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Axial super-resolution optical coherence tomography via complex-valued network

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Abstract:

Optical coherence tomography (OCT) is a fast and non-invasive optical interferometric imaging technique that can provide high-resolution cross-sectional images of biological tissues. OCT's key strength is its depth resolving capability which remains invariant along the imaging depth and is determined by the axial resolution. The axial resolution is inversely proportional to the bandwidth of the OCT light source. Thus, the use of broadband light sources can effectively improve the axial resolution and however leads to an increased cost. In recent years, real-valued deep learning technique has been introduced to obtain super-resolution optical imaging. In this study, we proposed a complex-valued super-resolution network (CVSR-Net) to achieve an axial super-resolution for OCT by fully utilizing the amplitude and phase of OCT signal. The method was evaluated on three OCT datasets. The results show that the CVSR-Net outperforms its real-valued counterpart with a better depth resolving capability. Furthermore, comparisons were made between our network, six prevailing real-valued networks and their complex-valued counterparts. The results demonstrate that the complex-valued network exhibited a better super-resolution performance than its real-valued counterpart and our proposed CVSR-Net achieved the best performance. In addition, the CVSR-Net was tested on out-of-distribution domain datasets and its super-resolution performance was well maintained as compared to that on source domain datasets, indicating a good generalization capability.

Keywords: Optical coherence tomography, Complex-valued network, Super-resolution

1. Introduction

Optical coherence tomography (OCT) is an optical interferometric imaging technique that can provide high-resolution three-dimensional imaging of weak-scattering biological tissues [1]. Over the past decades, many efforts have been made to translate OCT into diagnostic technique in various clinics, such as ophthalmology [2, 3], cardiology [4, 5], and dermatology [6, 7]. The success of OCT is mainly attributed to its good depth-resolving capability without physical depth scanning, which is usually delineated with axial resolution. A higher axial resolution allows for better capturing micro-structure features, which provides more detailed insights into the samples. Therefore, increasing the axial resolution of OCT is continuing to receive research efforts.

The axial resolution of an OCT (Δz) is determined by the center wavelength (λ_c) and bandwidth ($\Delta\lambda$) of the light source as illustrated by the equation: $\Delta z = 2 \ln 2 \lambda_c^2 / \pi \Delta\lambda$. Thus, increasing the spectral bandwidth of OCT light source helps obtain a better axial resolution. For example, Leitgeb et al. developed an ultrahigh resolution (UHR)-OCT with an axial

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8 resolution of $\sim 2.5 \mu\text{m}$ in tissue by employing a broad bandwidth Titanium:sapphire laser with
9 a full-width-at-half-maximum of 120 nm centered at 800 nm [8]. Similarly, Werkmeister et al.
10 used a similar laser to obtain an axial resolution of $\sim 1.2 \mu\text{m}$ on human cornea [9]. However, the
11 use of Titanium:sapphire laser leads to a significantly increased system cost. According to the
12 equation above, the axial resolution is proportional to the central wavelength of OCT light
13 source and consequently can be improved by employing a short-wavelength light source, e.g.,
14 visible light [10, 11]. Chong et al. designed a multi-functional fiber-based visible-light (Vis)-
15 OCT for human retinal imaging with an axial resolution of $< 2 \mu\text{m}$ in tissue [12]. Pi et al.
16 presented a fiber-based Vis-OCT with an axial resolution of $\sim 1.2 \mu\text{m}$ which allows for
17 quantifying the thickness of large vessel walls in the chicken embryo [13]. However, Vis-OCT
18 usually suffers from a reduced imaging depth than conventional near-infrared OCT for the
19 higher scattering property of visible light in tissue.

20 In recent years, deep learning has been extensively applied to realize super-resolution
21 optical imaging [14]. For example, Ozcan et al. demonstrated a superb performance of super-
22 resolution in optical microscopy [15], scanning electron microscopy [16], and fluorescence
23 microscopy [17]. Particularly, for OCT, deep learning has been utilized for developing axial
24 super-resolution OCT. Huang et al. proposed a generative adversarial network (GAN) based on
25 enhanced super-resolution GAN (ESRGAN) [18] to denoise and upscale OCT B-scan images
26 (super-resolution) [19]. The semi-supervised deep learning approach was utilized for a similar
27 purpose by using a dataset of paired noisy images [20]. This approach overcomes the drawback
28 of supervised networks, i.e., the requirement of low quality-high quality pairs. However, down-
29 sampling OCT B-scan image only blurs the structures and cannot mimic axial resolution
30 degradation caused by the reduced spectral bandwidth of light sources [21]. Hence, the
31 upscaling process will probably not be applicable to generate super-resolution OCT image from
32 low depth resolution image. Residual-in-residual dense block (RRDB) network [18] was
33 employed to obtain axial super-resolution OCT image from the truncated spectra [21]. Liang et
34 al. reported the use of conditional GAN to enhance the axial resolution of OCT image
35 accompanied with a good recovery of realistic speckle [22]. Furthermore, deep learning has
36 also been applied to OCT lateral super-resolution. For example, GAN was utilized for
37 refocusing OCT *en-face* images by mapping defocused image onto focused image [23]. Note
38 that OCT image reconstruction is typically obtained by Fourier-transforming of the interference
39 spectra with the resulted image being complex-valued. However, the super-resolution methods
40 based on deep learning above are implemented with OCT image intensity while the phase
41 information is ignored, even though the phase of an image can provide structural information
42 [24, 25]. Theoretically, complex-valued network is superior against its real-valued counterpart
43 by fully utilizing both amplitude and phase [26]. Furthermore, complex-valued networks are
44 advantageous in easy optimization, fast learning, and noise-robust memory mechanisms [27-
45 29]. It has been successfully applied to achieve super-resolution for Terahertz imaging [30],
46 hyperspectral imaging [31], and millimeter-wave imaging [32].

