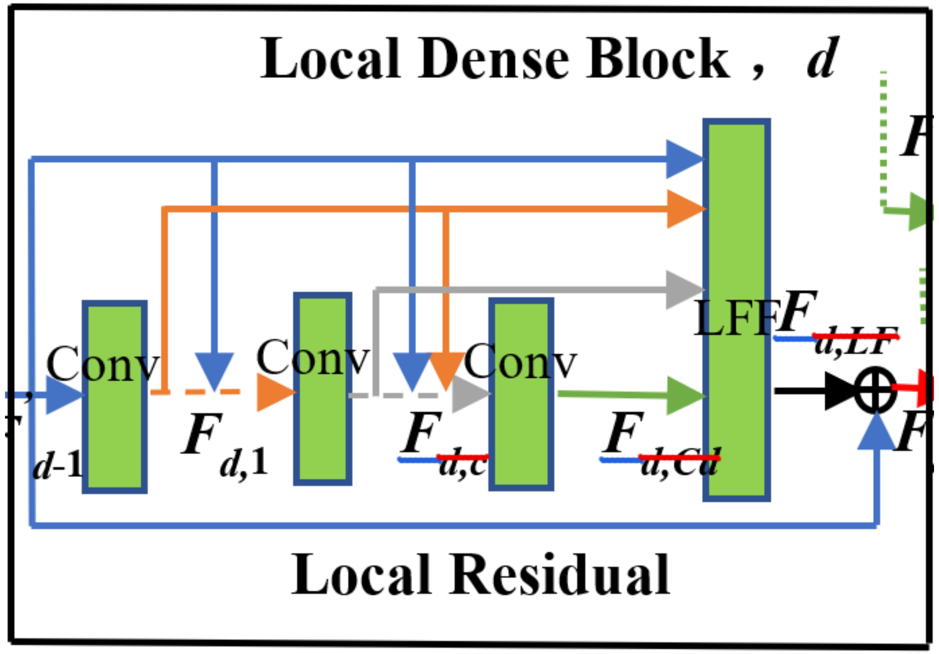
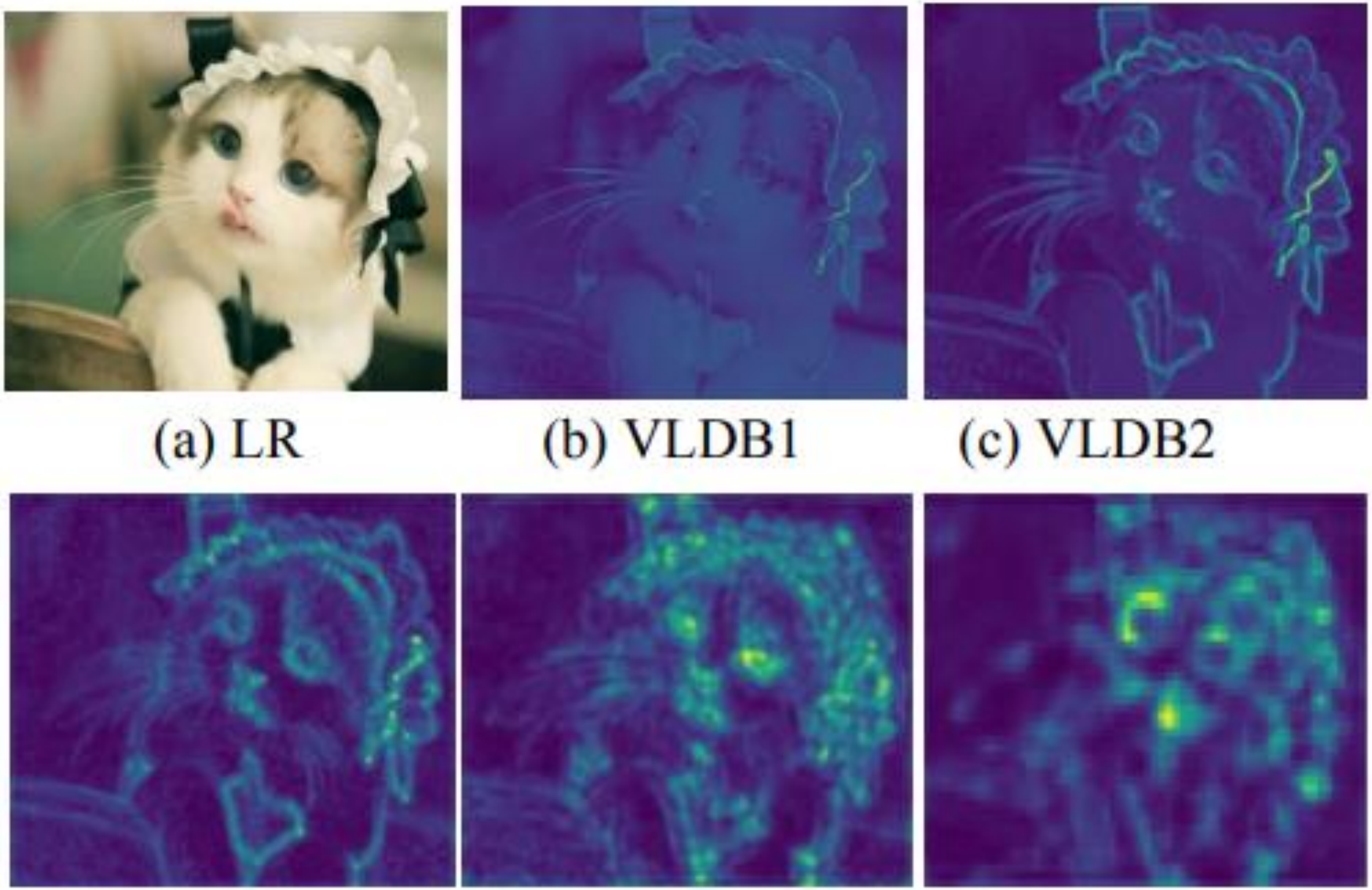


