

Contrast-dependent decrease in task-transfer function area with increasing strength of iterative reconstruction / deep learning in low-contrast lesions

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ABSTRACT

Purpose: Iterative and deep learning image reconstruction (IR and DLIR) are valuable for reducing dose in modern CT but have the effect of reducing edge sharpness. If sharpness loss is contrast dependent at some threshold, the decrease in sharpness may exceed the detectability gained from noise reduction. We propose that for targets with contrast below 100 HU, the rate of edge degradation with increasing IR strength is contrast-dependent.

Methods: A custom anthropomorphic liver phantom, including fourteen <100 HU lesions, was scanned on a GE Revolution CT at 10 mGy CTDI_{vol}. Image sets were reconstructed for 0-100% ASIR-V in 10% increments, and for DLIR strengths low, medium, and high. 14 acquisitions were averaged together for each image set.

Two line-profiles were drawn through each lesion's center at symmetric angles and pixels were projected to oversample the lesion edge. Lesion line profiles were reflected about the center and the edge regions were aligned, combined, and averaged. The resultant edge profile was smoothed using a Savitzky-Golay filter and the gradient determined by central-difference approximation. Fast Fourier transform was used to find the task transfer function, with the area under the TTF curve as the spatial resolution metric.

Results: The dependence of edge spatial resolution on IR strength was contrast-dependent below 80 HU and increased by 2.5x as contrast decreased from 85 HU to 10 HU. Regarding DLIR, the spatial resolution metric decreased linearly from "similar to high ASIR-V" to "similar to low ASIR-V" between 10 - 80 HU.

Conclusion: Noise suppression from IR was observed to be contrast dependent for low-contrast lesion edges. The fit indicates that the effect will be the spatial resolution metric for DLIR results was comparable to high IR (more blurring) below 30 HU but was comparable to low IR (less blurring) above 60 HU.

Clinical Relevance Statement: It has been shown that increasing the IR strength increased the width (blurriness) of the edge region of a (clinically relevant and low-contrast) phantom liver lesion, and the loss of edge sharpness was greatest for low contrast lesions.

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INTRODUCTION

Iterative reconstructions (IR) of various forms have been widely proposed and implemented for the purposes of dose reduction and possible image quality improvement. Studies involving the noise-power-spectrum (NPS) showed the noise frequency shifted lower with higher IR strength, making the image "blotchy", which can partially explain the resistance to using strong IR in practice. Although the noise in the image is reduced as IR strength is increased, beyond a certain point tumor visibility could also be reduced.

In addition to the shift to lower frequencies in the noise texture, the nature of the non-linearity of the recent IR algorithms makes the assumption of shift-invariance questionable. Therefore, it is not complete to characterize the entire image using the MTF of high contrast targets. Unlike high contrast targets, the edges of low contrast lesions are degraded as iterative recon strength increases.

We aimed to address whether spatial resolution is contrast dependent, and to quantify the dependency as different IR strengths are applied. It is of particular interest to study lesions with contrast lower than 10% (< 100 HU) in the liver as these lesions may be the most susceptible to the loss of edge conspicuity as the IR strength increases.

We have improved our previous work by developing a metric that is more sensitive to high spatial frequency content, and by including Deep Learning reconstructions.

METHODS AND MATERIALS

We used an in-house liver phantom, custom made with CIRS; it simulated a patient of medium size and had a liver substitute of realistic shape and attenuation properties following ICRU report 44. The rest of the phantom is soft tissue equivalent with a spine substitute.

The liver parenchyma was perfused with iodine to simulate the late arterial and portal venous phases. Various iodinated lesion targets were encapsulated and inserted in the liver. The nominal contrast of these lesions at 120 kVp ranged from 10 to 90 HU relative to the liver background.

Images were acquired on a GE Revolution 256-slice CT scanner at 10 mGy CTDI_{vol}, with a slice width of 2.5 mm and DFOV of 33 cm. Scans were reconstructed using 0 – 100% ASIR-V; fourteen repetitions were performed.

