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Lightweight Wavelet-based Transformer for Image Super-resolution

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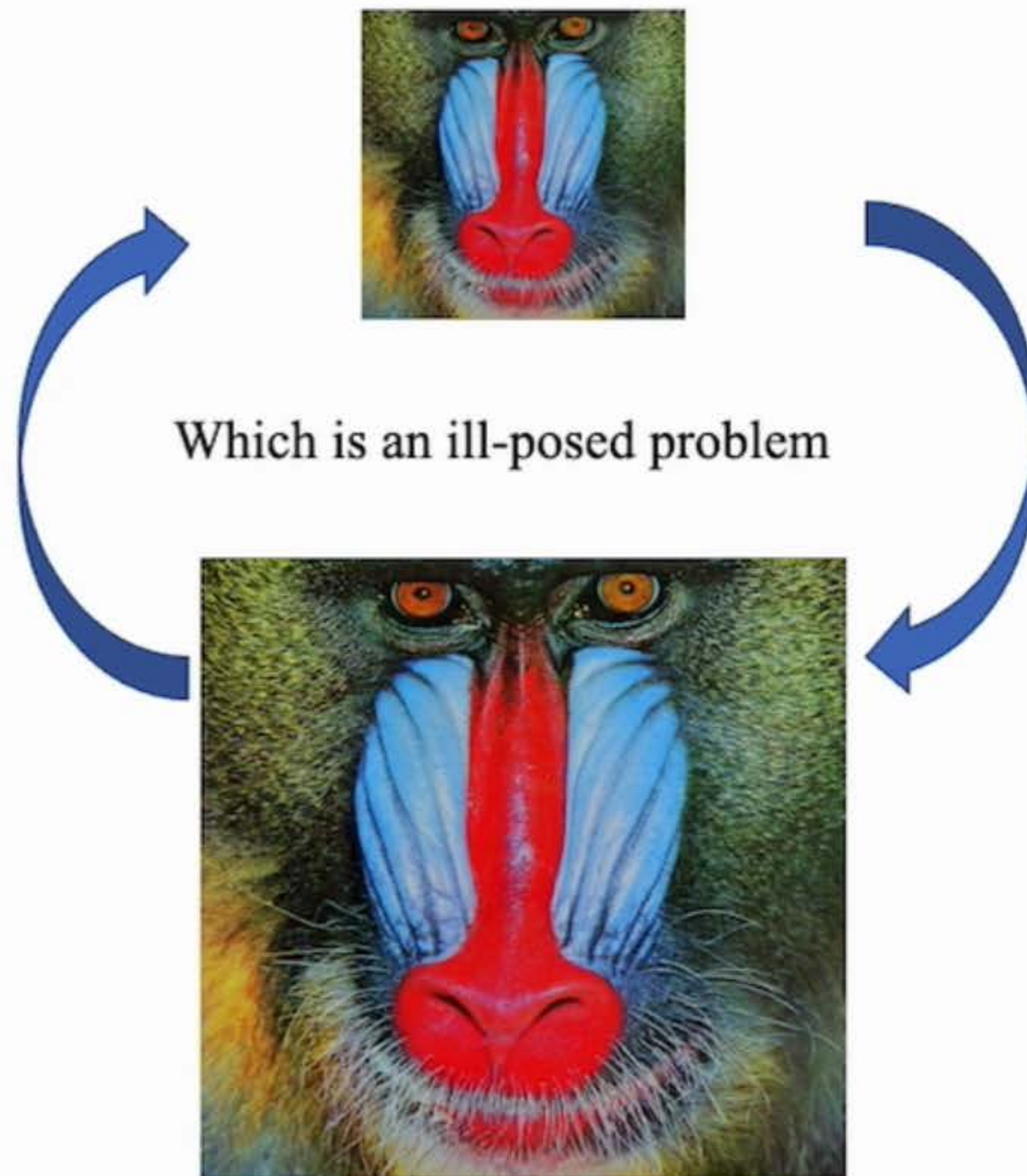
Introduction

- Problem Definition

- Super-resolution (SR) aims to recover a high-resolution (HR) image from a low-resolution (LR) image counterpart.
- Pursuing the SR quality of the model while ignoring the lightweight problem.