Fig.2.The architecture of VLDB



(a) LR (b) VLDB1 (c) VLDB2

(d) VLDB3 (e) VLDB4 (f) VLDB5

Fig.3. The output of different VLDB.

4. Dense in Dense(DID)-Network Structure

DID network: a super RDN, using VLDBs as basic nodes.

- **Global Dense Connections**

  F_{DID}: Final output

$$F_{\mathrm{DID}} = H_{Dense}(F_1^{out}, F_2^{out}, \ldots, F_D^{out})$$
$$= H_{Dense}(H_{Dense}(F_{1,1}, \ldots, F_{1,C_1}), \ldots,$$
$$H_{Dense}(F_{D,1}, \ldots, F_{D,C_D}))$$

- **Global Feature Fusion**

  FDF: GFF output

$$F_{DF} = H_{GFF}([F_0, F_1^{out}, \ldots, F_D^{out}])$$

- **Residual Learning**

  F_{GF}: global feature maps

$$F_{GF} = F_{-1} + F_{DF}$$

* **Loss Function**

$$L(\theta) = \frac{1}{T}\sum_{t=1}^{T} W^t ||I_{HR}^t - I_{SR}^t||_1$$

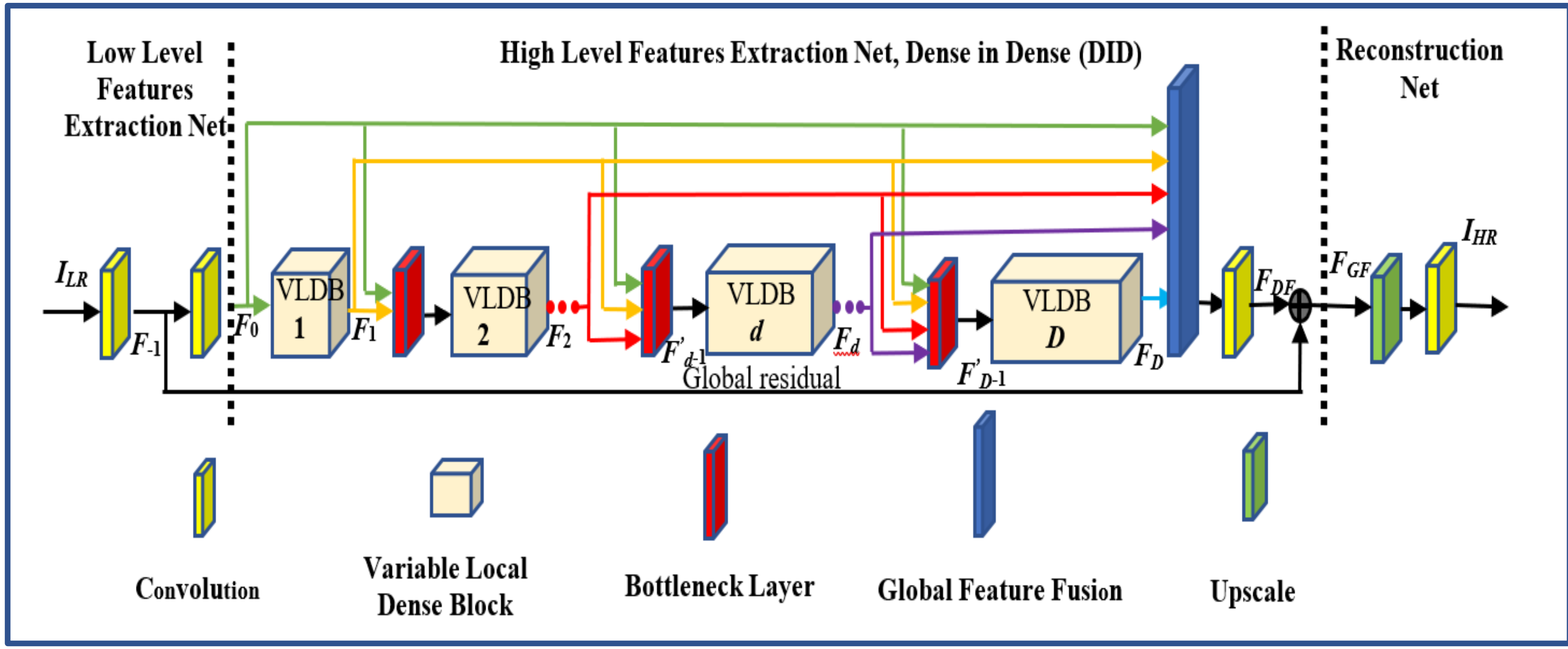


Fig.4. our DID network.

5. Experimental Results

EX1 Study of D & C, numbers DBs & Conv.layers

- Larger D or a larger C benefits PSNRs
- The VLDB effects on improving PSNRs
- Mismatching with the RFs deteriorates PSNRs

