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

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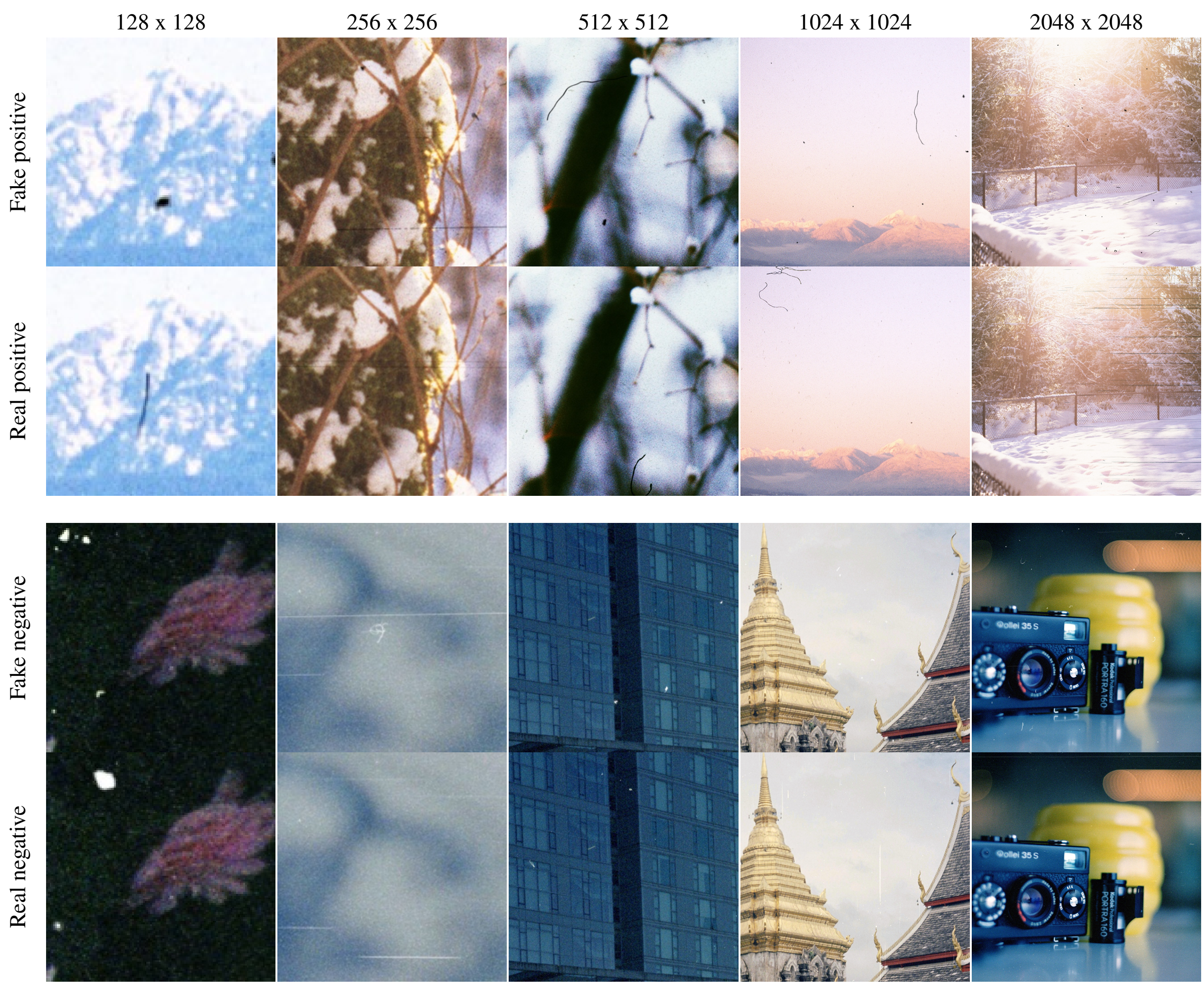
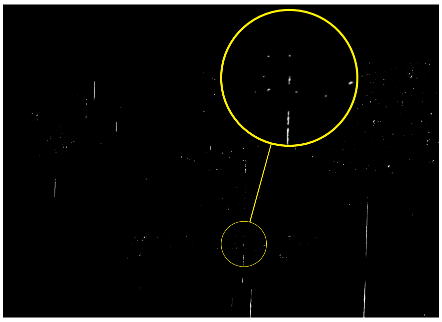
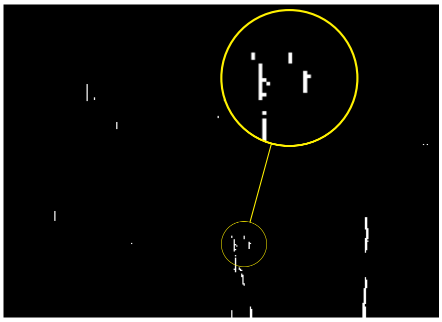


Figure S1: Example image pairs (positives and negatives) shown to perceptual study participants at five different crop resolutions (in pixels).

