A novel deep learning based OCTA de-striping method

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Abstract. Noise in images presents a considerable problem, limiting their readability and hindering the performance of post-processing and analysis tools. In particular, optical coherence tomography angiography (OCTA) suffers from stripe noise. In medical imaging, clinicians rely on high quality images in order to make accurate diagnoses and plan management. Poor quality images can lead to pathology being overlooked or undiagnosed. Image denoising is a fundamental technique that can be developed to tackle this problem and improve performance in many applications, yet there exists no method focused on removing stripe noise in OCTA. Existing OCTA denoising methods do not consider the structure of stripe noise, which severely limits their potential for recovering the image. The development of artificial intelligence (AI) have enabled deep learning approaches to obtain impressive results and play a dominant role in many areas, but require a ground truth for training, which is difficult to obtain for this problem. In this paper, we propose a revised U-net framework for removing the stripe noise from OCTA images, leaving a clean image. With our proposed method, a ground truth is not required for training, allowing both the stripe noise and the clean image to be estimated, preserving more image detail without compromising image quality. The experimental results show the impressive de-striping performance of our method on OCTA images. We evaluate the effectiveness of our proposed method using the peak-signal-to-noise ratio (PSNR) and the structural similarity index measure (SSIM), achieving excellent results as well.

Keywords: OCTA · Stripe noise removal · Image decomposition · Deep learning.

1 Introduction

In recent years, deep convolutional networks have achieved considerable success in image-level diagnostics in many areas of medical imaging [9, 5], including ophthalmology [17, 3]. Several deep learning (DL) algorithms have been very efficient in detecting clinically significant features for ophthalmic diagnosis and prognosis of many diseases including diabetic retinopathy (DR) [6] and age related macular degeneration (AMD) [1].

Optical Coherence Tomography (OCT) is a non-invasive imaging technique, capable of providing tomographic images of the retina and contributing to the clinical diagnosis of several diseases including glaucoma, AMD and DR. Particularly, OCT angiography (OCTA), which is functional extension of OCT measuring motion of blood flow contrast, can provide a near-microscopic view of the retina in-vivo with high resolution. This results in a fast imaging modality that reveals structural detail of the retina vascular network [13]. Due to attractive qualities and capabilities of OCTA, it is widely used in ophthalmology studies to test for and predict DR and other diseases.

Although OCTA images provide high resolution retinal fundus information, the images are composed of strip data, resulting is visible striped artefacts, which hinder analysis and further processing. These strip OCTA artefacts can cause incorrect evaluation in segmentation for both traditional and more recent DL approaches, resulting in correct features not being detected with good accuracy and ultimately false predictions. In order to eliminate this strip noise data from OCTA images, with the help of Chang et al. [2], we propose a decomposition-based loss function to separate the desired, clean OCTA image from the stripe components.

The aim of this study is to build a model that is capable of reconstructing OCTA images by estimating and removing strip noise by incorporating a suitable loss function into a deep convolutional neural network. To the best of the authors' knowledge, this paper is first study to incorporate stripe-noise removal into deep learning framework.

With the recent improvements in deep neural networks and their excellent results in medical imaging, we focus on developing a DL technique in this study. The popular and widely used U-net, which is a fully convolutional network (FCN) variant, has demonstrated state-of-the-art performance in various medical image segmentation tasks [16], increasing sensitivity and prediction accuracy. In this paper, we propose a revised U-net for estimating clean OCTA images from noisy OCTA images. We estimate the strip noise within the model which enables us to use the low rank matrix of the stripe noise as a constraint in the loss function. In addition, the TV (total variational) norm of the estimated clean image is used as a constraint on the image.

The main contributions of this paper: 1. We develop a stripe noise removal framework based on U-net, introducing a new multi-outputs layer to estimate both the clean image and the noisy image. 2.We design a loss function which regularizes both the noise information and the predicted clean image. 3. We introduce a novel training process that removes the need for ground truth data which is important for applications where a ground truth is not available.

The rest of this paper is organized as follows. In the second section, we review related work from the different aspects including image de-noising, stripe noise removal, deep learning and loss functions. The third section introduces our method, and we present results with evaluation and discussion in the fourth section before concluding this work in section 5.

2 Related work

There have been several developments in de-noising with deep learning in recent years [11, 21, 10]. An adversarial and multi-scale feature extraction approach was used to remove image noise with a three-stage training procedure, and it is demonstrated that convolutional neural networks can be used for removing image noise [4]. Nam et al.[14] explored a noise modelling and analysing method and applied a cross-channel image noise method to show that the colour channels are independent. However, the existing methods only focus on removing noise while these noise types can be easily imitated.

Chang et al. introduced an image stripe noise removal method [2] on remote sensing image dataset and explored both the clean image and noise image quality from image decomposition perspective. Johnson et al. [8] considered that an input image can be transformed into an output image with training convolutional neural networks by introducing a perceptual loss function. Their experimental results proved that high-level features can be extracted from pre-trained networks by optimizing perceptual loss functions.

