OCT image noise reduction using deep learning without additional priors

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PURPOSE

OCT image quality is often limited by various noise sources, which may hinder the ability to visualize fine tissue features. Recent advances in deep learning techniques have made it possible to perform effective image noise reduction. Such methods based on image translation require prior knowledge such as high resolution images or predefined noise characteristics. We propose a formulation of the noise reduction problem based on the U-Net architecture which does not require additional prior knowledge by directly learning from the input images, adapted from Ref 1.

METHODS

A CIRRUS 5000 HD-OCT with AngioPlex® OCT Angiography (ZEISS, Dublin, CA) was used to acquire 3x3mm scans (245 B-scans, 245 A-scans/B-scan and 1024 pixels/A-scan). Each B-scan location was repeated 4 times.

We trained a custom convolutional neural network (CNN, Figure 4) on pairs of images from B-scans from the same scan. A pre-processing step registered the four B-scans within a cluster, and each cluster of registered B-scans was used to generate three pairs of training sets.

What is novel?

Existing approaches using averaged images as priors suffer from 'blurring' caused by imperfect registration. Those instead using additive noise are biased towards the noise statistic added. The proposed network instead only <u>learns to denoise directly from the content noise characteristics</u>. (Figure 3)

Our network is a modified five layer U-Net architecture with deep supervision and a custom loss function that enforces a symmetric loss between training images using a linear combination of L1 and L2 loss. (Figure 4)

CONCLUSIONS

We present a robust feature preserving denoising method which can automatically learn the characteristic noise in OCT data without additional information.

Reference:

[1]Lehtinen et al. "Noise2Noise: Learning Image Restoration with Clean Data." arXiv:1803.04189v3 (2018).

RESULTS

Figure 1 shows the results of one of our test cases. First column shows a single input slice and the corresponding output slice. The volume rendering (middle column) shows the rendering of 50 slices (1024x245x50).

The cropped images (A,B) show closeups of regions of interest from the original and network output images.

The network learns anisotropic feature-preserving smoothing.

Figure 2 shows the histogram along the yellow line (from one A-scan) for a single original slice (in blue) and the network output (in red). Following the curves, we see that the network reduces noise without affecting the peaks that represent the signal ranges.

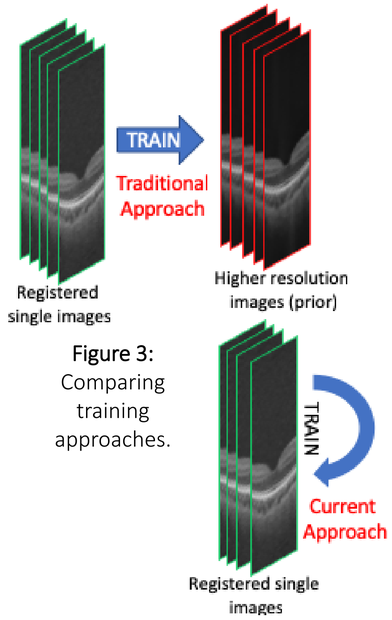

Figure 3: Comparing training approaches.