47 In this paper, to the best of our knowledge, we are the first to propose a complex-valued
48 network, namely, complex-valued super-resolution network (CVSR-Net) for realizing axial
49 super-resolution of OCT imaging. CVSR-Net utilizes local residual connections, global
50 residual connections, channel concatenation, and dense connections to extract the complex-
51 valued image features and learn the mapping of low-resolution image onto high-resolution
52 image. The loss function was specially designed by summing weighted Charbonnier loss and
53 multiscale structural similarity. The CVSR-Net was evaluated on three OCT datasets and
54 spectral truncation was employed to produce low axial resolution image. To show the
55 advantage of complex-valued network, comparisons were conducted among seven super-
56 resolution networks and their real-valued counterparts. The results demonstrate that the
57 complex-valued network can super-resolve images with more realistic speckles and structures
58 than the real-valued network and the CVSR-Net achieved the best performance. Next, the
59 CVSR-Net and its real-valued counterpart RCSR-Net were tested on two micro-OCT datasets.
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8 The results show that the CVSR-Net can restore axial resolution well from the largely truncated
9 spectra with better image metrics than the RVSr-Net on all the datasets. Last, the generalization
10 ability of the CVSR-Net was evaluated by testing the model trained with the source-domain
11 dataset (*ex vivo* micro-OCT images of swine esophagus) on out-of-distribution domain datasets
12 (*ex vivo* micro-OCT images of swine cornea and *in vivo* swept-source OCT images of human
13 retina). The CVSR-Net appeared to have a good generalization capability.

14 The main contributions of this work are summarized as follows:

15 1. We developed a complex-valued deep learning network for the first time to achieve axial
16 super-resolution OCT which was demonstrated to be superior to real-valued deep learning
17 network. The CVSR-Network is able to super-resolve fine structures by extracting features
18 from both amplitude and phase of OCT signals.

19 2. We demonstrated the superiority of the complex-valued deep learning network against
20 its real-valued counterpart on several prevailing super-resolution networks. The complex-
21 valued networks can super-resolve images with more detailed structures than the corresponding
22 real-valued networks. Our proposed network achieved the best performance among all those
23 evaluated complex-valued and real-valued networks.

24 3. The good generalization capability of the CVSR-Net was demonstrated by testing the
25 model trained with the source-domain dataset on out-of-distribution dataset (cross tissue/cross
26 system).

27 2. Methods

28 2.1 Data acquisition and image pre-processing

29 Two datasets acquired by a micro-OCT prototype system [33, 34] and one dataset acquired by
30 a home-built 1060 nm swept-source OCT system were included in this study, including four *ex*
31 *vivo* volumetric images of swine esophagus from four swine samples, four *in vivo* volumetric
32 images of swine cornea from four swines, and four *in vivo* volumetric images of human retina
33 images from one human subject. This study was approved by the ethics review board of The
34 First Affiliated Hospital of Soochow University and abided by the tenets of the Declaration of
35 Helsinki (clinical trial registration number: ChiCTR1800014446). The size of each volumetric
36 image from the micro-OCT system and the swept-source OCT system is $1024 \times 1024 \times 512$ and
37 $512 \times 1000 \times 500$ (A-scan \times B-scan \times C-scan), respectively. The pixel size of the image from the
38 micro-OCT system and the swept-source OCT system is $0.85 \times 1.53 \mu\text{m}$ and $10 \times 7.4 \mu\text{m}$
39 (lateral \times axial), respectively. The OCT image reconstruction comprises the following steps: (1)
40 reference spectrum subtraction, (2) k-linearization (exclusively for micro-OCT), (3) spectrum
41 windowing with a Hanning function, (4) dispersion compensation, and (5) fast Fourier
42 transform (FFT).

43 To simulate low axial resolution OCT images, the raw spectrum was truncated using a
44 Hanning window with a size smaller than the spectrum length, e.g., quarter or half of the
45 spectrum length. Note that the axial resolution of OCT imaging is inversely proportional to the
46 spectral bandwidth of the light source and thus tuning the window width can effectively
47 simulate the use of narrow band light source to obtain low axial resolution of OCT imaging. In
48 comparison, downsampling can only degrade the digital resolution instead of the optical
49 resolution. The truncated spectrum was zero-padded to make up the loss due to the truncation.
50 Then, a complex-valued OCT image was obtained by FFT, called low-resolution (LR) image.
51 The OCT image produced from the non-truncated spectra was taken as high-resolution (HR)
52 image. LR and HR images were used as the input and ground truth (GT) of the deep learning
53 network, respectively, for training, validation and testing. Due to the limitation of GPU memory,
54 the original LR and GT images were randomly cropped to be 300×300 pixels. For each dataset,
55 three volumes were taken for training (900 images) and validation (100 images) and one volume
56 was used for testing (100 images) to ensure that they are independent and the training process
57 is blind to the validation and testing process. The models for different types of tissues were
58 trained separately.
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2.2 Complex-valued network architecture

A) Complex-valued convolution layer

To perform the convolution in complex domain, for a complex-valued input image $I = x + iy$ and a complex-valued convolution kernel $W = A + iB$, the complex-valued convolution (CConv) can be expressed as $W * I = (A * x - B * y) + i(B * x + A * y)$. The matrix notation of this equation is:

$$\begin{bmatrix} \Re(W * I) \\ \Im(W * I) \end{bmatrix} = \begin{bmatrix} A & -B \\ B & A \end{bmatrix} * \begin{bmatrix} x \\ y \end{bmatrix}. \quad (1)$$

This complex-valued convolution layer can be realized by utilizing two real-valued 2D convolution layers in Pytorch.