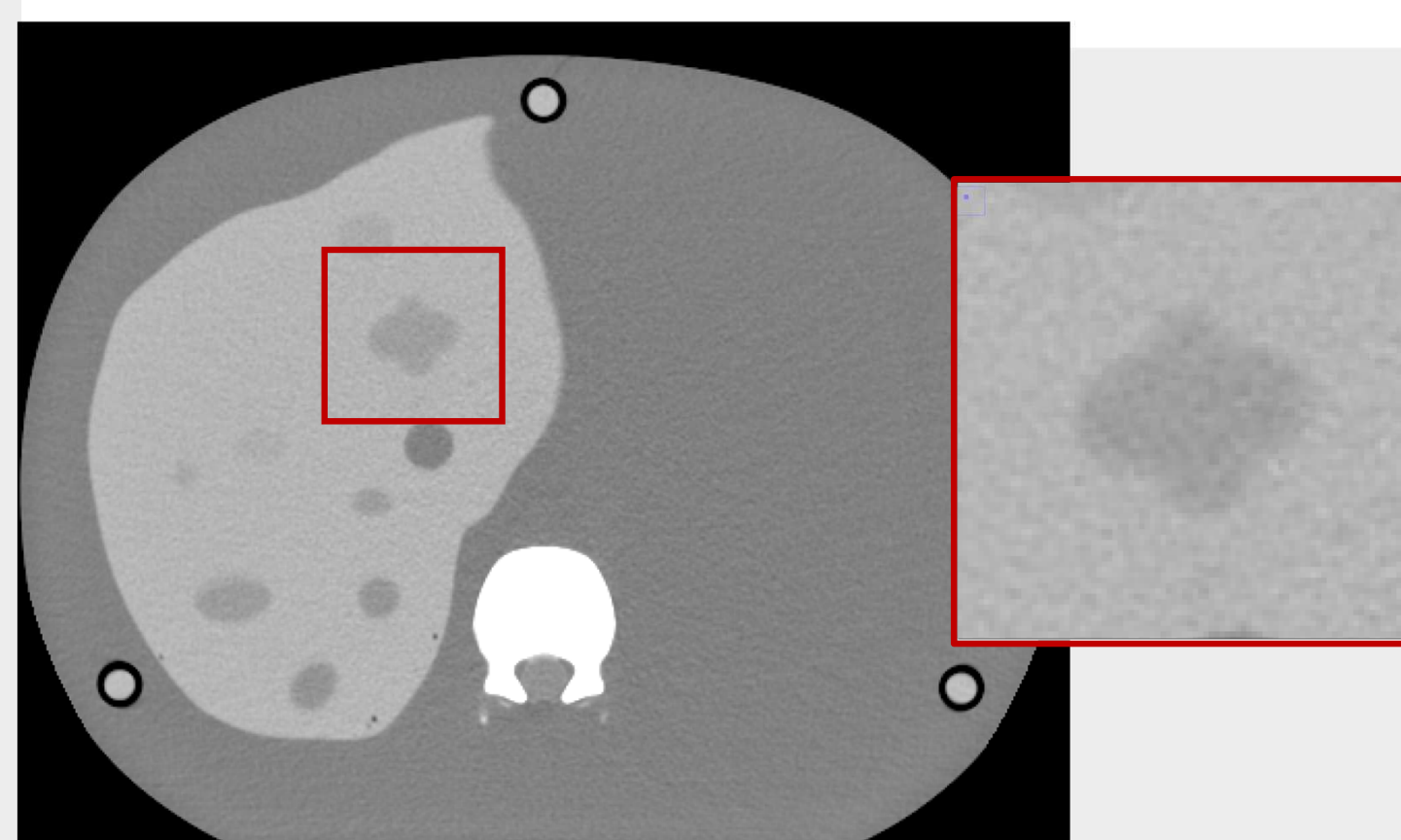