- Main Challenge

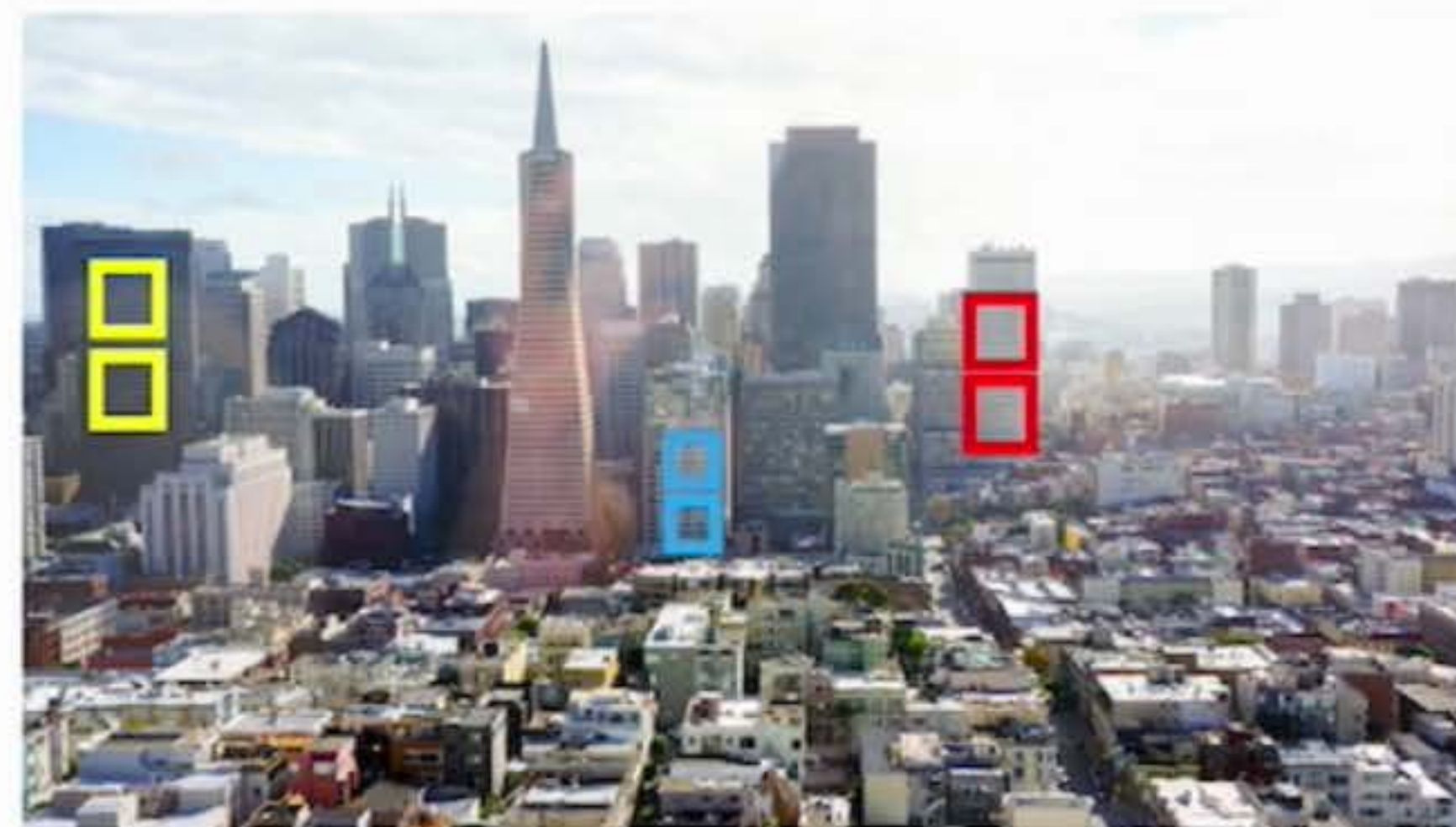
- Generally, model scale and model quality are a trade-off issue.
- How to get a better SR quality on an acceptable model scale?



Introduction

- Contribution

- A Lightweight Transformer Backbone (LTB) is designed to implicitly mine self-similarity information in images to ensure SR quality.
- The mapping from LR to HR is fitted on the wavelet domain, while the stability of the inverse wavelet transform is guaranteed by Wavelet Coefficient Enhancement Backbone (WCEB).
- Achieve competitive results on multiple publicly available benchmarks.



