Learning to Refine: Spectral-Decoupled Iterative Refinement Framework for Precipitation Nowcasting

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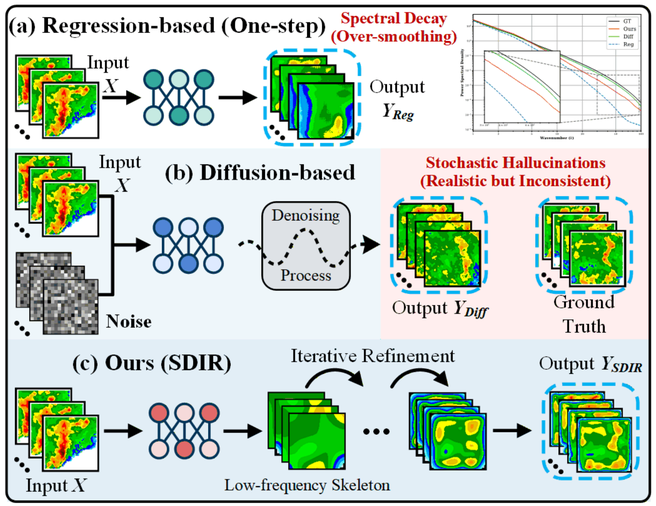
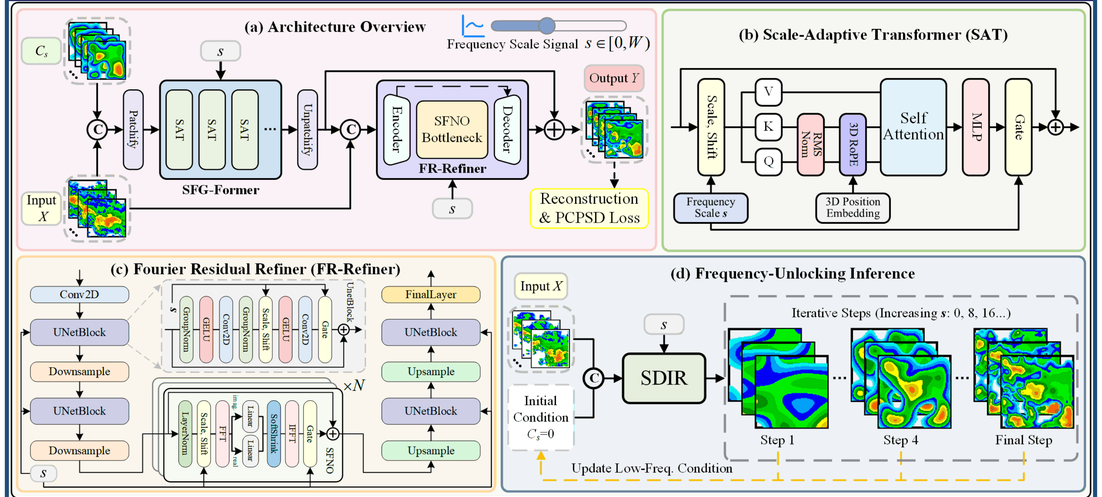
1. Motivation



- **Regression: suffers from spectral decay, where high-frequency energy collapse leads to the loss of peak intensity. This is demonstrated by the PSD plot (top right), which shows regression falling significantly below the GT.**
- **Diffusion: generates high-frequency detail but lacks physical grounding, resulting in stochastic hallucinations that are realistic but inconsistent with the GT.**
- **SDIR (Ours): reformulates nowcasting as a deterministic spectral evolution. By iteratively refining the low-frequency synoptic skeleton, our method progressively restores high-frequency details.**