B) Complex-valued activation

Complex-valued activation can be obtained by splitting the activation function [26, 35], and then conducting the activation by adopting the real-valued activation. Thus, the complex-valued ReLU (CReLU) is given by:

$$\text{CReLU}(z) = \text{ReLU}(\Re(z)) + i\text{ReLU}(\Im(z)), \quad (2)$$

where $\text{ReLU}(\cdot)$ is the real-valued ReLU as follows:

$$\text{ReLU}(x) = \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

C) Complex-valued super-resolution network architecture

Figure 1 shows the network architecture of our proposed CVSR-Net. The architecture was inspired by Residual Dense Network (RDN) [36, 37] and Residual Network (ResNet) [38]. The CVSR-Net consists of a shallow feature extraction part, a deep feature extraction part, and a final reconstruction part.

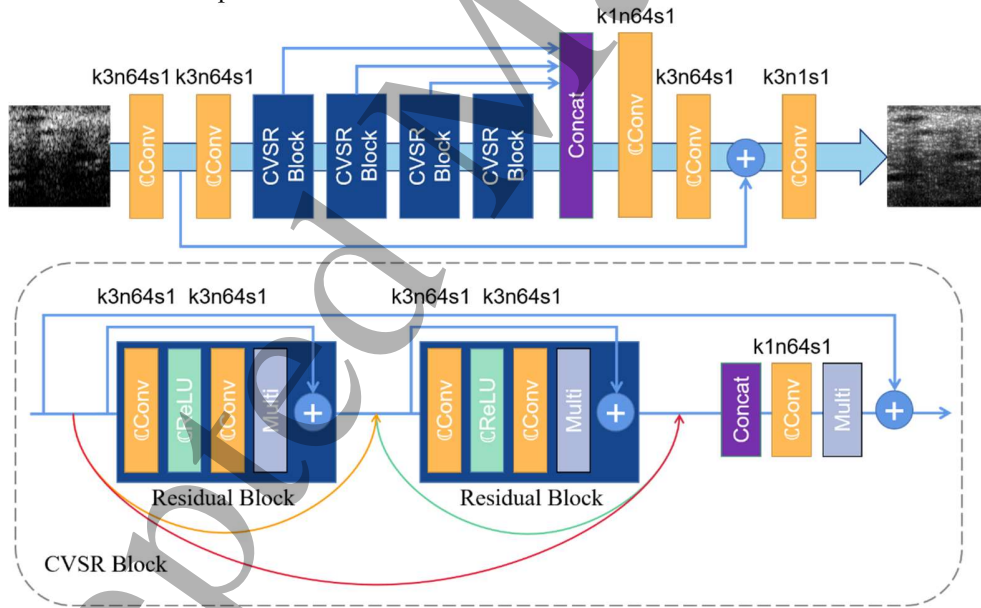


Fig. 1. The network architecture of the CVSR-Net.

In the shallow feature extraction part, two CConv layers with a kernel size of 3, 64 channels and a stride size of 1 learn the low-level features of the image. The features extracted by the first CConv layer are connected to the reconstruction part to achieve a global residual learning. This not only helps transfer the low-level features to the final image, but also avoids learning a complicated mapping of two images [39, 40].

The deep feature extraction comprises four CVSR blocks and a channel concatenation layer. As shown in Fig. 1, the basic unit in the CVSR block is built as the residual block in EDSR [41]. The two residual blocks are utilized to extract the high-level features. The red, orange, and green curves denote dense connections as used in DenseNet [36]. Therefore, the feature-maps in the CVSR block can be fully used and fused by the dense connections. Next, the feature channel is recompressed to 64 by a 1×1 CConv layer.

The multi in Fig. 1 means that the feature-maps are multiplied by a residual scaling factor to make the training process more stable [42]. Before the feature-map is transferred to the next CVSR block, the input feature-map is added with the local residual learning to reduce the degradation and improve the learning ability of the network [43, 44]. The feature-maps produced by four CVSR blocks are concatenated at the end of the deep feature extraction part to fuse the features at various levels.

Finally, the 1×1 CConv layer compresses the channel number of the feature from 256 to 64, and the final image can be generated by two CConv layers with a kernel size of 3. Note that the output of the proposed CVSR-Net is in complex-value domain. To conduct the backpropagation and visualize the image, the amplitude of the output is utilized.

2.3 Quantitative evaluation

To evaluate the performance of our proposed method, three commonly used image quality metrics were employed: peak signal-to-noise ratio (PSNR), structural similarity (SSIM) index, and learned perceptual image patch similarity (LPIPS) [40, 45, 46]. PSNR can reflect the pixel-wise difference between two images and is defined as follows:

$$\text{PSNR} = 10 \log_{10} \left(\frac{\max(I)^2}{\frac{1}{N} \sum_{i=1}^N (I(i) - I_{GT}(i))^2} \right), \quad (4)$$

where I is the processed image, e.g., LR image or SR image, and I_{GT} represents the GT image.

However, PSNR cannot completely depict the image resolution enhancement as only pixel-wise difference is considered, and consequently an individual use of PSNR may not be reliable [40]. Therefore, SSIM was employed to provide a good evaluation of the perceptual similarity. SSIM is calculated by incorporating luminance, contrast, and structure of two images as defined in the following equations:

$$l = \frac{2\mu_l \mu_{l_{GT}} + C_1}{\mu_l^2 + \mu_{l_{GT}}^2 + C_1}, \quad (5)$$

$$c = \frac{2\sigma_l \sigma_{l_{GT}} + C_2}{\sigma_l^2 + \sigma_{l_{GT}}^2 + C_2}, \quad (6)$$

$$s = \frac{\sigma_{ll_{GT}} + C_3}{\sigma_l \sigma_{l_{GT}} + C_3}, \quad (7)$$

where l , c , and s represent luminance, contrast, and structures, respectively; μ_l and $\mu_{l_{GT}}$ are the mean pixel values of the processed image and the GT image, respectively; σ_l and $\sigma_{l_{GT}}$ represent their standard deviations; $\sigma_{ll_{GT}}$ is the covariance. The constants- C_1 , C_2 , and C_3 are 0.01, 0.03 and 0.015, respectively. α , β , and γ are set to be 1. Then, SSIM can be obtained according to the following formula:

$$\text{SSIM} = [l]^\alpha [c]^\beta [s]^\gamma = \frac{(2\mu_l \mu_{l_{GT}} + C_1)(2\sigma_{ll_{GT}} + C_2)}{(\mu_l^2 + \mu_{l_{GT}}^2 + C_1)(\sigma_l^2 + \sigma_{l_{GT}}^2 + C_2)}, \quad (8)$$

LPIPS is another often-used metric dedicated to evaluating the perceptual similarity of two images. It can provide an image similarity evaluation complementary to PSNR and SSIM. Other than calculating the difference in the pixel level, LPIPS assesses the images based on the high-level features extracted by a trained CNN. More specifically, a pre-trained AlexNet was used in this work to extract two high-level features of the GT image and the LR image. Then, the Euclidean distance between two high-level features was calculated to reflect the structural similarity. The small LPIPS value represents the high similarity between the two images.