Approach

- Overall Architecture

$$F_0 = f_{1*1}(f_{3*3}(I_{LR}))$$

$$I^W = \text{concat}(\text{SWT}(F_0))$$

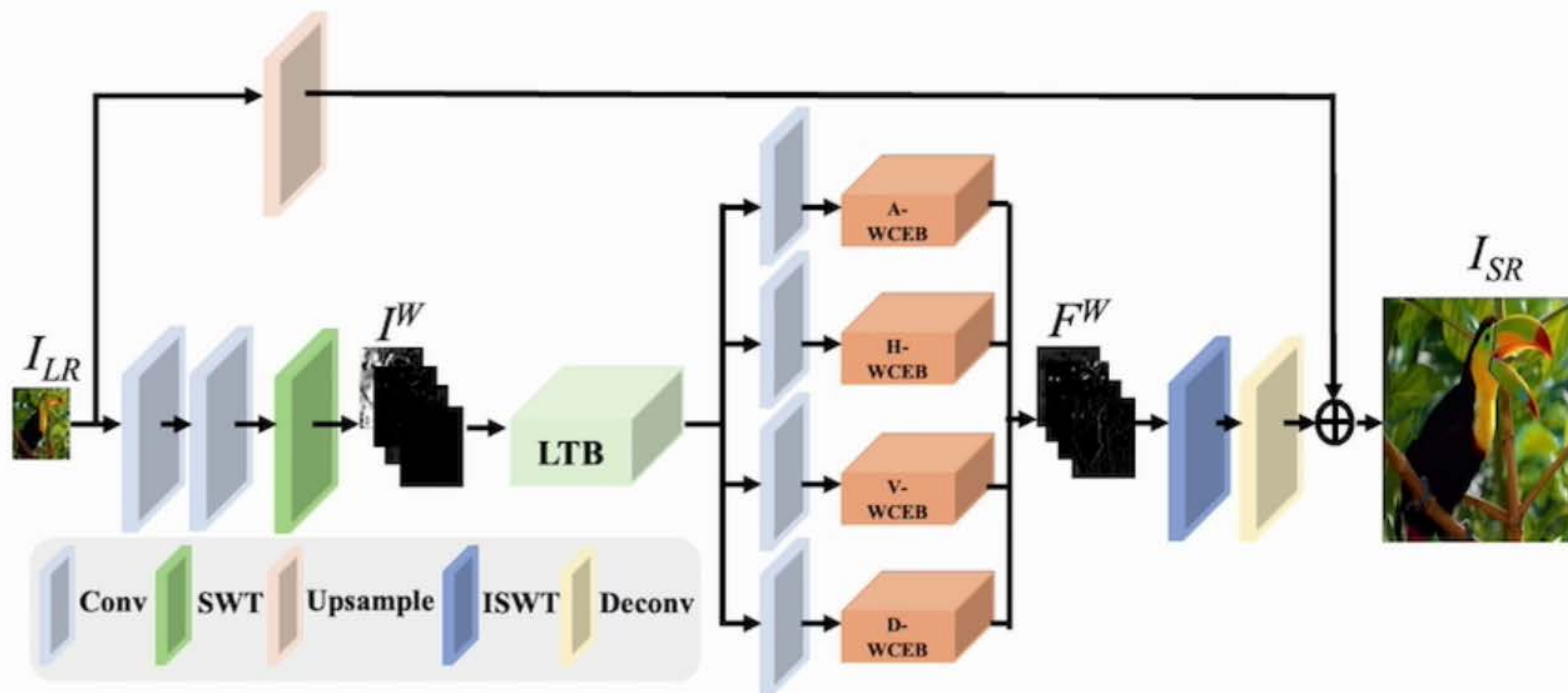
$$F_L = \phi^5(\psi(\phi^8(f_{\text{group}}(I^W))))$$