2. Method: SDIR



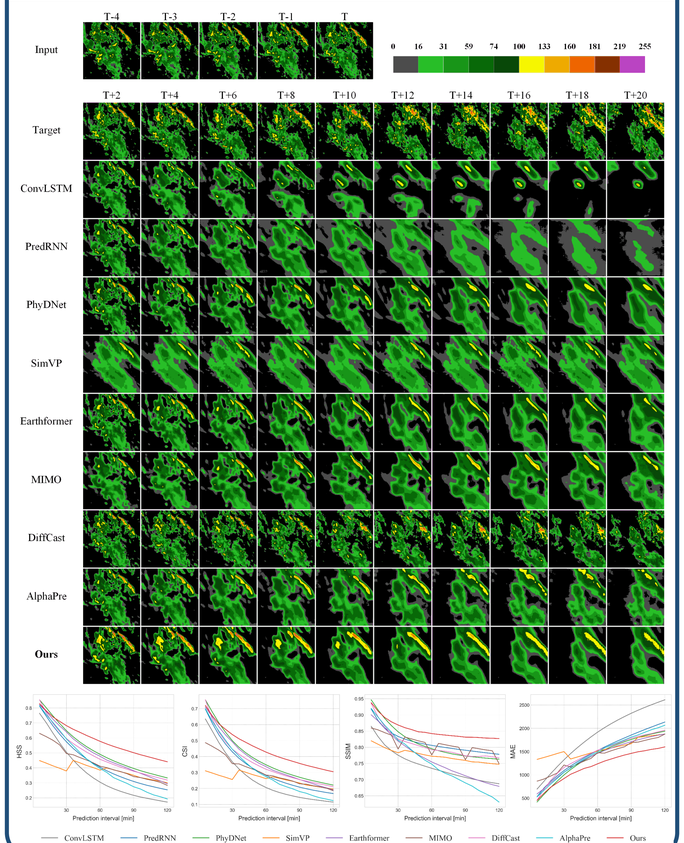
Algorithm 1 SDIR Training Process

Input: Sequence X, Ground truth Y, Resolution W.
Parameters: θ_1 (SFG-Former), θ_2 (FR-Refiner).
repeat
  Sample $\sigma \sim \mathrm{Beta}(\alpha, \beta)$, set $s = \lfloor W \cdot \sigma \rfloor$.
  $C_s = \mathrm{IDCT}(\mathrm{Trunc}_{s\times s}(\mathrm{DCT}(Y)))$.
  $\hat{Y}_{base} = \text{SFG-Former}(X, C_s, s; \theta_1)$.
  $\hat{Y}_{res} = \text{FR-Refiner}([X \| \hat{Y}_{base}], s; \theta_2)$.
  $\hat{Y} = \hat{Y}_{base} + \hat{Y}_{res}$.
  $\mathcal{L} = \mathcal{L}_{base} + \mathcal{L}_{res} + \phi(s)\mathcal{L}_{pcpsd}$.
  Update θ_1, θ_2 via AdamW.
until Convergence

Algorithm 2 SDIR Inference Process

Input: Sequence X, Schedule $\mathcal{S} = \{s_1, \ldots, s_K\}$, $s_1 = 0$.
Initialize: $C_s = \mathbf{0}$.
for $k = 1$ **to** K **do**
  $s = \mathcal{S}[k]$
  $\hat{Y}^{(k)}_{base} = \text{SFG-Former}(X, C_s, s)$.
  $\hat{Y}^{(k)}_{res} = \text{FR-Refiner}([X \| \hat{Y}^{(k)}_{base}], s)$.
  $\hat{Y}^{(k)} = \hat{Y}^{(k)}_{base} + \hat{Y}^{(k)}_{res}$.
  if $k < K$ **then**
    $C_s = \mathrm{IDCT}(\mathrm{Trunc}_{s_{k+1}\times s_{k+1}}(\mathrm{DCT}(\hat{Y}^{(k)})))$.
  end if
end for
Return: $\hat{Y}^{(K)}$.

5. Visual Results



3. Main Results

Models	HSS↑	CSI↑	SSIM↑	MAE↓	HSS↑	CSI↑	SSIM↑	MAE↓	HSS↑	CSI↑	SSIM↑	MAE↓
ConvLSTM	0.3142	0.2615	0.4860	738.05	0.3602	0.2611	0.7438	1846.20	0.3512	0.2715	0.6062	2896.90
PredRNN	0.3737	0.3359	0.5157	784.84	0.4419	0.3248	0.8156	1487.80	0.3772	0.2991	0.5703	3058.90
PhyDNet	0.4128	0.3563	0.4306	694.99	0.5203	0.3892	0.8133	1386.00	0.4172	0.3311	0.7063	2103.30
SimVP	0.3543	0.3047	0.4482	707.43	0.3812	0.2587	0.7747	1572.50	0.2674	0.2149	0.6530	2623.50
Earthformer	0.4159	0.3544	0.4903	674.99	0.5015	0.3711	0.7643	1395.80	0.4066	0.3230	0.6706	2241.80
MIMO	0.3944	0.3448	0.5180	687.67	0.4275	0.3041	0.8085	1413.00	0.3687	0.2873	0.6970	2326.80
DiffCast	0.4071	0.3477	0.4710	669.01	0.4920	0.3628	0.8080	1450.10	0.3972	0.3057	0.6690	2595.50
AlphaPre	0.3633	0.3092	0.4775	661.40	0.4276	0.3145	0.7534	1445.30	0.4052	0.3193	0.6100	2463.00
Ours	**0.4724**	**0.4043**	**0.5574**	**600.37**	**0.5882**	**0.4497**	**0.8548**	**1129.10**	**0.4401**	**0.3499**	**0.7544**	**1897.90**

4. Ablation Study

Exp.	S-I	S-II	PCPSD	HSS	CSI	SSIM	MAE
(a)	✓			0.3529	0.2559	0.8478	1248.8
(b)		✓		0.4614	0.3266	0.8125	1586.1
(c)	✓	✓		0.5367	0.4057	0.8512	1138.3
Ours	✓	✓	✓	**0.5882**	**0.4497**	**0.8548**	**1129.1**

Distribution	HSS	CSI	SSIM	MAE
$\mathrm{Beta}(0.8, 1.5)$	0.5606	0.4206	0.8485	1299.2
$\mathrm{Beta}(1.0, 2.5)$	0.4835	0.3759	0.8493	1241.5
$\mathrm{Beta}(1.0, 3.0)$	**0.5882**	**0.4497**	**0.8548**	**1129.1**
$\mathrm{Beta}(1.0, 3.5)$	0.5582	0.4222	0.8543	1140.5

Configuration	HSS	CSI	SSIM	MAE
$\mathcal{L}_{base+res}$	0.4509	0.3420	**0.8555**	**1106.4**
Uniform	0.2842	0.2097	0.8458	1284.1
w/o AN	0.5073	0.3725	0.8102	1476.4
Ours	**0.5882**	**0.4497**	0.8548	1129.1

Steps	HSS	CSI	SSIM	MAE	Time
1-step	0.5584	0.4243	0.8522	**1111.0**	**0.30s**
8-step	0.5882	**0.4497**	**0.8548**	1129.1	1.17s
16-step	**0.5898**	0.4487	0.8533	1190.1	2.14s
32-step	0.5564	0.4164	0.8475	1352.6	4.09s

6. Resources

Paper

Code

WeChat