2.4 Loss function

To guide the model optimization, a loss function was designed by combining Charbonnier loss and multiscale structural similarity (MS-SSIM). Charbonnier loss is a variant of L1 loss and can handle outliers better than L1 loss. It has shown an improved performance and convergence as compared to L2 loss [47]. However, Charbonnier loss is a loss calculated from the pixel-wise difference while not considering the structure variation. Consequently, this loss function can maximize PSNR but may lead to an over-smoothing which may smear fine structures [46]. To address the limitation of Charbonnier Loss, MS-SSIM was combined with Charbonnier loss through a linear addition. MS-SSIM is yielded from implementing SSIM at multiple scales, measuring the image details at different resolutions [48, 49]. Moreover, MS-SSIM loss avoids the selection of the standard deviation of the Gaussian filter which may influence the results [49]. Thus, in principle, the new loss function should be able to preserve the pixel intensity well (Charbonnier loss), and simultaneously increase the similarity between two images and retain the texture well (MS-SSIM loss function). The three loss functions above are given by:

$$\mathcal{L}_{\text{Charbonnier}} = \frac{1}{hw} \sum_{i,j} \sqrt{(I_{i,j} - I_{GT,i,j})^2 + \epsilon^2}, \quad (9)$$

$$\mathcal{L}_{\text{MS-SSIM}} = 1 - [I_M]^{\alpha_M} \prod_{j=1}^M [c_j]^{\beta_j} [s_j]^{\gamma_j}, \quad (10)$$

$$\mathcal{L}_{\text{our}} = k_1 \cdot \mathcal{L}_{\text{Charbonnier}} + k_2 \cdot \mathcal{L}_{\text{MS-SSIM}}, \quad (11)$$

where h and w are the height and width of the image, respectively; ϵ is set to 0.003 to make Charbonnier loss more robust for outliers; M means the highest scale; α_M , β_j and γ_j are all set to be 1. k_1 and k_2 are empirically set to be 0.16 and 0.84, respectively.

2.5 Implementation details

In this work, three LR datasets were created with various degraded axial resolutions through spectrally truncating the raw data with percentages of 25%, 37.5%, and 50%. In the training process, all the networks were optimized by Adam optimizer with $\beta_1 = 0.9$ and $\beta_2 = 0.999$ [50]. The initial learning rate was set to be 1e-3 for all the layers and decayed by a factor of two every twenty epochs. The batch size was two and all the networks were trained by 100 epochs (45,000 iterations) to guarantee a convergence. Each dataset with a different axial resolution was trained separately to realize a mapping of a low axial resolution onto its corresponding high axial resolution.

All the experiments were implemented in Python 3.7 with Pytorch 1.13.1 deep learning framework on a server with a 2.4 GHz Intel Xeon Silver 4210R CPU and NVIDIA RTX 3090.

3. Results and discussion

The proposed CVSR-Net trained with the swine esophagus dataset was first evaluated on the *ex vivo* swine esophagus test set from micro-OCT. Three low-resolution image datasets were created by truncating the spectra using a Hanning window function with three truncation percentages (truncated/non-truncated)-25%, 37.5% and 50%, corresponding to Figs. 2(a)-2(c), respectively. It is clearly seen that all the three images above were blurred and exhibited axially

enlarged speckles as compared with the GT image (Fig. 2(g)). Moreover, the image degraded more as the truncation percentage decreased from 50% to 25%. For example, as the truncation percentage decreased, the grainy speckle pattern became coarser which can be explained by the broadened axial coherence function due to the spectral truncation. Meanwhile, in the region of interest (ROI, the region framed with rectangle), the flat blood vessel's (denoted by red arrow) boundary underwent a larger destruction, resulting in a decreased vessel visibility. Figures 2(d)-2(f) describe the SR images produced by the CVSR-Net with Figs. 2(a)-2(c) as inputs, respectively. Overall, for all the three different truncation percentages, the images were recovered well to be close to the GT image. In details, similar speckle patterns and image sharpness were obtained. This can also be illustrated by the depth profile along the dashed red line in Fig. 2(g) as shown in Fig. 3. Obviously, more structure loss occurred as the truncation percentage increased, for example, some neighboring peaks were merged into a broad peak, i.e., in the region denoted by dashed rectangle. The SR image appeared to be well overlapped with the GT image for the truncation percentage of 37.5%. This can be further improved on the 50% truncated data. It is also observed that the signal-to-noise (SNR) loss in the deep region resulting from the reduced axial resolution was restored well which was manifested as the increased peaks (SR images). For the truncation percentage of 25%, although peaks were not fully recovered, the SNR was significantly increased, indicating an axial resolution enhancement.