$$F_A, F_H, F_V, F_D = \text{split}(F_L)$$

$$F^W = \text{concat}(\sigma_{A,H,V,D}(F_A, F_H, F_V, F_D))$$

$$F_D = \text{ISWT}(F^W)$$

$$I_{SR} = f_{\text{Deconv}}(f_{3*3}(F_d)) + f_{\text{up}}(I_{LR})$$



Approach

- Lightweight Transformer Backbone

$$S_{m1} = f_{partitioning}(f_{reduction}(S_i))$$

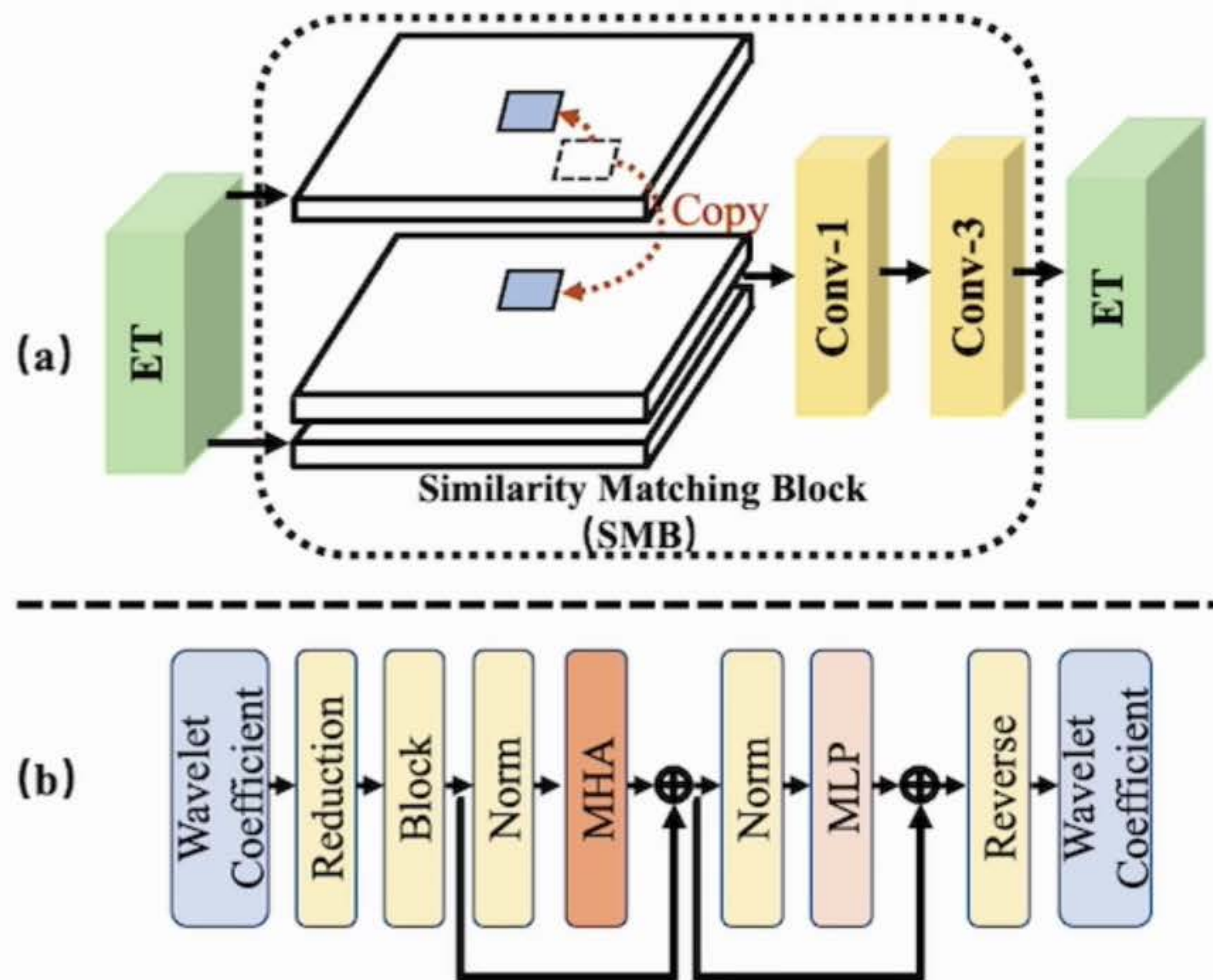
$$S_{m2} = MHA(Norm(S_{m1})) + S_{m1}$$

$$S_o = f_{reverse}(MLP(Norm(S_{m2})) + S_{m2})$$

- Similarity Matching Block

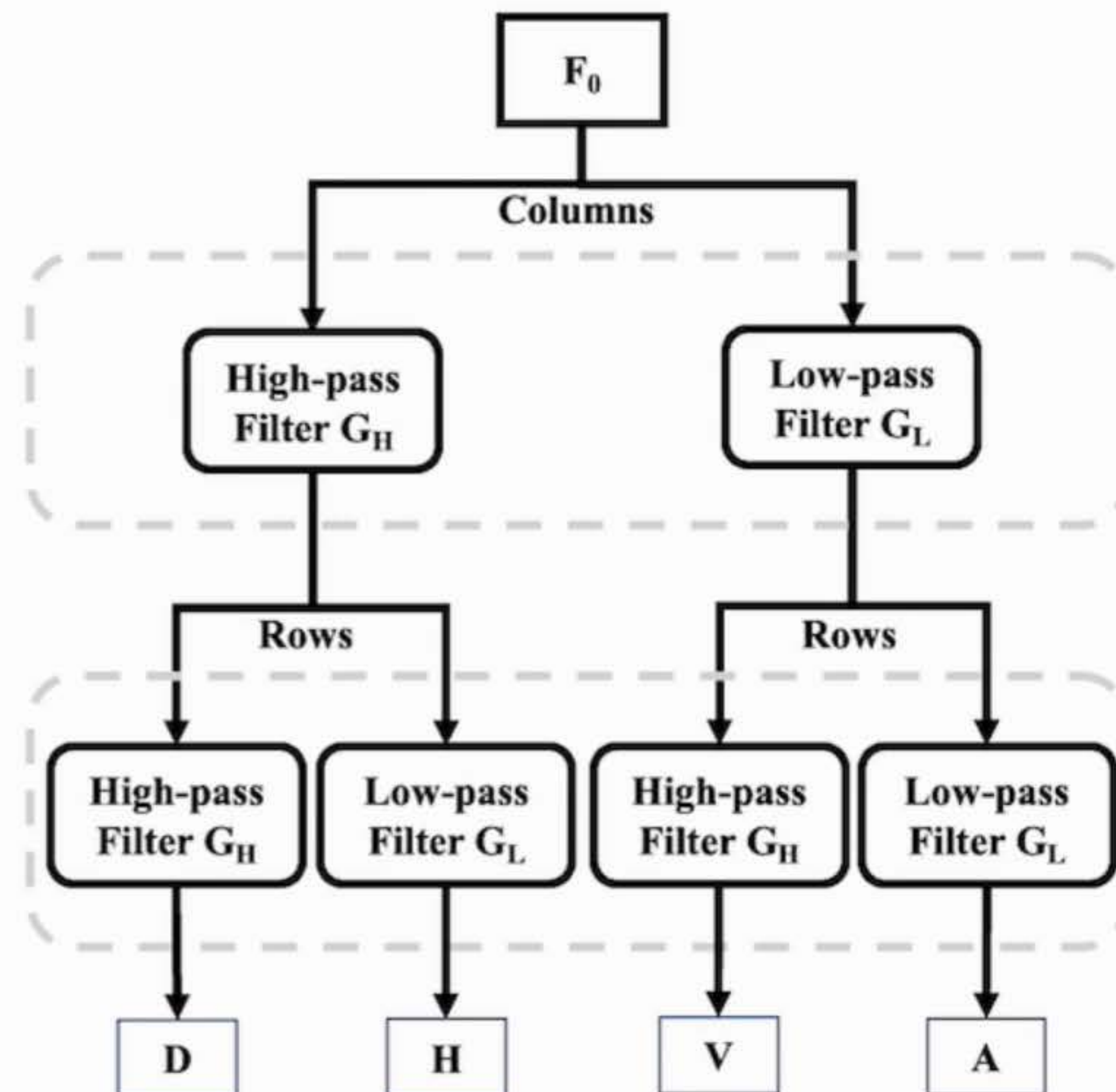
$$p_{i1c,j1c} = \arg \max_{p_{i2,j2}} \left\langle \frac{p_{i1,j1}}{\|p_{i1,j1}\|}, \frac{p_{i2,j2}}{\|p_{i2,j2}\|} \right\rangle$$

