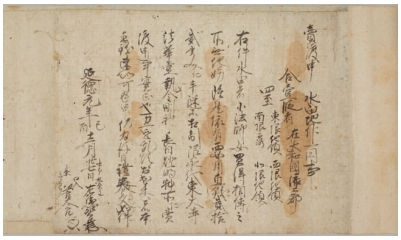
Diffusion-Based Restoration of Japanese Classical Documents with Multi-Level Synthetic Degradation

Hanzhe Gao, Honghui Yuan, Junwen Chen, Peilin Xiong, Keiji Yanai

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IS2-201

Japanese Classical Documents



出典：東大寺文書



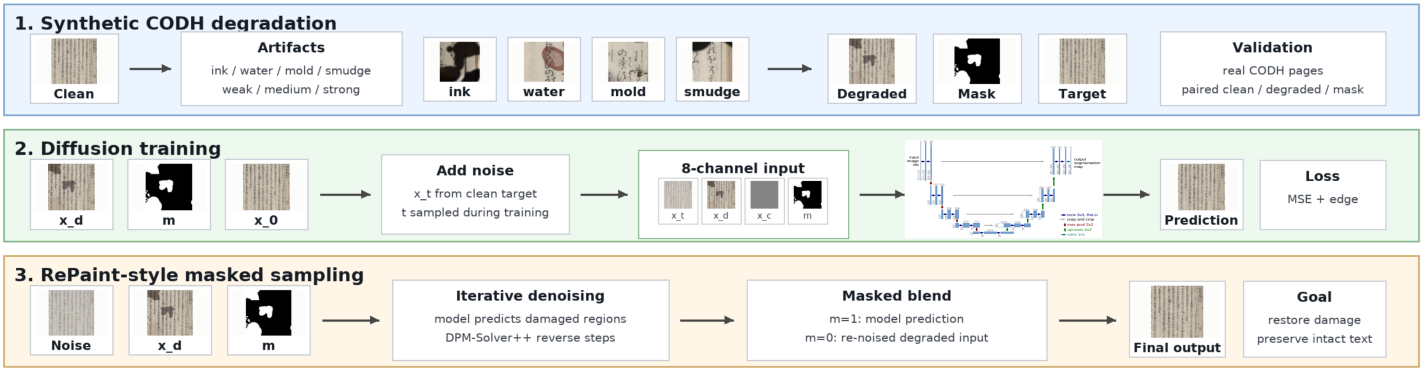
出典：新続犬筑波集



出典：特定歴史公文書等の劣化状況等に係る調査研究業務 報告書 (有限会社 東京修復保存センター)

- Japanese classical documents are valuable cultural resources, but many surviving pages contain **ink stains**, **water damage**, **mold**, **smudges**, and **paper aging**.
- These artifacts obscure characters and make both human reading and downstream document analysis difficult.

Dataset & Method



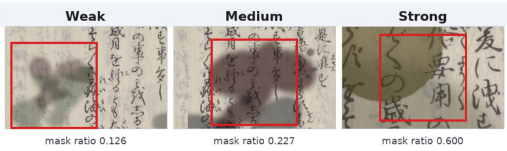
1. **C**enter for **O**pen **D**ata in the **H**umanities (**CODH** [1]) pages + ink/water/mold/smudge artifacts at weak, medium, and strong levels.
2. An **image-to-image diffusion framework** that learns a conditional restoration distribution by denoising a noisy target image.
3. At each reverse step, damaged regions use the model prediction, whereas intact regions are replaced by a re-noised version of the degraded input

$$x_{t-1} = (1-m)\cdot \mathrm{noise}(x_d, t-1) + m \cdot x_{t-1}^{\mathrm{pred}}$$

Table 1 Degradation parameters per level.

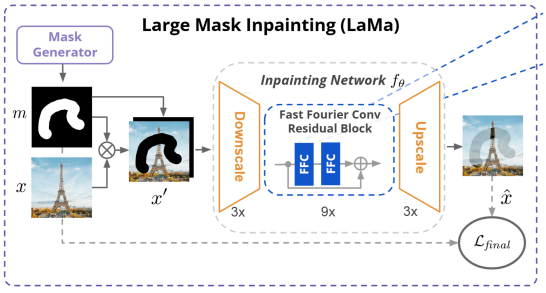
Parameter	Weak	Medium	Strong
Ink opacity	0.28–0.45	0.40–0.65	0.78–0.95
Ink count/variant	2–3	2–4	3–6
Stain size (% dim)	12–28%	15–40%	20–50%
Target damage ratio	6–10%	16–25%	35–50%
Max damage ratio	20%	35%	55%

Degradation parameters per level.