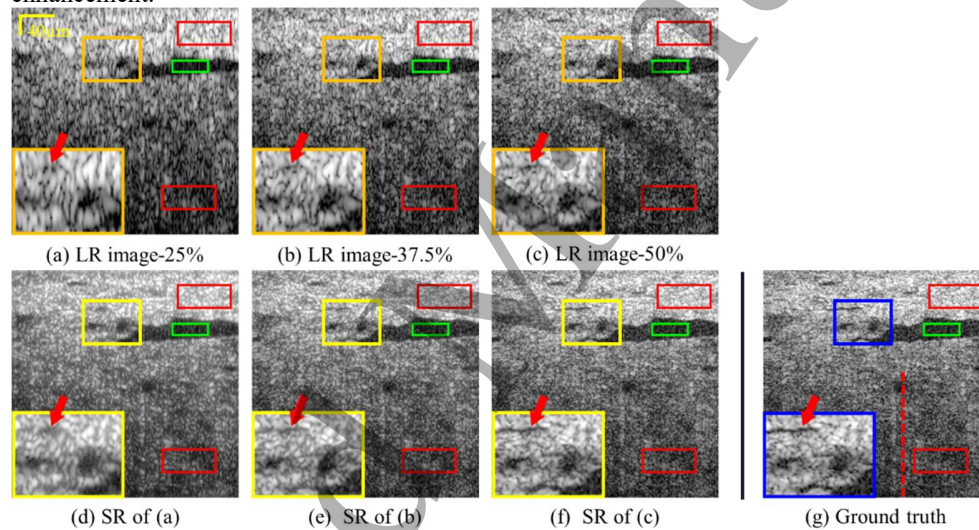


Fig. 2 Super-resolution results of the CVSR-Net on *ex vivo* swine esophagus test set: (a)-(c) are LR images reconstructed from 25%, 37.5% and 50% spectrally truncated data, respectively; (d)-(f) are the corresponding resolution-enhanced images generated by the CVSR-Net; (g) is the Ground truth.

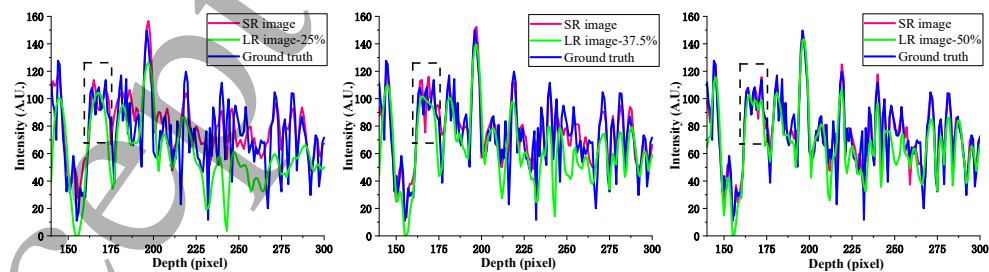


Fig. 3 Depth profiles along the red dashed line in Fig. 2(g) and its corresponding trajectories in Figs. 2(a)-2(c) and 2(d)-2(f).

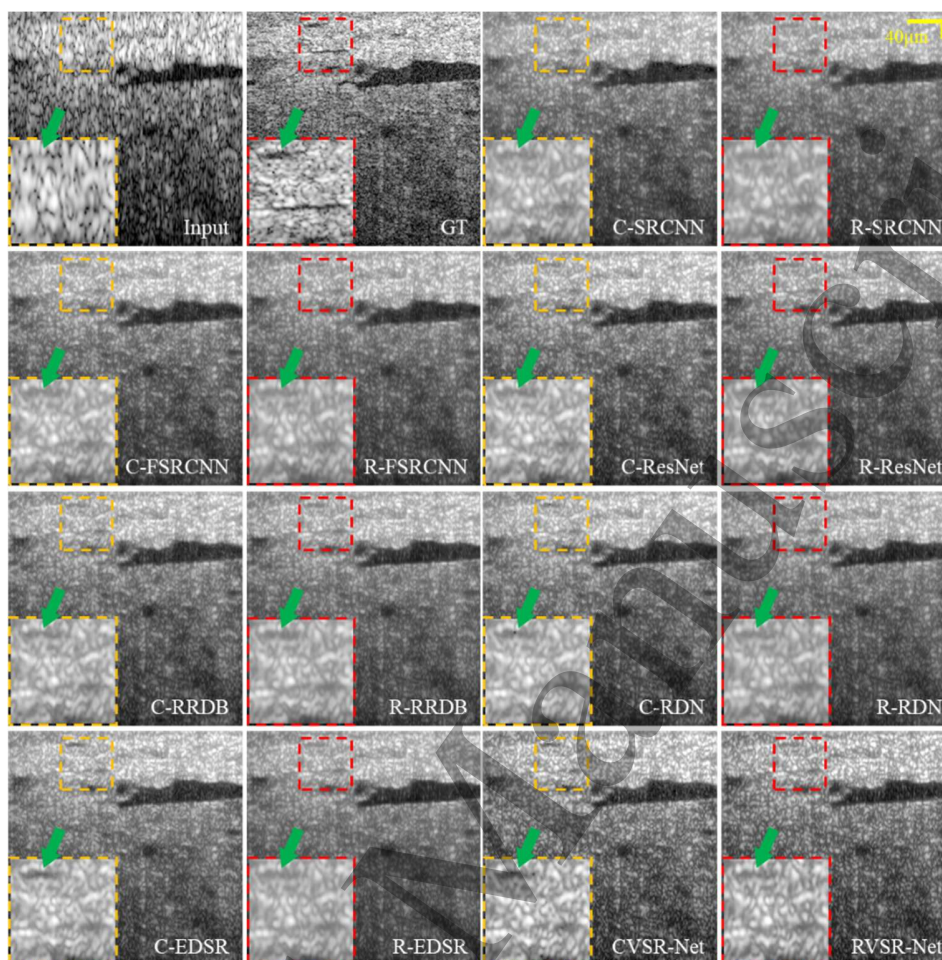


Fig. 4 Comparisons between the complex-valued networks and the real-valued networks. C- and R- represents complex-valued and real-valued, respectively. The input is the image with a 25% spectral truncation.

Table 1. Image metrics of the *ex vivo* swine esophagus test set.