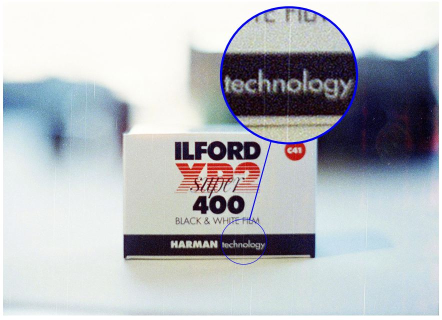
(a) **Input**: 4K film scan with authentic damage



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



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



(d) **Restoration by U-Net + perceptual loss** [ISW22]: using originally provided model weights.

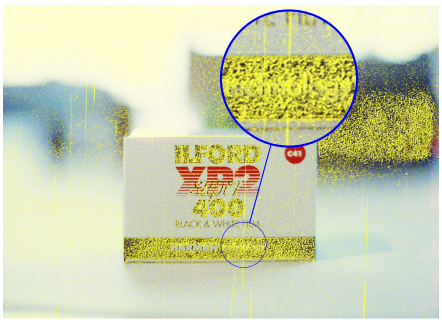
(e) **Restoration by BOPB** [WZC*20]: using our segmentation.

(f) **Restoration by BOPB** [WZC*20]: using their segmentation.

(g) **Restoration by U-Net + perceptual loss** [ISW22]: retrained on our synthetic damage.

