Supplementary Material for Simulating analogue film damage to analyse and improve artefact restoration on high-resolution scans

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Figure S1: Example image pairs (positives and negatives) shown to perceptual study participants at five different crop resolutions (in pixels).

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(a) Input: 4K film scan with authentic damage



(b) Artefact Segmentation: prediction from U-Net trained on synthetically damaged data.



(c) Segmentation by BOPB [WZC*20].







(d) Restoration by U-Net + perceptual (e) Restoration by BOPB [WZC*20]: using our (f) Restoration by BOPB [WZC*20]: using their loss [ISW22]: using originally provided model segmentation. weights.

segmentation.



(g) Restoration by U-Net + perceptual (h) Restoration by LaMa [SLM*22]: best perloss [ISW22]: retrained on our synthetic damage.



forming model, using our segmentation.



(i) Restoration by Stable Diffusion [RBL*21]: using our segmentation.



our synthetic damage.

segmentation.

(j) Restoration by BVMR [ISW22]: retrained on (k) Restoration by RePaint [LDR*22]: using our (l) Ground Truth: manually restored by human expert.

Figure S2: Input and ground truth from our authentic artefact damage dataset, along with chosen restorations.

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(a) Input: 4K film scan with authentic (b) Artefact Segmentation: predic- (c) Segmentation damage tion from U-Net trained on syntheti- BOPB [WZC*20]. cally damaged data.

by (d) Restoration by LaMa [SLM*22]: best performing model, using our segmentation.





(e) Restoration by U-Net + percep- (f) Restoration by BOPB [WZC*20]: (g) tual loss [ISW22]: using originally using our segmentation. provided model weights.







[LDR*22]: using tion.

segmenta- by human expert.

© 2023 The Authors. Figure S3: Input and ground truth from our authentic artefact damage dataset, along with chosen restorations. Computer Graphics Forum published by Eurographics and John Wiley & Sons Ltd.



Restoration BOPB [WZC*20]: using segmentation.

by (h) Restoration by Stable Diffutheir sion [RBL*21]: using our segmentation.



Restoration by our RePaint (1) Ground Truth: manually restored

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damage

- (a) Input: 4K film scan with authentic (b) Artefact Segmentation: predic- (c) Segmentation tion from U-Net trained on syntheti- BOPB [WZC*20]. cally damaged data.
- by (d) Restoration by LaMa [SLM*22]: best performing model, using our segmentation.









(e) Restoration by U-Net + percep- (f) Restoration by BOPB [WZC*20]: (g) tual loss [ISW22]: using originally using our segmentation. provided model weights.

Restoration BOPB [WZC*20]: using segmentation.

by (h) Restoration by Stable Diffutheir sion [RBL*21]: using our segmentation.



(i) Restoration by U-Net + percep- (j) Restoration by BVMR [ISW22]: (k) Restoration by tual loss [ISW22]: retrained on our retrained on our synthetic damage. [LDR*22]: using our synthetic damage. tion.

RePaint (1) Ground Truth: manually restored segmenta- by human expert. © 2023 The Authors.

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Figure S4: Input and ground truth from our authentic artefact damage dataset, along with chosen restorations.

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Figure S5: Spatial frequencies aggregated across all 10 scans, broken down by artefact type ((a), (b), (c), (d), (e)) and for all artefact types ((f)).

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References

- [ISW22] IVANOVA. D., SIEBERT. J., WILLIAMSON. J.: Perceptual loss based approach for analogue film restoration. In Proceedings of the 17th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications - Volume 4: VISAPP, (2022), INSTICC, SciTePress, pp. 126–135. doi:10.5220/0010829300003124.2,3,4
- [LDR*22] LUGMAYR A., DANELLJAN M., ROMERO A., YU F., TIMOFTE R., VAN GOOL L.: Repaint: Inpainting using denoising diffusion probabilistic models. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (2022), pp. 11461–11471. 2, 3, 4
- [RBL*21] ROMBACH R., BLATTMANN A., LORENZ D., ESSER P., OMMER B.: High-resolution image synthesis with latent diffusion models, 2021. arXiv: 2112.10752. 2, 3, 4
- [SLM*22] SUVOROV R., LOGACHEVA E., MASHIKHIN A., REMIZOVA A., ASHUKHA A., SILVESTROV A., KONG N., GOKA H., PARK K., LEMPITSKY V.: Resolution-robust large mask inpainting with fourier convolutions. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision* (2022), pp. 2149–2159. 2, 3, 4
- [WZC*20] WAN Z., ZHANG B., CHEN D., ZHANG P., CHEN D., LIAO J., WEN F.: Bringing old photos back to life. In proceedings of the IEEE/CVF conference on computer vision and pattern recognition (2020), pp. 2747–2757. 2, 3, 4