Net	PSNR	SSIM	LPIPS
LR Image-25%	16.83	0.3439	0.5893
CVSR-Net	20.47	0.5404	0.4114
LR Image-37.5%	18.77	0.5298	0.4135
CVSR-Net	23.12	0.7648	0.2288
LR Image-50%	20.97	0.6993	0.2779
CVSR-Net	26.95	0.9098	0.0948

To quantitatively assess the performance of CVSR-Net, three image metrics, including PSNR, SSIM and LPIPS, were calculated and summarized in Tab. 1. It is found that for all the three truncation percentages, PSNR, SSIM and LPIPS were significantly improved by the CVSR-Net. Moreover, the improvement extent appeared to be comparable among all the three LR images, about 3.5-6 for PSNR, 0.2-0.25 for SSIM and 0.2-0.3 for LPIPS. As a result, the CVSR-Net did not change the rank of the three metrics of SR images generated from the three datasets with different truncation percentages. The image restored from LR image-50% always

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8 showed the best image quality, i.e., axial resolution, while the images from LR image-37.5%
9 and LR image-25% were ranked at the second and third, respectively. This was consistent with
10 the perceptual findings from the images in Fig. 2. In addition, it is worth mentioning that the
11 image restored from LR image-50% had a PSNR-26.95, SSIM-0.9098, and LPIPS-0.0948,
12 indicating that the enhanced image was very close to the GT image. Besides the evaluation of
13 CVSR-Net for various truncation percentages, the effect of the image SNR was also
14 investigated. The SNR was calculated according to the equation $SNR = 20\log_{10}(\mu_s / \sigma_b)$, where
15 μ_s and σ_b represent the mean intensity of the signal ROI (framed with red rectangle) and the
16 standard deviation of the background ROI (framed with green rectangle), respectively. Two
17 ROIs were chosen with high SNR in the upper red rectangle which was 18.3, 18.4, and 18.0 for
18 Fig. 2(a)-2(c), respectively and low SNR in the lower red rectangle which was 6.6, 7.8, and 7.9
19 for Fig. 2(a)-2(c), respectively. In the corresponding reconstructed image, the SSIM for these
20 two ROIs (high SNR vs low SNR) was 0.51 vs 0.55, 0.73 vs 0.79 and 0.90 vs 0.92 for Fig. 2(a)-
21 2(c), respectively. It's obvious that although the two ROIs showed a significantly different SNR,
22 they exhibited a similar SSIM to the ground truth. This implies that the proposed method has a
23 good robustness and the SNR's effect may be negligible.

24 Prior to further applying the CVSR-Net to OCT imaging of different biological tissues, the
25 superiority of the CVSR-Net against its real-valued counterpart was verified extensively. To
26 do so, a real-valued super-resolution network (RVSR-Net) was designed with the same network
27 architecture as CVSR-Net. To make the comparison between the complex-valued network and
28 the real-valued network fair and generic, six prevailing SR networks, including EDSR, RDN,
29 RRDB network [18], ResNet [51], fast super-resolution convolutional neural network
30 (FSRCNN) [52], super-resolution convolutional neural network (SRCNN) [39] and their
31 complexed counterparts were included. It should be noted that the upsampling layers in the
32 above networks were removed as the size of each image was kept constant in the training and
33 testing processes. In addition, each network and its complex-valued counterpart were trained
34 with the loss function from the original papers on the *ex vivo* swine esophagus dataset and all
35 the training processes were conducted in the same way as mentioned in section 2.5.

36 Figure 4 describes the comparisons of SR images produced by the complex-valued
37 networks and the real-valued networks. The image reconstructed from 25% truncated spectral
38 data was used as the input of the network. It is obvious that the images produced by both
39 complex-valued networks and real-valued networks showed a similar speckle pattern and an
40 image sharpness. Besides, the SR image looked smoother as compared to the GT image,
41 indicating that the image reconstruction by deep learning network comes with a denoising effect
42 in addition to the resolution enhancement. This may be because the noise distribution and
43 intensity of the LR image and the GT image are different, and the networks fail to learn the
44 noise mapping. The denoising effect makes the morphological structure more distinguishable
45 in the SR image than the GT image. Among all these seven paired networks, the CVSR-Net
46 showed the weakest denoising effect and consequently the generated SR images looked most
47 like the GT image. In addition, the CVSR-Net achieved the best performance in reconstructing
48 the blood vessel (pointed out by green arrow) in the ROI. However, it may not be easy to judge
49 whether the complexed-value network performed better than the real-valued network from the
50 images except the CVSR-Net and the C-EDSR.

51 Therefore, PSNR, SSIM and LPIPS were computed to make an objective and reliable
52 comparison between complexed-value network and real-valued network as depicted in Tab. 2.
53 Each complex-valued network achieved a higher PSNR, higher SSIM, and lower LPIPS as
54 compared with its real-valued counterpart. The complexed-value network's superiority was
55 more obvious in SSIM and LPIPS than in PSNR. This may be because the phase of the signal
56 contains structure information of an image, and therefore by incorporating the phase in the
57 learning process, the complexed-value network has a better capability to recover those high-
58 frequency structures. The PSNR of the image by the real-valued network was close to that of
59 the complexed-valued network, indicating that both networks appeared to have a comparable
60

denoising capability. In addition, the CVSR-Net yielded the highest SSIM and the smallest LPIPS, demonstrating that the CVSR-Net performed better than the other networks in axial resolution enhancement. On the other hand, the complex-valued network also had the advantage of easier optimization over the real-valued network. Figure 5 shows the loss of training before overfitting for the CVSR-Net and the RVSR-Net. It is obvious that the CVSR-Net converged more quickly and had a smaller loss than the RVSR-Net.

Table 2. Comparisons of image metrics between complex-valued networks and real-valued networks on the *ex vivo* swine esophagus test set.

