2-fold resolution increase and all-depth linearization using a neural network

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ABSTRACT

A neural network is proposed as a much better performing alternative to Fourier transformation. It processes raw OCT spectra into A-scans with twice better nominal axial resolution which remains intact at all depths even for an uncalibrated spectrometer and uncompensated chromatic dispersion.

1. INTRODUCTION

Increased axial resolution in Optical Coherence Tomography (OCT) and removal of all resolution-degrading nonlinearities, particularly those originating from the object's chromatic dispersion, are challenging tasks, especially now that OCT is reaching its practical limitations due to its rapid technological progress.

Problem. To improve axial resolution, the light source needs to be changed to one with a shorter central wavelength or one with a wider wavelength range. In practice, the increase in axial resolution is counteracted by the resolution-degrading effects of chromatic dispersion of the layers of the object, especially when that object is bulky. This sets the practical limit for axial resolution at 1 µm [1] which was achieved several years ago with visible-range OCT [2]. Extending the spectral bandwidth to shorter wavelengths introduces the risk of biotoxicity, while extending it to longer wavelengths results in no significant resolution gain, challenges in maintaining high beam quality due to chromatic aberrations, and makes imaging water-rich samples impossible.

Current solutions. Current methods for removing depth-dependent dispersion rely on piece-wise phase corrections [3] or a priori knowledge of dispersion variability [4]. An approach showing partial immunity to nonlinearities in the spectrum and enabling resolution improvement is quantum-mimic OCT [5,6]. It allows the resolution increase of around $\sqrt{2}$ and the cancellation of even-order nonlinearities, leaving intact the third-order nonlinearity – which becomes significant in deep OCT imaging. The application of this method remains impractical due to the presence of image-scrambling artefacts which can only be removed in very well-defined cases. Similarly, there are resolution-improving algorithms which use Fourier-transformation-based alternatives [7,8,9], but again they are limited in their applicability. Neural networks were shown to improve axial resolution, but this work has focused on comparing low-resolution images with high-resolution ones [10] leading to networks trained how to narrow the image elements, rather than truly increase the resolving power. All these methods work within the limitations of Fourier transformation: they either try to best fit into its requirements, as exhibited in hardware resolution-improving approaches, or try to outsmart it, as seen in the all-depth dispersion removing algorithms.

Our solution. In our approach, Fourier transformation is completely abandoned in favour of a neural network. We show, using both numerical and experimental data, that our network produces A-scans with no nonlinearities-induced resolution degradation and twice the better axial resolution at all depths. The current limitations and future work are discussed..

2. CONCEPT AND PERFORMANCE

Traditional OCT spectrum processing typically consists of two steps: spectral calibration which removes spectrometer-induced nonlinearities, and dispersion compensation, which cancels the nonlinearities caused by unbalanced dispersion in the interferometer. Whereas the spectral calibration is done by interpolating the spectrum for non-integer indices that correspond to linear positions of the fringes, dispersion compensation is multiplication of the spectrum by a complex exponential. The application of these two algorithms ensures the optimum axial resolution which is dictated by the constraints of the Fourier transformation.

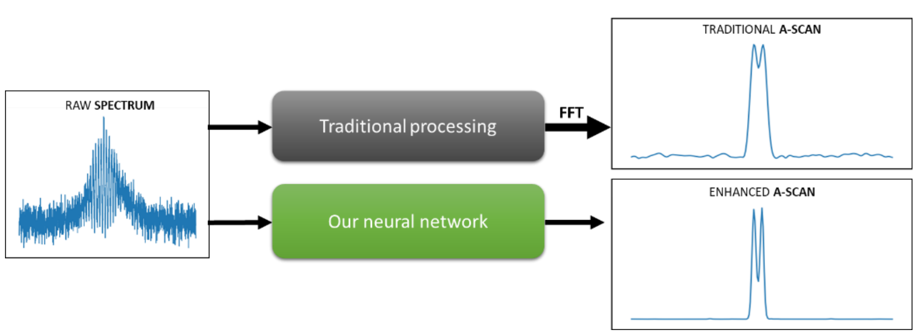

Figure 1. ***Traditional processing vs. our network***. Our network processes a raw spectrum into an A-scan where nonlinearities are completely removed and additionally the axial resolution is increased by the factor of 2.