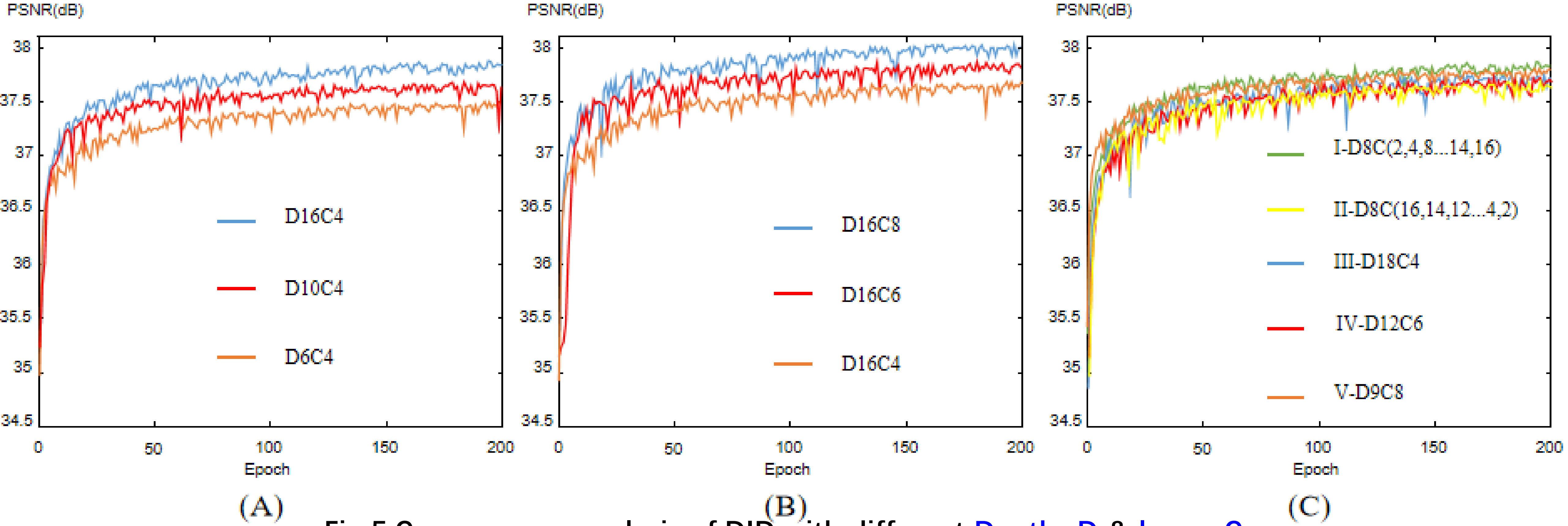


Fig.5.Convergence analysis of DID with different Depths D & layers C

Ex2 Convergence rate of DID and RDN

⁎ Rapid training due to its RF matched advantage.

Ex3 Importance of combination of VLDB & DID

⁎VLDBs & DID performed separately → PSNR ⬆

⁎Both VLDBs+DID consistently work, combined effects.