Net	PSNR	SSIM	LPIPS
LR Image-25%	16.83	0.3439	0.5893
CVSR-Net	20.47	0.5404	0.4114
RVSR-Net	20.07	0.4796	0.4716
C-EDSR	20.75	0.5061	0.4433
R-EDSR	20.29	0.4218	0.5171
C-RDN	20.68	0.4951	0.4699
R-RDN	20.22	0.4233	0.5212
C-RRDB	20.48	0.4680	0.4820
R-RRDB	20.27	0.4297	0.5107
C-ResNet	20.60	0.4760	0.4808
R-ResNet	20.26	0.4287	0.5116
C-FSRCNN	20.49	0.4604	0.5089
R-FSRCNN	20.07	0.3988	0.5400
C-SRCNN	20.37	0.4498	0.4835
R-SRCNN	19.97	0.3862	0.5482

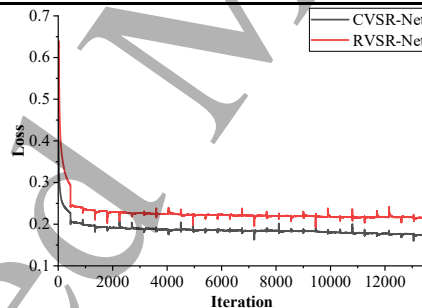


Fig. 5 The loss-iteration functions of training the CVSR-Net and the RVSR-Net.

Next, we evaluated the super-resolution performance of both the CVSR-Net and the RVSR-Net on the *in vivo* swine cornea test set from micro-OCT. As can be seen in Fig. 6, the corneal stroma was comprised of collagen bundles (stacked-layer structures) which is delineated clearly in the GT image. When the spectra were truncated by 25%, it was hard to identify the collagen bundles in the resulted image due to the degraded axial resolution. The axial resolution degradation caused by the spectral truncation is well illustrated by the thickening of the edge of the cornea. With the increase of the truncation to 50%, the visibility of the collagen bundles was highly improved and however remained far lower than in the GT image. By using either the CVSR-Net or the RVSR-Net, the collagen bundles can be recovered with a fairly good visibility for all the three truncation percentages. To better visualize the difference of super-resolution performance between the CVSR-Net and the RVSR-Net, a small rectangular region was chosen and zoomed in as framed with various colors (red: input, orange: output of the

RVSR-Net, green: output of the CVSR-Net, blue: Ground truth). It is seen that the CVSR-Net outperformed the RVSR-Net. In particular, the output image of the CVSR-Net bore a higher structural similarity to the Ground truth than that of the RVSR-Net. All the findings above were confirmed by the quantitative metrics, PSNR, SSIM and LPIPS as shown in Tab. 3. All the image metrics were significantly improved by the CVSR-Net and the RVSR-Net as compared to the low-resolution image. Meanwhile, the best metrics always occurred on the images output from the CVSR-Net for each truncation percentage. For example, for the images reconstructed from the data with 50% spectral truncation, although the SSIM was increased from 0.6925 to 0.8099 by the RVSR-Net, it was further improved to 0.9142 by the CVSR-Net. A similar trend is observed on the LPIPS which underwent a decrease from 0.2796 (LR image) to 0.1457 (RVSR-Net) and further to 0.0616 (CVSR-Net). This indicates that for a truncation percentage of 50%, the CVSR-Net can restore an image that is almost identical to the GT.

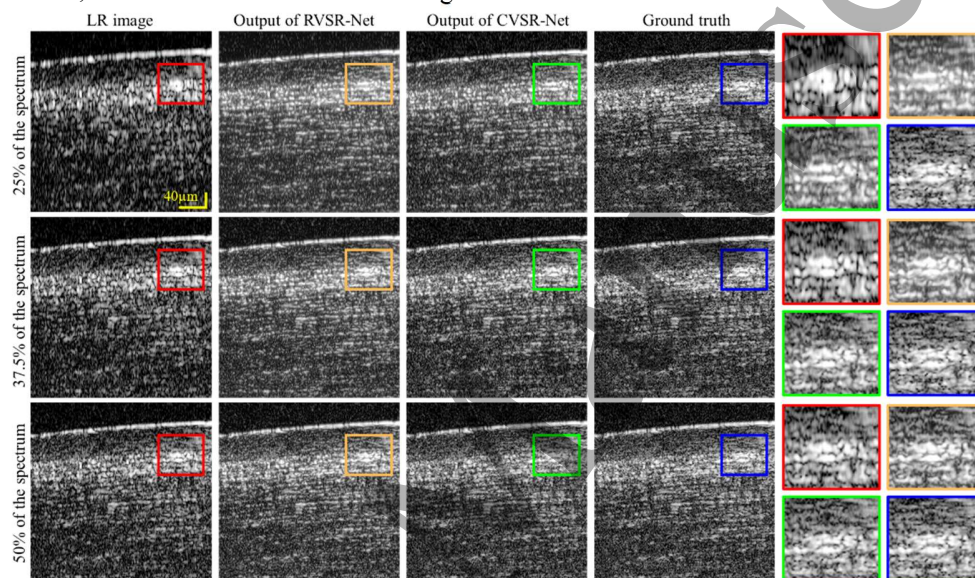


Fig. 6 Super-resolution results of the CVSR-Net and the RVSR-Net on the *in vivo* swine cornea test set.

Table 3. Image metrics of the *in vivo* swine cornea test set.