In contrast, processing with our network (Fig. 1) has no such limitations and can provide a much better axial resolution while also removing all the nonlinearities present in the input spectrum. Our neural network accepts 2048-element-long spectra irrespective of the spectral bandwidth the spectrum covers. On an i7-6500U processor, our unoptimized solution currently transforms one spectrum into an A-scan in 0.7s.

120 spectra incorporating both types of nonlinearities were simulated for a wedge (a two-interface object with varying thickness). The direct Fourier transformation of such a raw spectrum yields a very low resolution image (Fig. 2a). The axial resolution improves when spectral calibration is performed prior to Fourier transformation (Fig. 2b). Finally, using both spectral calibration interpolation and dispersion compensation aids in achieving the best possible resolution (Fig. 2c). When the raw spectra are used with our neural network, the output image is free of nonlinearities and has a higher resolution (Fig. 2d). It can be noticed that the positions of the interfaces are different in the traditionally processed image and the neural network output. This is because, unlike spectral calibration algorithms, the network does not relocate the peaks to their original positions after removing the spectrometer-related nonlinearities. This phenomenon is best illustrated by comparing A-scans representing a mirror at different depths obtained traditionally and via the network (Fig. 2e).

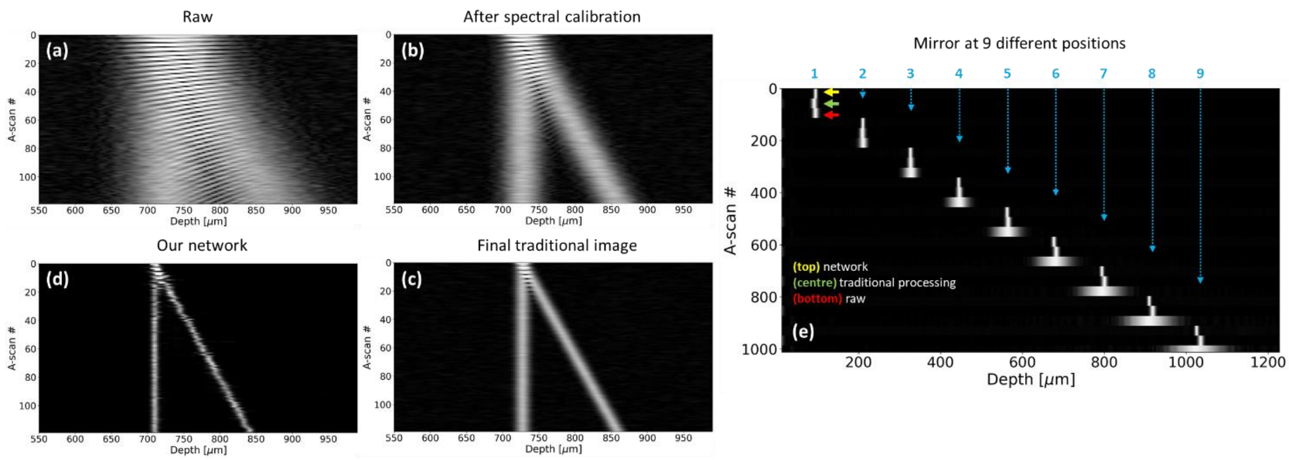

Figure 2. ***Axial resolution at depth.*** Fourier transformation gives images with significantly degraded resolution **(a)** for raw spectra – especially when the object is at greater depths – and **(b)** for spectra which are only spectrally calibrated. The optimum resolution is obtained when **(c)** spectra are both spectrally calibrated and dispersion compensated. **(d)** Our network processes the raw spectra directly into sharp A-scans whose resolution is additionally improved. **(e)** A-scans corresponding to a mirror placed at 9 different depths, obtained with the network (top elements, the yellow arrow for position 1), with traditional processing (middle elements, the green arrow for position 1) and by Fourier transforming the raw spectrum (bottom elements, the red arrow for position 1).