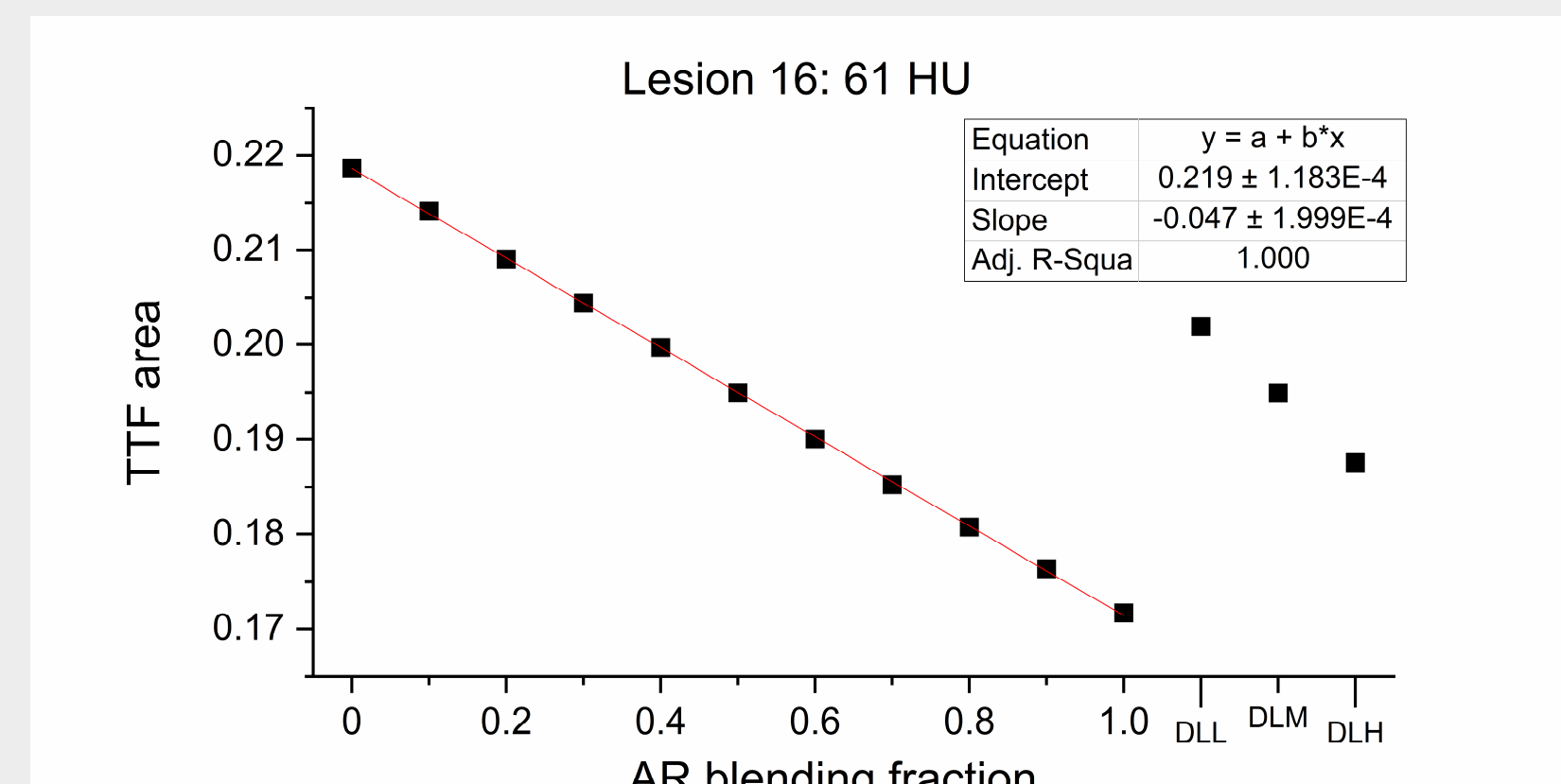
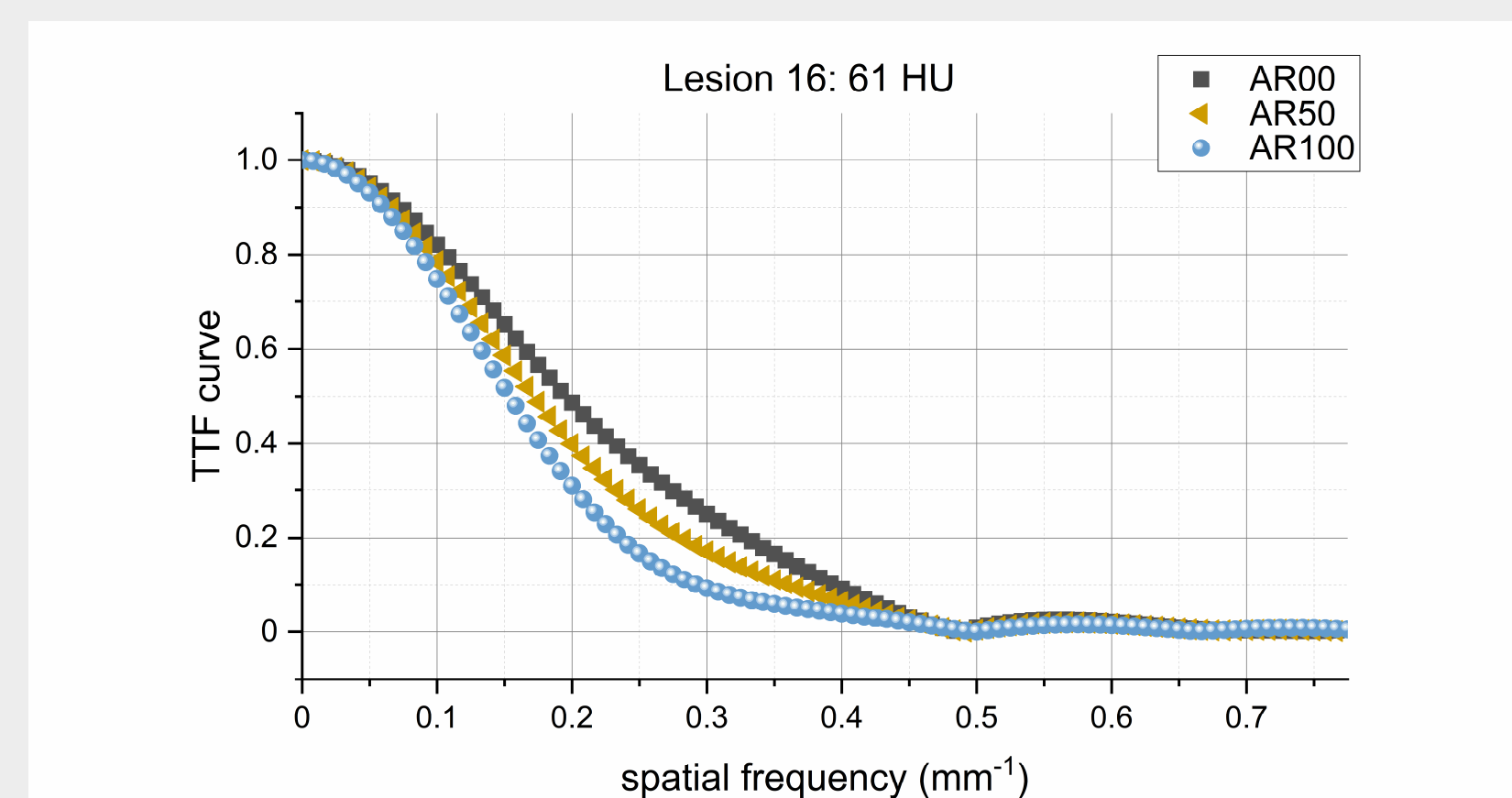