Net	PSNR	SSIM	LPIPS
LR Image-25%	13.80	0.3281	0.6194
RVSR-Net	16.69	0.4499	0.4489
CVSR-Net	17.19	0.5377	0.3669
LR Image-37.5%	15.72	0.5206	0.4428
RVSR-Net	18.51	0.6525	0.2676
CVSR-Net	19.90	0.7701	0.1623
LR Image-50%	17.87	0.6925	0.2796
RVSR-Net	20.86	0.8099	0.1457
CVSR-Net	24.11	0.9142	0.0616

Last, the CVSR-Net was evaluated from the aspect of the generalization ability. The *ex vivo* swine esophagus dataset (37.5% spectral truncation) was taken as the source domain dataset. The evaluation was conducted with two different out-of-distribution domain test sets as illustrated in Fig. 7. One is the *in vivo* swine cornea test set (37.5% spectral truncation) acquired

by the same micro-OCT system as the source domain dataset. The other out-of-distribution domain test set is the *in vivo* human retina test set acquired by 1060nm swept-source OCT system. Figures 7(c) and 7(d) describe the SR images of the cornea generated by the model trained with the source domain dataset and the out-of-distribution domain dataset, respectively. It can be seen that the SR image from the out-of-distribution domain model showed a good recovery of the image as compared to the GT image (Fig. 7(a)) while a slightly reduced sharpness is observed as compared to that from the source domain model. The fine adjacent collagen bundles were discernible. Similar findings can be obtained from the human retina results. Overall, the retinal layer structure and choroid vasculature were resolved well in the SR image by the model trained with the source domain dataset. However, due to the reduced image sharpness, some edge structure was not as clear as in the SR image by the model trained with the out-of-distribution domain dataset, such as the upper edge of the inner limiting membrane. Table 4 summarizes the quantitative metrics of the images in Fig. 7. It is observed that, as compared to the model trained with the out-of-distribution domain dataset, SSIM dropped obviously for the model trained with source domain dataset for both two test sets, PSNR decreased for human retinal test set and LPIPS increased for swine cornea test set. This is reasonably acceptable as the metrics change was far less than the improvement against the LR images and the SR performance for out-of-distribution domain was visually close to that for source domain. The results demonstrate that the proposed CVSR-Net has a good generalization capability and can be potentially used to super-resolve unseen OCT data.

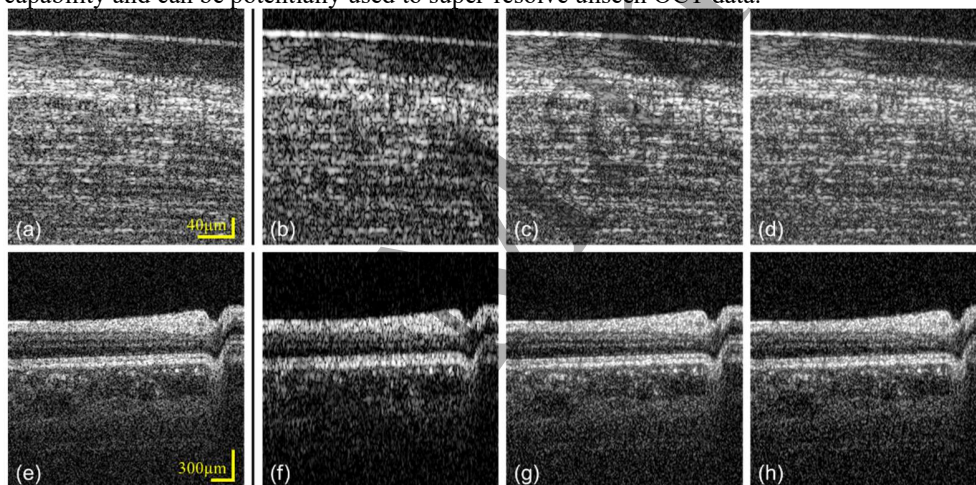


Fig. 7 Generalization performance of the CVSR-Net: (a) and (e) are the GT images of the *in vivo* swine cornea dataset and the *in vivo* human retina dataset respectively; (b) and (f) are the LR images; (c) and (g) are the SR images generated by the model trained with their respective source domain datasets; (d) and (h) are the SR images generated by the model trained with the *ex vivo* swine esophagus dataset. The LR images are created by the 37.5% spectral truncation.

Table 4. Image metrics of the SR images from both source-domain and out-of-distribution domain.

Tissue	Image	PSNR	SSIM	LPIPS
Swine Cornea	LR Image	15.72	0.5206	0.4428
	SR Image: source-domain	19.90	0.7701	0.1623
	SR Image: out-of-distribution domain	19.88	0.7451	0.2019
Human Retina	LR Image	17.68	0.3824	0.5274
	SR Image: source-domain	21.51	0.7243	0.2160
	SR Image: out-of-distribution domain	20.93	0.6883	0.2130

4. Conclusion

In this paper, we proposed a complex-valued super-resolution network (CVSR-Net) to achieve axial super-resolution for OCT imaging. The CVSR-Net's performance was evaluated on three micro-OCT datasets of various biological tissues. The results demonstrate that the CVSR-Net has a good capability to recover the axial resolution and the speckles from spectrally truncated data. Moreover, the CVSR-Net was also proven to be superior to its counterpart-RVSR-Net. This can be accounted for by the fact that the CVSR-Net can resolve more detailed structures of images by fully utilizing not only the amplitude but also the phase of OCT signals while the real-valued network only uses the amplitude. In addition, the superior performance of the complex-valued network against the real-valued network was verified on other prevailing super-resolution deep learning networks, including EDSR, RDN, RRDB, ResNet, FSRCNN, and SRCNN. Among all the complex-valued and real-valued networks, the CVSR-Net yielded the best super-resolution performance. Last, the CVSR-Net was proven to have a good generalization ability through comparing the performance of the models trained with source domain datasets and out-of-distribution domain datasets. Thus, it is reasonable to conclude that the CVSR-Net has a good potential to aid in developing axial super-resolution OCT imaging and may be able to help reduce the OCT system cost by using narrow-band light source while retaining the axial resolution. In addition, the CVSR-Net can be potentially introduced to other imaging techniques which can produce complex-valued image, such as magnetic resonance imaging. In the future, it is worth investigating the feasibility of the complex-valued network to obtain a lateral super-resolution or an extended depth of focus by using low and high numerical aperture objectives to create paired dataset to train the network.

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Declaration of competing interest. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability. The data cannot be made publicly available upon publication due to legal restrictions preventing unrestricted public distribution. The data that support the findings of this study are available upon reasonable request from the authors.

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