3. EXPERIMENTAL RESULTS

Spectra were acquired while a thin foil was spatially scanned with an OCT using a laser source at 840 nm (total bandwidth of 160 nm, one of the spectra in Fig. 3d). Axial resolution was worsened by multiplying the spectra by a Gaussian function (see Fig. 3a). While the two interfaces of the foil are barely distinguishable in the image obtained by traditional processing of such reduced spectra (Fig. 3b), the output image obtained with our neural network (Fig. 3c) shows the interfaces clearly. The image obtained by traditional processing of the original, unreduced spectra is shown in Fig. 3e for comparison.

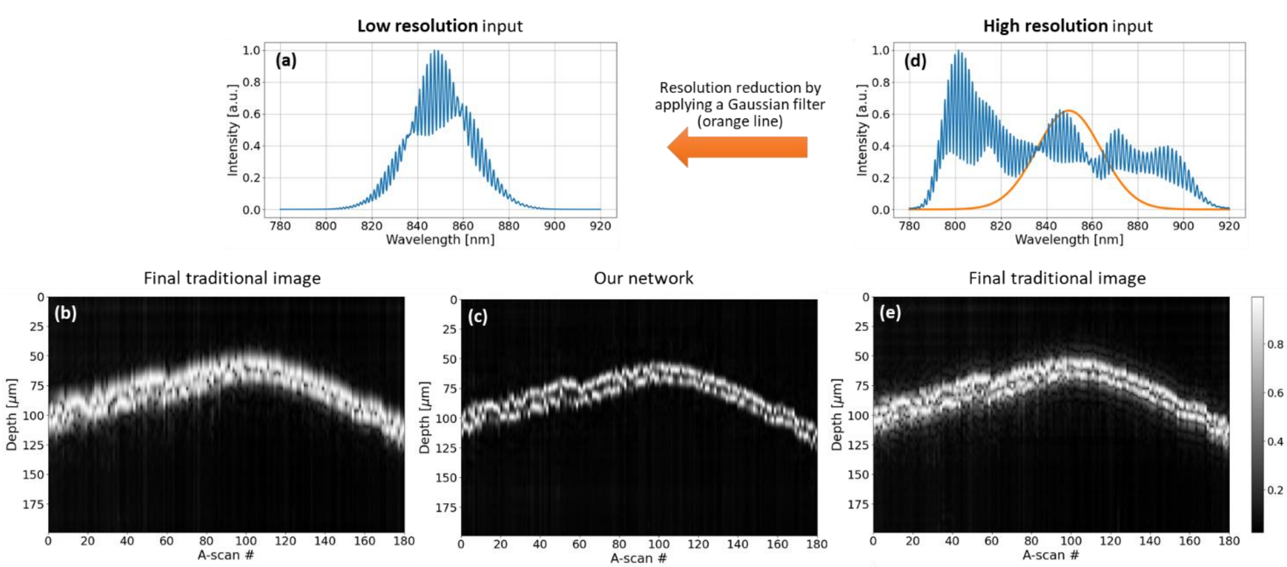

Figure 3. Thin foil (experimental). (a) Low-resolution spectrum is obtained by reducing the width of **(d)** the original experimental spectrum using a Gaussian filter (orange line). **(b)** The image calculated by traditional processing of the low-resolution spectra. **(c)**

The same low-resolution spectra are fed to our neural network which outputs a high-resolution image whose quality is very competitive to **(e)** a B-scan obtained by traditional processing of the original high-resolution spectra.

Next, a blueberry and a grape were imaged (Fig. 4). In both cases, the structure of these objects was retrieved with high fidelity. A closer inspection suggests that the network loses detail if the reflection in the object is too low (Fig. 4a-c) or if the area is too dense (Fig. 4def and insets). As it can be observed for the blueberry, the tilted line in the images remains blurred after traditional processing due to its limitations but is narrow in the network output.