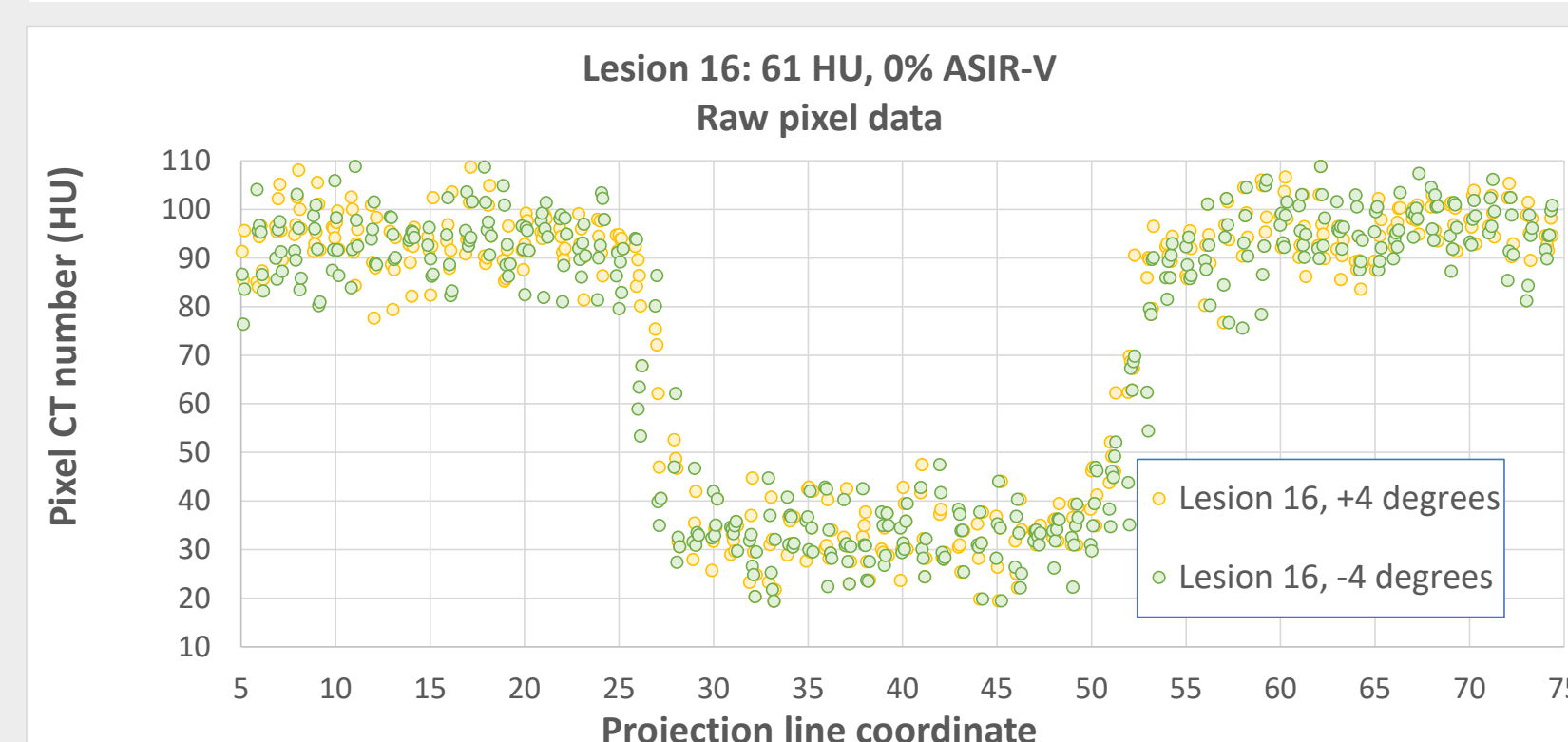