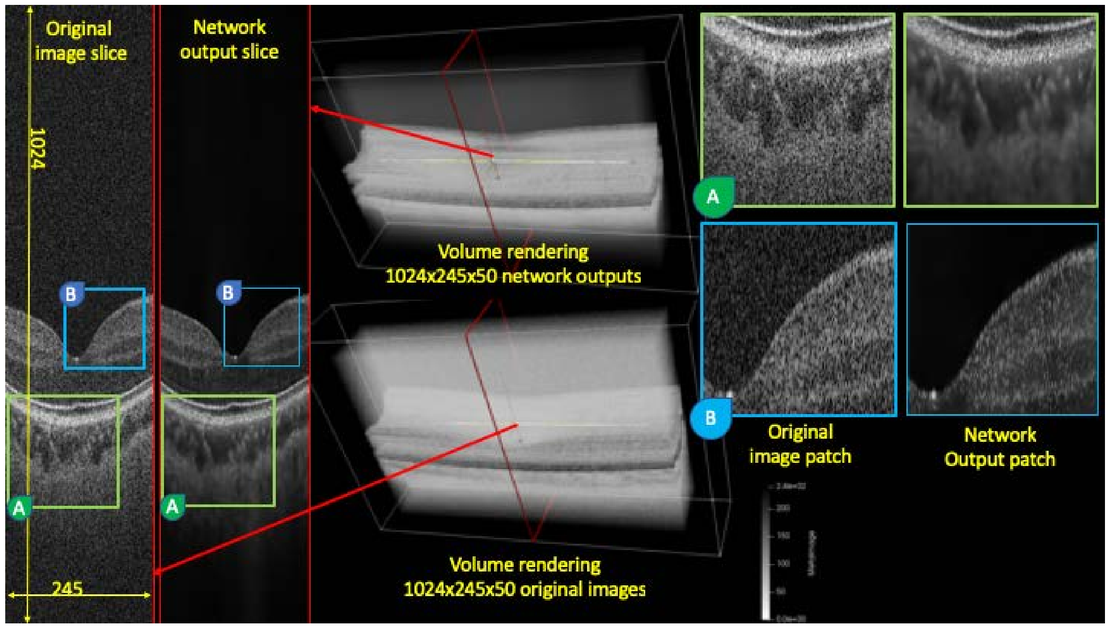

Figure 1: Slices, volume rendering and closeups of test case.

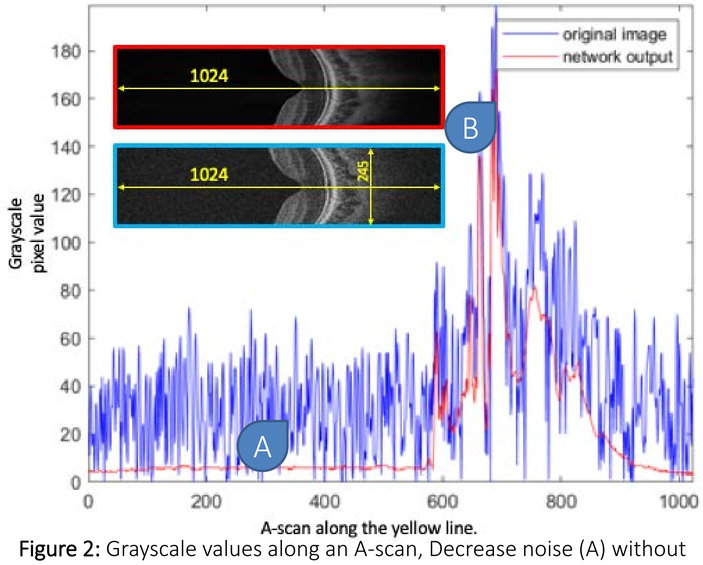

Figure 2: Grayscale values along an A-scan, Decrease noise (A) without losing signal (B). Original in blue and network output in red.

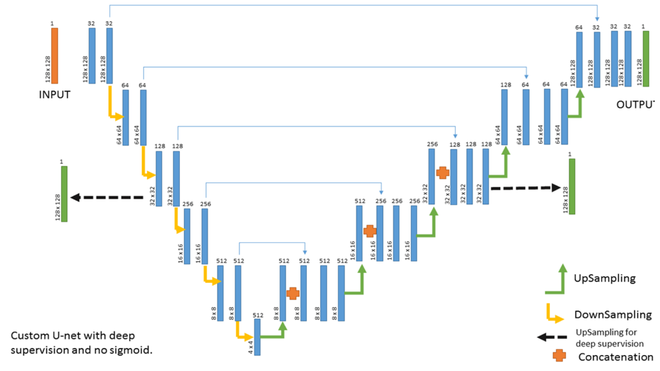

Figure 4: Modified network with deep supervision.

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Disclosures: AB (E), MD (E) : Carl Zeiss Meditec, Inc.