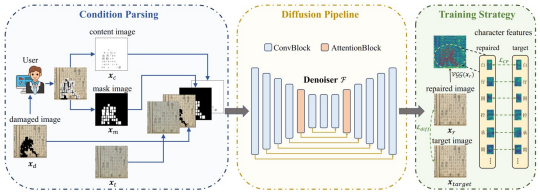


Examples of the synthesized degradation levels

Related Work

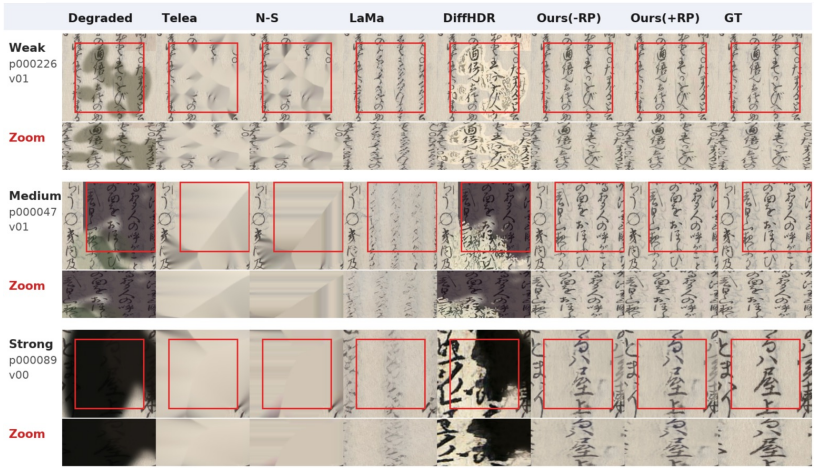


Source: LaMa [8]



Source: DiffHDR [9]

- [6] ROIS-DS Center for Open Data in the Humanities: CODH Japanese Dataset, https://codh.rois.ac.jp/ (2026). National Institute of Informatics, Research Organization of Information and Systems.
- [8] Suvorov, R., Logacheva, E., Mashikhin, A., Remizova, A., Ashukha, A., Silvestrov, A., Kong, N., Goka, H., Park, K. and Lempitsky, V.: Resolution-Robust Large Mask Inpainting with Fourier Convolutions, Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pp. 2149–2159 (2022).
- [9] Yang, Z., Peng, D., Shi, Y., Zhang, Y., Liu, C. and Jin, L.: Predicting the Original Appearance of Damaged Historical Documents, Proceedings of the AAAI Conference on Artificial Intelligence, pp. 9382–9390 (2025).
- [7] Saharia, C., Chan, W., Chang, H., Lee, C. A., Ho, J., Salimans, T., Fleet, D. J. and Norouzi, M.: Palette: Image-to-Image Diffusion Models, ACM SIGGRAPH 2022 Conference Proceedings, pp. 1–10 (2022).



Qualitative comparison on one weak, one medium, and one strong sample

Method	Weak PSNR↑	Weak SSIM↑	Weak LPIPS↓	Medium PSNR↑	Medium SSIM↑	Medium LPIPS↓	Strong PSNR↑	Strong SSIM↑	Strong LPIPS↓
LowerBound	28.3	.9831	.0322	20.2	.9459	.0909	13.3	.7449	.2947
Telea	31.1	.9535	.0788	26.9	.8906	.1754	23.2	.7796	.3726
N-S	31.1	.9534	.0793	27.0	.8896	.1760	24.2	.7761	.3846
LaMa	31.5	.9512	.0270	27.5	.8846	.0599	23.9	.7447	.2560
DiffHDR	30.5	.9593	.0449	22.4	.8960	.1050	13.8	.6950	.3192
Ours(-RP)	40.2	.9882	.0130	38.0	.9844	.0167	28.0	.9024	.1266
Ours(+RP)	44.8	.9960	.0055	39.9	.9914	.0097	29.1	.9056	.1206

Ours(+RP) medians: Weak 44.9/.9968/.0015; Medium 39.9/.9919/.0028; Strong 28.6/.9506/.0627

Quantitative comparison under the proposed synthetic benchmark

	Weak	Medium	Strong
Ours(-RP) $\mathrm{PSNR}_{\mathrm{mask}}$	34.1	32.7	23.8
Ours(+RP) $\mathrm{PSNR}_{\mathrm{mask}}$	34.0	32.6	23.8
$\Delta\mathrm{PSNR}_{\mathrm{mask}}$	−0.1	−0.0	−0.0
Ours(-RP) $\mathrm{PSNR}_{\mathrm{known}}$	41.7	42.0	41.0
Ours(+RP) $\mathrm{PSNR}_{\mathrm{known}}$	65.1	63.3	62.3
$\Delta\mathrm{PSNR}_{\mathrm{known}}$	+23.4	+21.3	+21.4

Mask-aware RePaint ablation in dB

- +12.4 dB over LaMa at medium degradation; strongest under severe damage.
- RePaint improves known-region PSNR by 21–23 dB across all degradation levels, while damaged-region PSNR remains almost unchanged