Figure 1: Representative slice of anthropomorphic liver phantom showing parenchyma and lesions used in analysis. Irregular lesions included for greater clinical relevance.

ANALYSIS

To determine edge sharpness for a range of target contrasts (86 to 12 HU), the following steps were taken:

1. Fourteen repetitions were averaged together in ImageJ to create a low-noise image.
2. Data points through the center of the target were projected onto two line profiles at $\pm 4^\circ$ relative to the horizontal to achieve oversampling.
3. Using the target center as a point of symmetry, the two line profiles were reflected and combined by averaging every 4 data points.
4. The averaged line profile (ESF) was smoothed twice;
 - 3rd order Savitzky-Golay filter (window 15) to smooth while preserving the global behavior
 - 1st order Savitzky-Golay filter to smooth locally
5. The gradient of the smoothed ESF was padded with zeroes and an FFT was used to produce the task transfer function (TTF).
6. The TTF was truncated at the Nyquist frequency of the image (0.775 mm^{-1}) and the area under the TTF curve was used as the relative sharpness metric.
7. The area was fitted as a function of IR strength, and that slope (TAS) was compared as function of contrast.

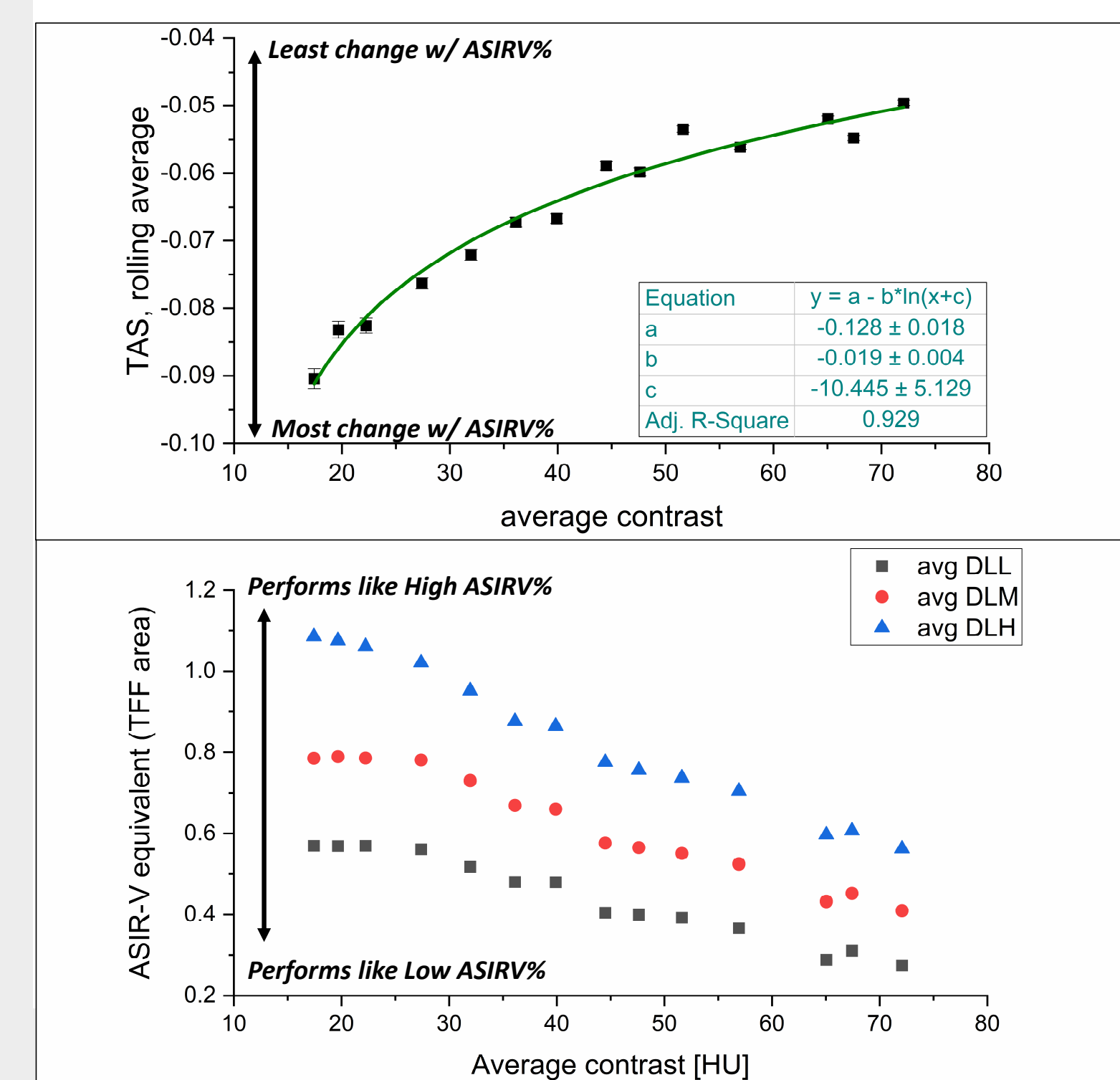


Figures 2 - 5: Demonstrates analysis of one lesion, from edge profiles of raw data, to smoothed data, to FFT of edge profiles yielding a TTF curve, to a fit for TTF area vs. IR strength (DL has no numeric value).

RESULTS & DISCUSSION

A total of 14 different targets that could be well visualized were used in this analysis.