$$s.t. \quad |i1 - i2| + |j1 - j2| \neq 0$$



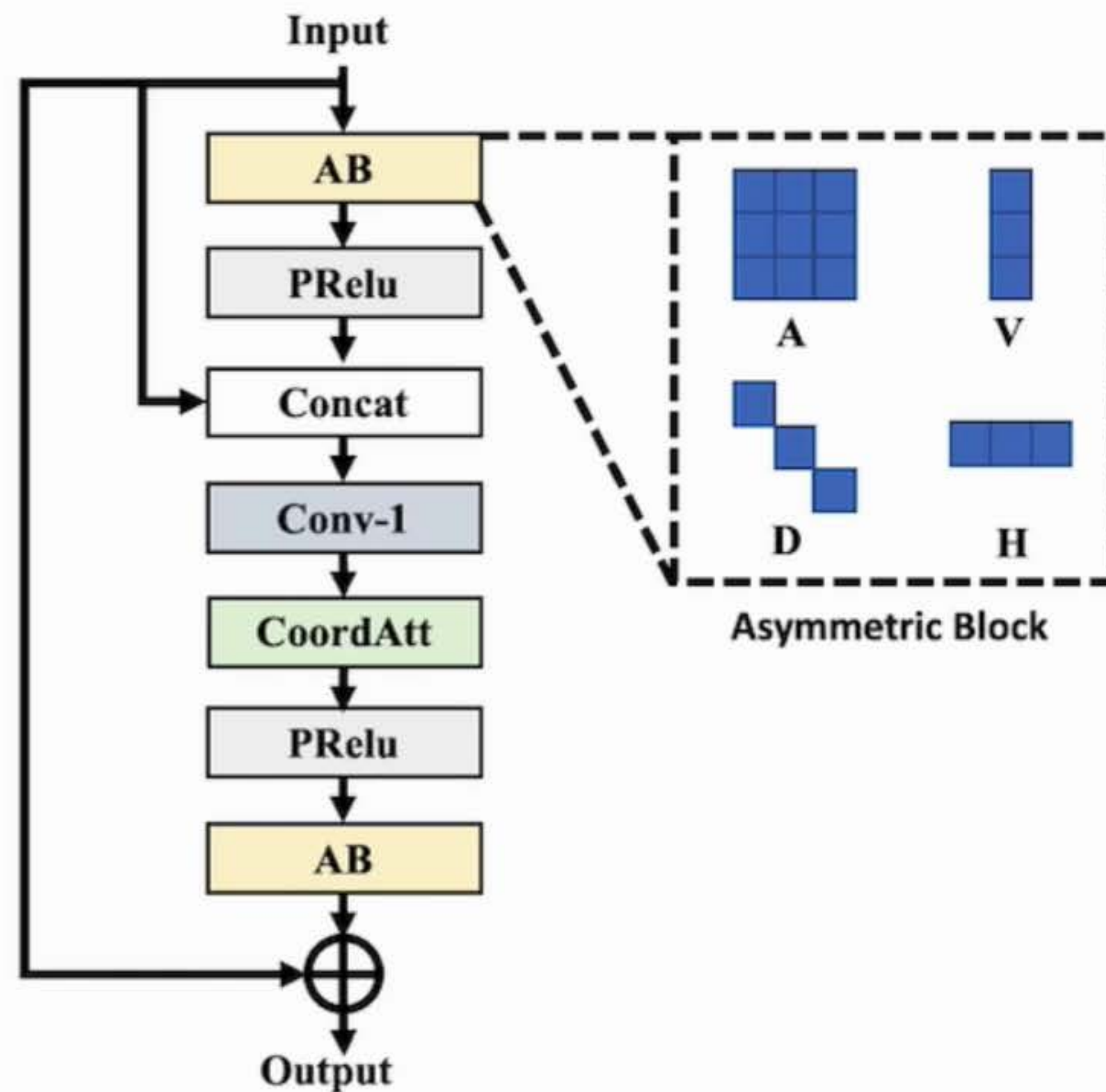
Approach

- Wavelet Transform
 - Stationary wavelet transform
 - Inverse stationary wavelet transform
 - Advantages of wavelet transform



Approach

- Wavelet coefficient Enhancement Backbone
 - Different Asymmetric Block for different wavelet coefficients
 - Different wavelet coefficients' channel redundancy
 - Different wavelet coefficients' structure information