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

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

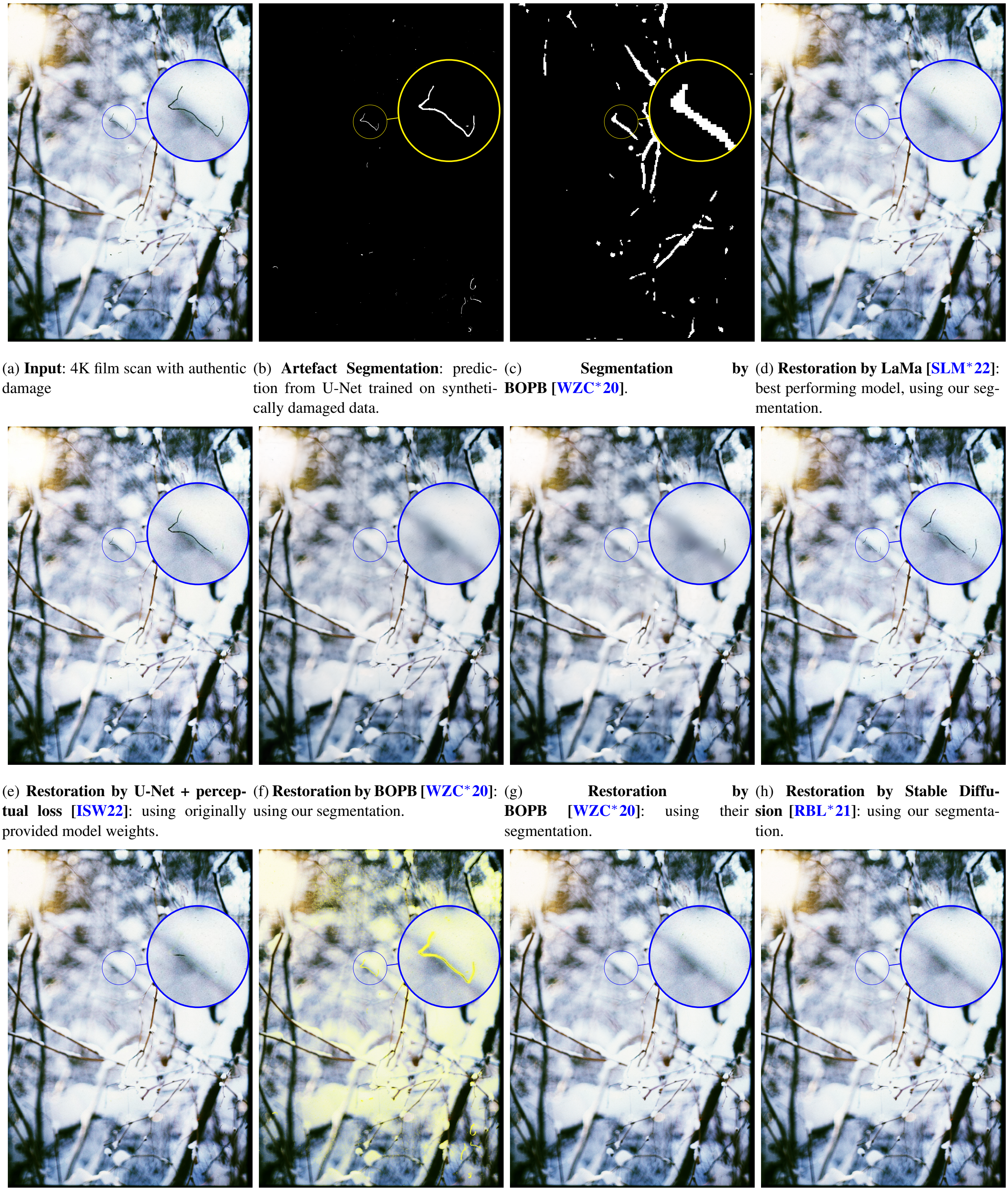


(j) **Restoration by BVMR** [ISW22]: retrained on our synthetic damage.

(k) **Restoration by RePaint** [LDR*22]: using our segmentation.

(l) **Ground Truth**: manually restored by human expert.

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



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

(e) **Restoration by U-Net + perceptual loss [ISW22]**: using originally provided model weights.

(f) **Restoration by BOPB [WZC*20]**: using our segmentation.

(g) **Restoration by BOPB [WZC*20]**: using their segmentation.

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

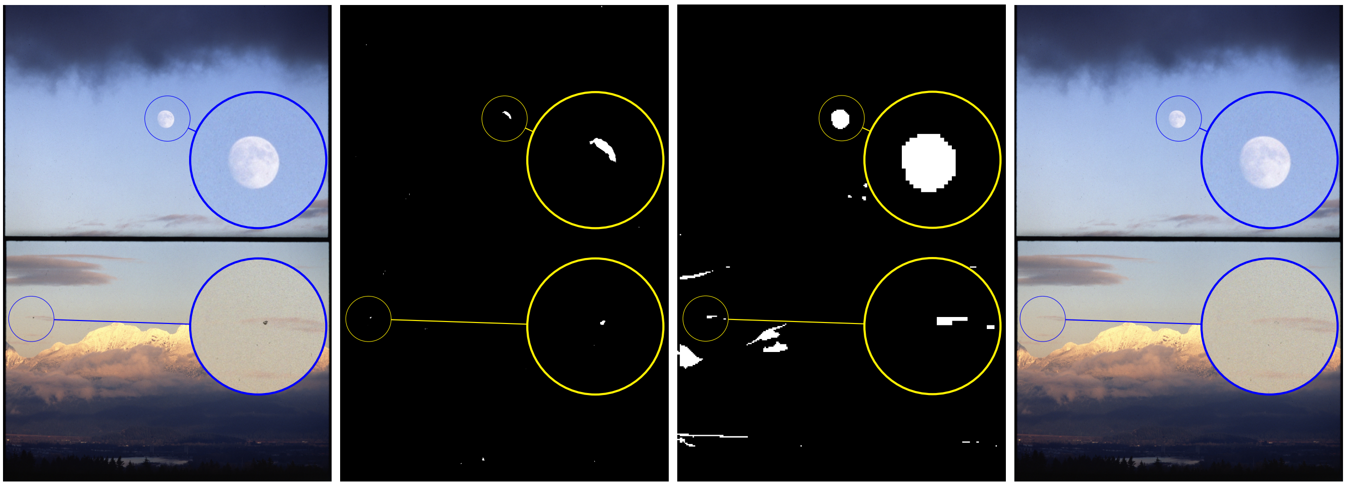
(i) **Restoration by U-Net + perceptual loss [ISW22]**: retrained on our synthetic damage.

(j) **Restoration by BVMR [ISW22]**: retrained on our synthetic damage.

(k) **Restoration by RePaint [LDR*22]**: using our segmentation.

(l) **Ground Truth**: manually restored by human expert.