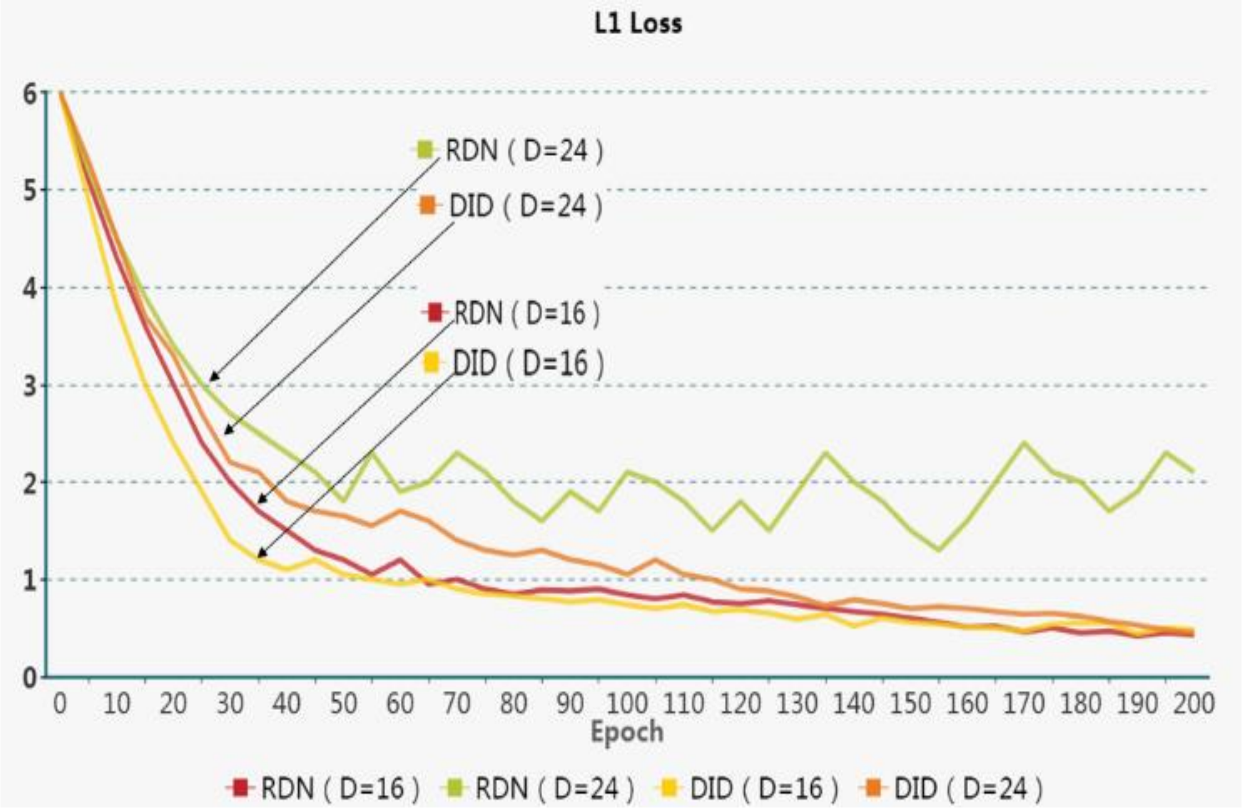


Fig.6.Loss Comparison: Loss curves of DID net. & RDNs.

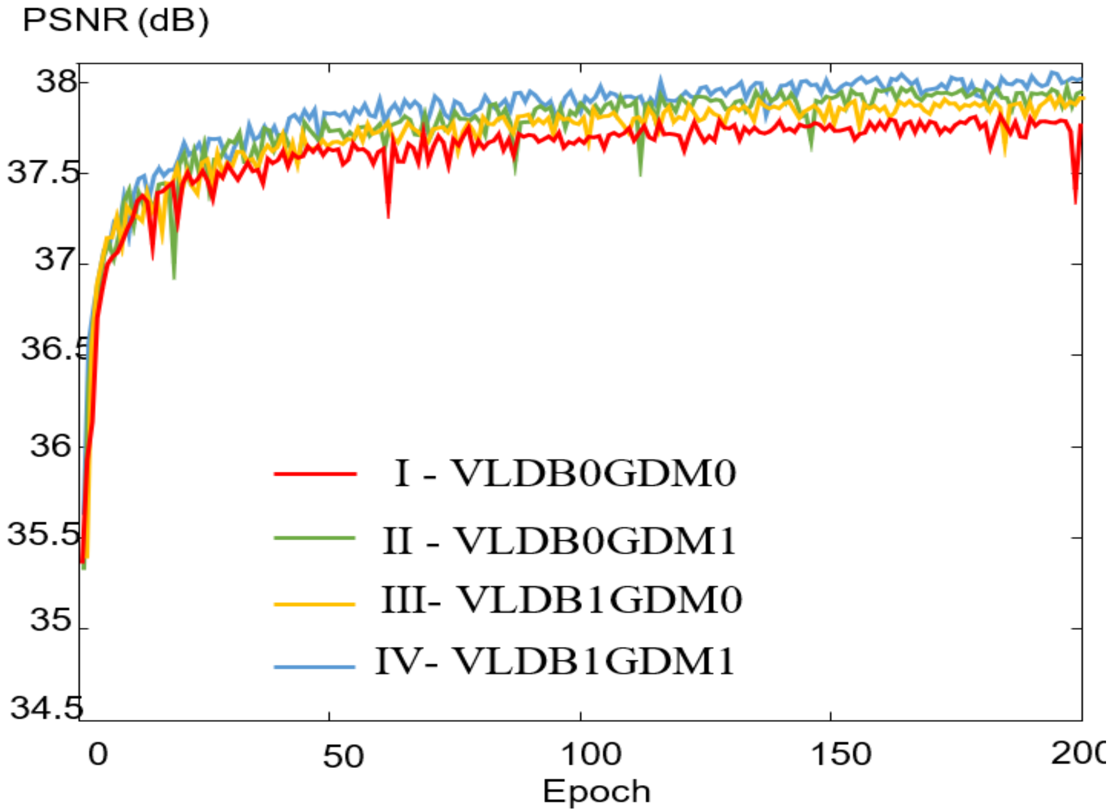


Fig.7.Different combinations of modules.

Ex4 Performance comparison with other methods.

⋆ DID has the superior advantage to preserved edges best

⋆ Little weak in vertical details than RCAN

119082 from B100 (x4)

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- DID has the superior advantage to preserved edges best
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img 073 from Urban100 (x4)

6. Conclusion

- We propose a very deep nested dense residual network, VLDBs and DID structure are core parts.
- VLDBs fully utilize the hierarchical features from each Conv. layer to extract local features
- DID network makes full use of hierarchical features in layer-wise and in DB-wise

Thank You !