Evaluation

- Benchmark

- Set5, Set14, BSD100, Urban100, Manga109

- Qualitative evaluation

- PSNR/SSIM
- $\times 2 \times 3 \times 4$

- Quantitative evaluation

- Subjective visual

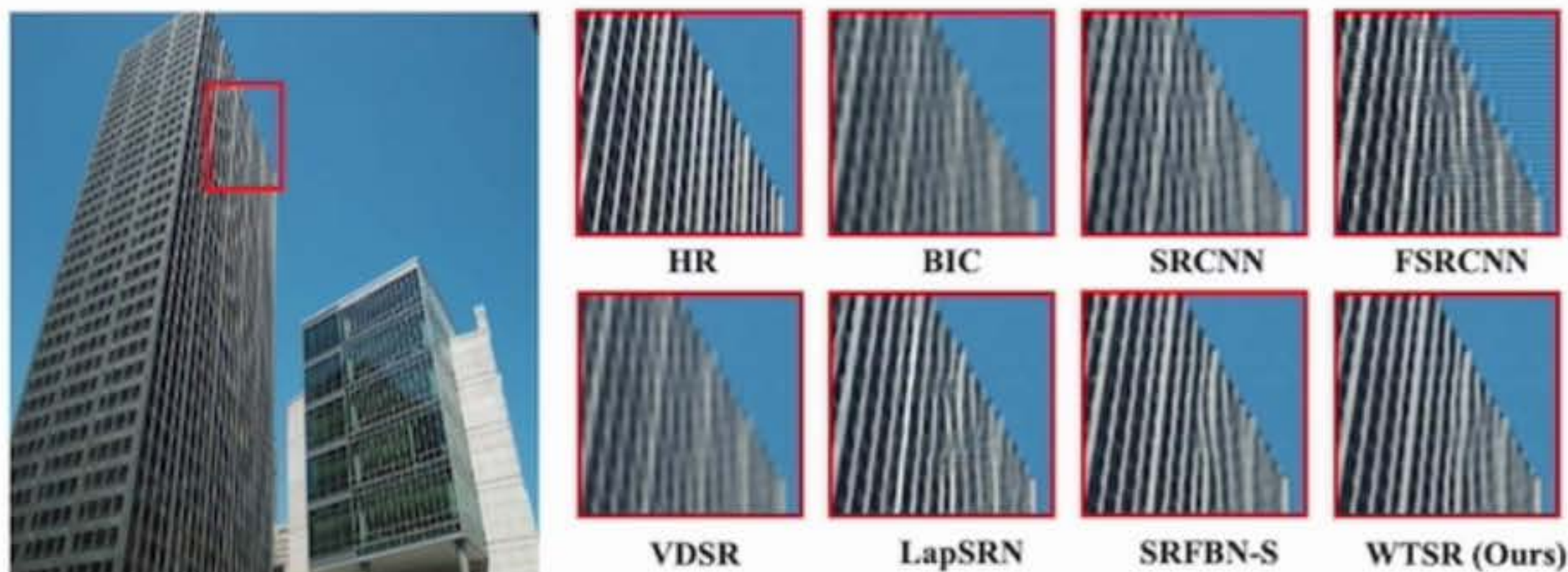


Table 1. Quantitative results of WTSR compared with other lightweight super-resolution network, the best model performance is **highlighted** and the second performance is underlined.

Methods	Scales	Params	Set5	Set14	BSD100	Urban100	Manga109
			PSNR/SSIM	PSNR/SSIM	PSNR/SSIM	PSNR/SSIM	PSNR/SSIM
Bicubic	-	-	33.66/0.930	30.24/0.869	29.56/0.843	26.88/0.840	30.30/0.934
SRCNN[32]	8K	8K	36.66/0.954	32.45/0.907	31.36/0.888	29.50/0.895	35.60/0.966
FSRCNN[6]	13K	13K	37.00/0.956	32.63/0.909	31.53/0.892	29.88/0.902	36.67/0.971
VDSR[15]	666K	666K	37.53/0.959	33.03/0.912	31.90/0.896	30.76/0.914	37.22/0.975
DWSR[8]	374K	374K	37.43/0.957	33.07/0.911	31.80/0.894	31.46/0.916	-/-
LapSRN[19]	x2 813K	813K	37.52/0.959	32.99/0.912	31.80/0.895	30.41/0.910	37.27/0.974
MemNet[31]	678K	678K	37.78/0.960	33.28/0.914	32.08/0.898	31.31/0.920	37.72/0.974
CARN-M[2]	412K	412K	37.53/0.958	33.26/0.914	31.92/0.896	31.23/0.919	-/-
SRFBN-S[20]	483K	483K	37.78/0.960	33.35/0.916	32.00/0.897	31.41/0.921	<u>38.06/0.976</u>
WDRN-S[33]	244K	244K	37.03/0.961	32.42/0.916	32.08/0.898	31.50/0.921	-/-
WTSR	528K	528K	37.95/0.961	33.51/0.915	32.09/0.893	31.91/0.928	38.42/0.976
Bicubic	-	-	30.39/0.868	27.55/0.774	27.21/0.739	24.46/0.735	26.95/0.856
SRCNN[32]	8K	8K	32.75/0.909	29.30/0.822	28.41/0.786	26.24/0.799	30.48/0.912
FSRCNN[6]	13K	13K	33.18/0.914	29.37/0.824	28.53/0.791	26.43/0.808	31.10/0.921
VDSR[15]	666K	666K	33.66/0.921	29.77/0.831	28.82/0.798	27.14/0.828	32.01/0.934
DWSR[8]	374K	374K	33.82/0.922	29.83/0.831	-/-	-/-	-/-
LapSRN[19]	x3 813K	813K	33.81/0.922	29.79/0.833	28.82/0.798	27.07/0.828	32.21/0.935
MemNet[31]	678K	678K	34.09/0.925	30.00/0.835	28.96/0.800	27.56/0.838	32.51/0.937
CARN-M[2]	412K	412K	33.99/0.924	30.08/0.837	28.91/0.800	27.55/0.839	-/-
SRFBN-S[20]	483K	483K	<u>34.20/0.926</u>	<u>30.10/0.837</u>	28.96/0.801	<u>27.66/0.842</u>	<u>33.02/0.94</u>
WDRN-S[33]	266K	266K	34.18/0.925	30.17/0.837	28.98/0.802	27.82/0.844	-/-
WTSR	558K	558K	34.27/0.925	30.12/0.836	28.98/0.802	27.69/0.841	33.11/0.941
Bicubic	-	-	28.42/0.810	26.00/0.703	25.96/0.668	23.14/0.658	24.89/0.787
SRCNN[32]	8K	8K	30.48/0.863	27.50/0.751	26.90/0.710	24.52/0.722	27.58/0.856
FSRCNN[6]	13K	13K	30.72/0.866	27.61/0.755	26.98/0.715	24.62/0.728	27.90/0.861
VDSR[15]	666K	666K	31.35/0.884	28.01/0.767	27.29/0.725	25.18/0.752	28.83/0.887
DWSR[8]	374K	374K	31.39/0.883	28.04/0.767	27.25/0.724	25.26/0.755	-/-
LapSRN[19]	x4 813K	813K	31.54/0.885	28.09/0.770	27.32/0.728	25.21/0.756	29.09/0.890
MemNet[31]	678K	678K	31.74/0.889	28.26/0.772	27.40/0.728	25.50/0.763	29.42/0.894
CARN-M[2]	412K	412K	31.92/0.890	28.42/0.776	27.44/0.730	25.62/0.769	-/-
SRFBN-S[20]	483K	483K	31.98/ <u>0.892</u>	<u>28.45/0.778</u>	<u>27.44/0.731</u>	25.71/0.772	<u>29.91/0.901</u>
WDRN-S[33]	266K	266K	32.02/0.890	28.47/0.774	27.47/0.730	25.82/0.776	-/-
WTSR	593K	593K	32.16/0.895	28.57/0.781	27.56/0.735	26.03/0.784	30.44/0.908