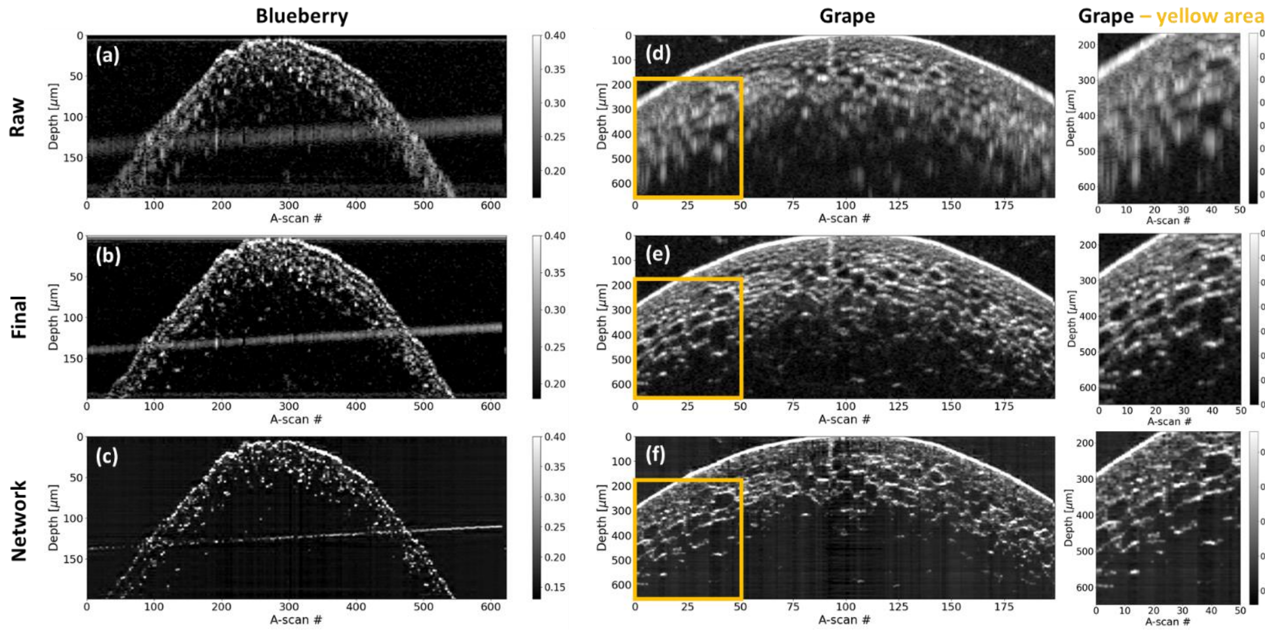

Figure 4. Blueberry. The line across the images, which corresponds to a back-surface of a glass in front of the blueberry, is blurred in **(a)** the image obtained by Fourier transforming raw spectra (due to nonlinearities originating from the spectrometer and interferometer dispersion), and in **(b)** the image obtained by traditionally processing the raw spectra (due to the limitations of dispersion compensation algorithm with regards to objects placed on the other side of the zero optical path difference point). The same line is sharp in **(c)** the output of the network, due to network's ability to indiscriminately remove all nonlinearities present in the spectrum. **Grape. (d)** Fourier transformed raw spectra, (e) traditional processing, (f) our network's output. Insets on the right show that processing using the network leads to slight loss of detail for denser parts of the image.

4. SUMMARY AND FUTURE WORK

A neural network is proposed as an enhanced, better-performing alternative to Fourier transformation. The neural network accepts a raw OCT spectrum and processes it into an A-scan with a twice better axial resolution and with no spectrometer- or dispersion-related resolution degradation. As shown on numerical data representing a wedge (Fig. 2a-d) and experimental data representing a mirror at different depths (Fig. 2e) and a blueberry (Fig. 4a-c), all nonlinearities – regardless of their origin – are removed, and the most optimum resolution is always achieved. Especially the images of a thin foil obtained traditionally and with the network (Fig. 3c,e) suggest that the increase of the OCT device performance does not have to require expensive hardware modifications, but simply a very cost-effective incorporation of a neural network in the processing unit. The current network version's speed, 0.7s, does not allow for real-time processing at the moment, but this time can be significantly reduced once processing time optimisation is completed.

Future work will concentrate on overcoming the problem of detail loss seen in blueberry and grape images when the signal is too low, or the object structure is too dense. Additional tests will be performed to determine how large the resolution increase can actually be, as current calculations indicate that the twofold resolution improvement reported here is not the upper possible limit. Finally, the network will be optimised so that real-time processing is possible.

5. REFERENCES

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