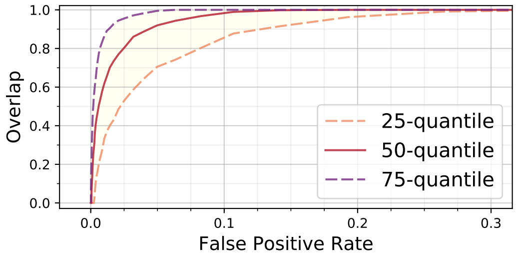

Figure 7: Per-region overlap for individual defects between our segmentation and the ground truth for different false positive rates using an SSIM autoencoder on the dataset of nanofibrous materials.

15 s and 55 s to process a single input image.

Figure 8 depicts qualitative advantages that employing a perceptual error metric has over per-pixel distances such as ℓ^2. It displays two defective images from one of the texture datasets, where the top image contains a high-contrast defect of metal pins which contaminate the fabric. The bottom image shows a low-contrast structural defect where the fabric was cut open. While the ℓ^2-norm has problems to detect the low-constrast defect, it easily segments the metal pins due to their large absolute distance in gray values with respect to the background. However, misalignments in edge regions still lead to large residuals in non-defective regions as well, which would make these thin defects hard to segment in practice. SSIM robustly segments both defect types due to its simultaneous focus on luminance, contrast, and structural information and insensitivity to edge alignment due to its patch-by-patch comparisons.

5. CONCLUSION

We demonstrate the advantage of perceptual loss functions over commonly used per-pixel residuals in autoencoding architectures when used for unsupervised defect segmentation tasks. Per-pixel losses fail to capture interdependencies between local image regions and therefore are of limited use when defects manifest themselves in structural alterations of the defect-free material where pixel intensity values stay roughly consistent. We further show that employing probabilistic per-pixel error metrics obtained by VAEs or sharpening reconstructions by feature matching regularization techniques do not improve the segmentation result since they do not address the problems that arise from treating pixels as mutually independent.

SSIM, on the other hand, is less sensitive to small inaccuracies of edge locations due to its comparison of local patch regions and takes into account three different statistical measures: luminance, contrast, and structure. We demonstrate that switching from per-pixel loss functions to an error metric based on structural similarity yields significant improvements by evaluating on a challenging real-world dataset of nanofibrous materials and a contributed dataset of two woven fabric materials which we make publicly available. Employing SSIM often achieves an enhancement from almost unusable segmentations to results that are on par with other state of the art approaches for unsupervised defect segmentation which additionally rely on image priors such as pre-trained networks.

Latent dimension	AUC	SSIM window size	AUC	Patch size	AUC
50	0.848	3	0.889		
100	0.935	7	0.965	32	0.949
200	0.961	**11**	**0.966**	64	0.959
500	**0.966**	15	0.960	**128**	**0.966**
1000	0.962	19	0.952		

Table 2: Area under the ROC curve (AUC) on NanoTWICE for varying hyperparameters in the SSIM autoencoder architecture. Different settings do not significantly alter defect segmentation performance.

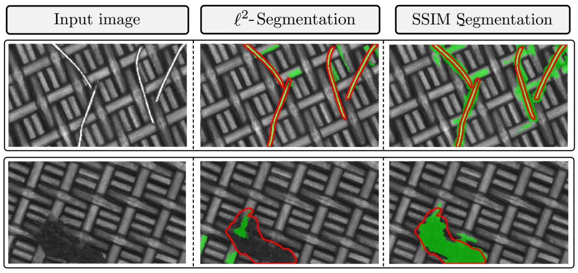

Figure 8: In the first row, the metal pins have a large difference in gray values in comparison to the defect-free background material. Therefore, they can be detected by both the ℓ^2 and the SSIM error metric. The defect shown in the second row, however, differs from the texture more in terms of structure than in absolute gray values. As a consequence, a per-pixel distance metric fails to segment the defect while SSIM yields a good segmentation result.

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