1. The TTF curve generally appeared as a Gaussian function convoluted with a sinc, and this is also reported in the literature.
2. The TTF(10%) at ASIR-V 0% ranged from 0.32 to 0.47 mm^{-1} with no trending by contrast. We believe that the low TTF compared to MTF is due to the low contrast of the targets.
3. TTF area vs. ASIR-V strength was linear, with R-squared ~ 0.99 , consistently across all lesions
4. The TTF vs. ASIRV slope (TAS) was plotted against contrast using a rolling average and fitted with a log-normal function. Likewise, the rolling average for DL "AR-equivalent" was plotted vs contrast. And appeared linear
5. Increasing AR had a 2.5x effect on edge sharpness for the lowest contrast lesion compared to the highest contrast lesion.



Figures 6 - 7: Rolling average of TAS vs. contrast and ASIRV equivalent vs. contrast. The lowest contrast lesions are much more affected by IR.

CONCLUSIONS

We observe a trend of greater "spatial resolution loss with increasing iterative strength" as lesion contrast decreases from 80 HU towards 10 HU. The loss of TTF at ASIR-V 50% was only 7.5% at 80 HU, compared to a loss of 16.5% at 12 HU. This means that, over the contrast range studied, low contrast edges were blurred more by high ASIR-V than high contrast edges.

We also observed that the Deep Learning "equivalent" AR, meaning the ASIR-V fraction with the same sharpness metric, decreased with increasing contrast. This means that the DL performance (in terms of edge blurring) was more like high ASIR-V at low contrast and vice versa.

REFERENCES

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