Figure S3: Input and ground truth from our authentic artefact damage dataset, along with chosen restorations.



(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].

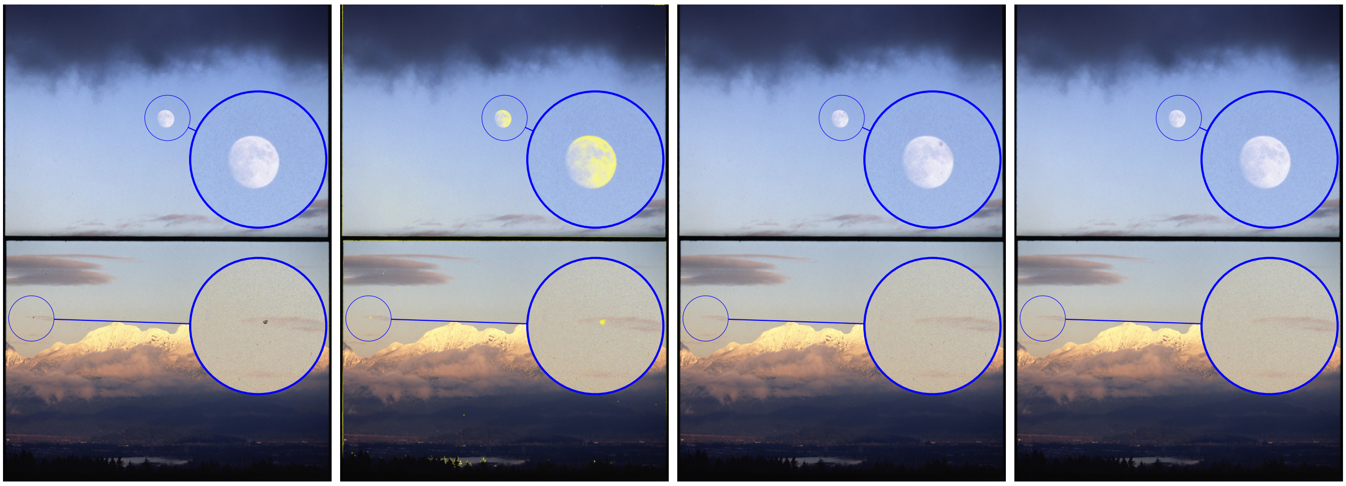
(d) **Restoration by LaMa** [SLM*22]: best performing model, using our segmentation.

(e) **Restoration by U-Net + perceptual loss** [ISW22]: using originally provided model weights.

(f) **Restoration by BOPB** [WZC*20]: using our segmentation.

(g) **Restoration by BOPB** [WZC*20]: using their segmentation.

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



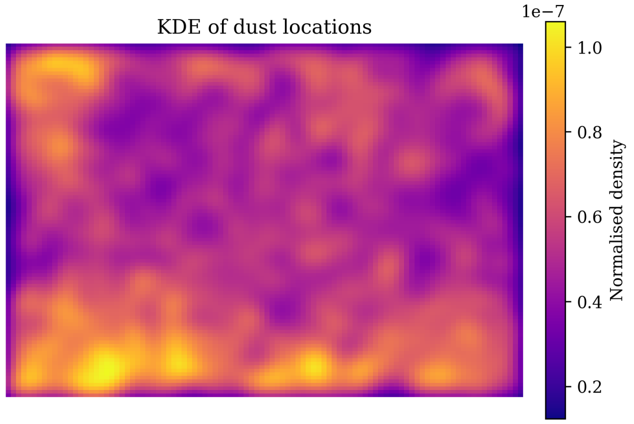
(i) **Restoration by U-Net + perceptual loss** [ISW22]: retrained on our synthetic damage.

(j) **Restoration by BVMR** [ISW22]: retrained on our synthetic damage.

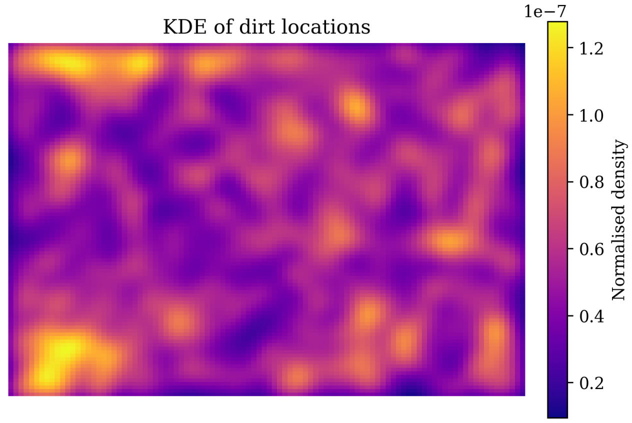
(k) **Restoration by RePaint** [LDR*22]: using our segmentation.