Ablation

• Ablation on different Wavelet Transform

- None
- DWT
- SWT

• Ablation on different LTB

- Similarity Matching Block
- Efficient Transformer Encoder's partitioning size
- Efficient Transformer Encoder's order

• Ablation on WCEB

- Different number of WECM
- Different type of WECM

Table 2. Comparisons on PSNR/SSIM of WTSR with different wavelet transform. Best results are **highlighted**.

Wavelet Transform	Params	PSNR/SSIM					
Type		Set5	Set14	BSD100	Urban100	Manga109	
None	593K	32.01/0.893	27.47/0.781	27.51/0.734	25.84/0.777	20.22/0.905	
DWT	593K	27.56/0.790	25.51/0.682	25.54/0.647	22.69/0.635	24.19/0.767	
SWT	593K	32.16/0.895	28.57/0.781	27.56/0.735	26.03/0.784	30.44/0.908	

Table 3. Comparisons on PSNR/SSIM of WTSR with different network of LTB. Best results are **highlighted**. The number after T indicates the partitioning size of ET encoder, S represents SMB, and the arrow denotes the direction of data flow.

The Network of LTB	Params	PSNR/SSIM				
		Set5	Set14	BSD100	Urban100	Manga109
T5 → T5	567K	31.92/0.892	27.43/0.779	27.46/0.734	25.78/0.777	30.06/0.904
T8 → T8	569K	31.96/0.892	28.46/0.779	27.48/0.733	25.79/0.776	30.09/0.904
T5 → T8	568K	31.97/0.893	28.44/0.779	27.48/0.733	25.79/0.776	30.04/0.903
T8 → T5	568K	32.00/0.893	28.47/0.779	27.50/0.733	25.87/0.778	30.11/0.904
T8 → S → T5	593K	32.16/0.895	28.57/0.781	27.56/0.735	26.03/0.784	30.44/0.908

Table 4. Study the effect of each WCEB on PSNR/SSIM, Best results are **highlighted**.

WCEM Type	Params	PSNR / SSIM				
		Set5	Set14	BSD100	Urban100	Manga109
None	416K	31.91 / 0.892	28.44 / 0.778	27.47 / 0.732	25.75 / 0.7735	29.92 / 0.901
A	482K	32.01 / 0.893	28.42 / 0.779	27.48 / 0.734	25.80 / 0.7782	29.99 / 0.924
A + H	519K	32.06 / 0.894	28.54 / 0.780	27.52 / 0.733	25.91 / 0.7791	30.27 / 0.905
A + H + V	556K	32.10 / 0.894	28.54 / 0.781	27.54 / 0.735	25.97 / 0.7823	30.31 / 0.907
A + H + V + D	593K	32.16/0.895	28.57/0.781	27.56/0.735	26.03/0.784	30.44/0.908



Potential Limitations

- Processing images at arbitrary resolution
 - Before the wavelet-based transformer, there is a fill operation that fills the resolution of the image to an integer multiple of the partitioning size. Although this does not increase the number of parameters in the wavelet-based transformer, it slightly affects the runtime of the model.
- Hyperparametric sensitivity
 - According to the existing experimental data, WTSR is very sensitive to the hyperparameters of the model, which is not conducive to the rapid iteration of the project.



Conclusions

- A lightweight network called WTSR is proposed to extend the application scenarios of super-resolution algorithm.
- In the WTSR, many useful components include LTB, SMB and WCEB, have been proposed to balance the size and accuracy of the network.
- In the future, we will extend the proposed WTSR to specific mobile devices.