(l) **Ground Truth**: manually restored by human expert.

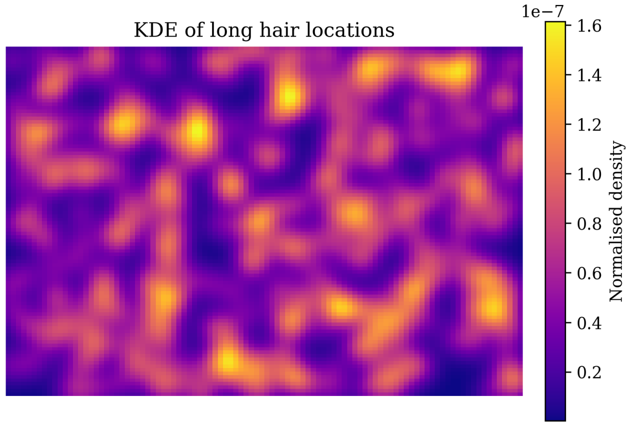
Figure S4: Input and ground truth from our authentic artefact damage dataset, along with chosen restorations.



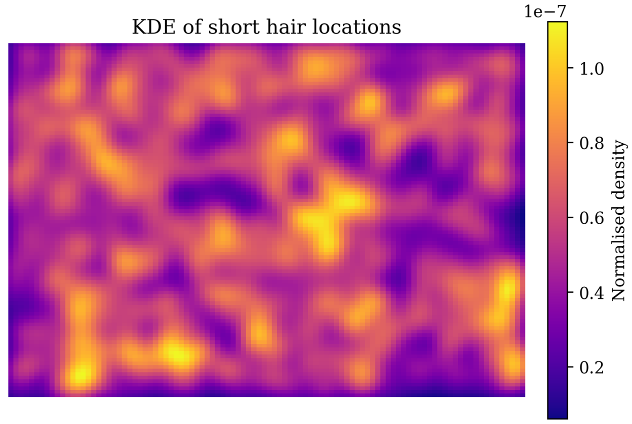
(a) Dust spatial frequency



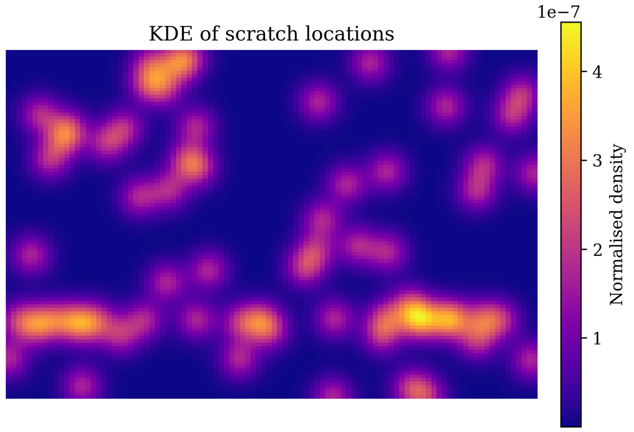
(b) Dirt spatial frequency



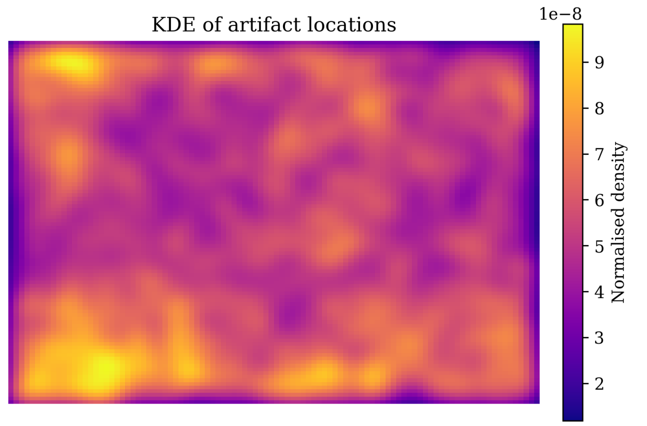
(c) Long hair spatial frequency



(d) Short hair spatial frequency



(e) Scratch spatial frequency



(f) All artefacts spatial frequency

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)).

Acknowledgements

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