Zhao et al. researched the importance of perceptual loss for image restoration and explored the image quality correlation between humans and algorithms. Although the mean squared error plays a dominant role across diverse fields, it does not correlate with human's judgement of image quality. However, there is still no individual loss function that can achieve impressive results across different problems [22]. Yair et al. applied the weighted nuclear norm values of a whole image as a regularization term and considered the image restoration as an optimization problem, and it can be solved by introducing a unique variable splitting method and achieved leading results on deblurring and inpainting problems[20].

Plotz et al. contributed a benchmark for real photograph denoising algorithms when realistic ground truth data is lacking[15]. Generally speaking, realistic settings limit the relevance of de-noising techniques from a scientific evaluation perspective. Zhang et al. [21] introduced a residual deep learning method for removing Gaussian noise of an image. The residual learning strategy provides a certain to model different Gaussian noise level.

A fully convolutional net (FCN) has been shown to achieve impressive results on many different tasks such as classification and segmentation[12]. Built upon the FCN, Ronneberger et al. [16] proposed a fast neural network architecture (U-net) for medical image segmentation. Benefiting from symmetric and skip connections, one of the advantages of this architecture is that a large number of feature maps can be extracted. In addition, it can predict the image pixel's class. Therefore, it is a favourable network in medical image processing area because of the high-resolution nature.

3 Method

3.1 Image model

In this paper, we will focus on stripe noise removal in OCTA images, below is the equation for describing the image model:

$$O = I + N \tag{1}$$

Where O represents an original image corrupted by stripe noise, I denotes the expected clean image without stripe noise, N is the stripe noise.

3.2 Model architecture

The U-net, which is an extension of FCN [12], is used as the base network because it is an encoder-decoder neural network. We revise the model for OCTA de-striping and make it has two outputs. The advantages of our revised model are : 1. A decoder enables the parallel computing of different features representation at pixel level without changing the original image resolution. It is very important that all the fine-grained information of the OCTA image can be kept. 2. Multiresolution features and multilevel features (such as multiple scales and abstraction levels) representation can be computed effectively with an encoder. 3. We introduced a multi-outputs layer and pass both the original image and the noise image to the loss function, so there is no need to use the ground truth for the training process.

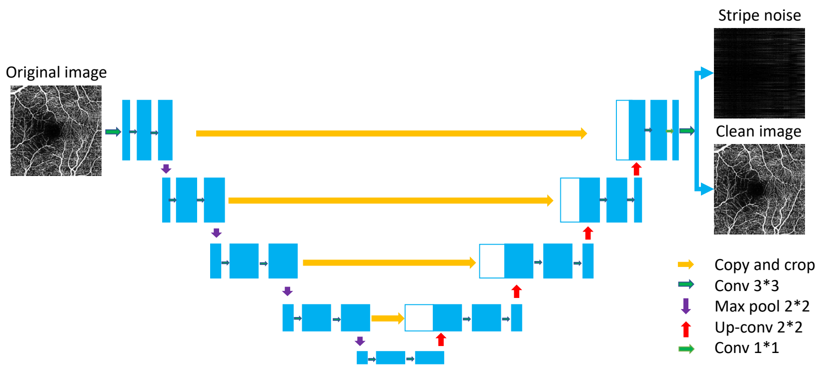

Fig. 1. The framework of Deep De-striping Net. The input is a measure OCTA image and the output is a de-noised image and a stripe noise image

Fig. 1 demonstrates the framework we developed. At the final layer, we introduce a multi-outputs layer which enables the model to output both the de-striped image and the stripe noise image. We also use a fully convolutional network to freely use different image sizes as input and output two images with the same size. The estimated stripe noise can be used for exploring more accurate stripe noise removal methods in future works .

3.3 Loss function

Different from previous loss functions for de-noising work, we build a loss function with the TV norm and the low rank matrix as regularization terms.

$$\min_{I,N} \left\{ \frac{1}{2}||I + N - O||_F^2 + \tau||I||_{TV} + \lambda \text{rank}\,(N) \right\} \tag{2}$$

Equation 2 defines our loss function. I is the predicted image, O is the original image and N is the noise image.

The TV norm regularization is based on the principle of signal processing and has been applied in noise removal issues [19]. The introduction of TV norm has the advantage of being a close match to the desired image. There is a positive correlation between the total variation and the integral of the absolute gradient. The sharp boundaries of I can be preserved when minimizing the TV norm. The low rank matrix was introduced for the stripe component with the low-rank constraint. Therefore, the introduction of the low rank matrix and TV norm makes the estimated image preserve important detail information.

4 Experiments and discussion

Our experiments are implemented using Keras 2.2.4 with Tensorflow 1.12 as backend and an Nvidia Titan XP GPU. The batch size is set as 64, the learning rate is 10^{-4}, τ is 0.005, λ is 0.005, epochs is 100, Adam is used as the optimizer, MSE (mean square error) loss function is used for comparison. The results using the method [2] are used for training our model with MSE loss function.

4.1 Dataset

We collected the OCTA images from 30 patients with 180 images (two eyes from 13 patients). Four images per eye from SVP (superficial vascular plexus), DVP (deep vascular plexus), AL (Avascular layer) and WR (whole retina) are collected from *** Hospital. In this paper, we treat each image separately for the purpose of training the deep learning models.

4.2 Results

Fig.2 shows the results of two selected examples including the original image, ground truth (predicted image with one stripe noise removal method [2] from the original image), predicted image with MSE loss function and our predicted image.

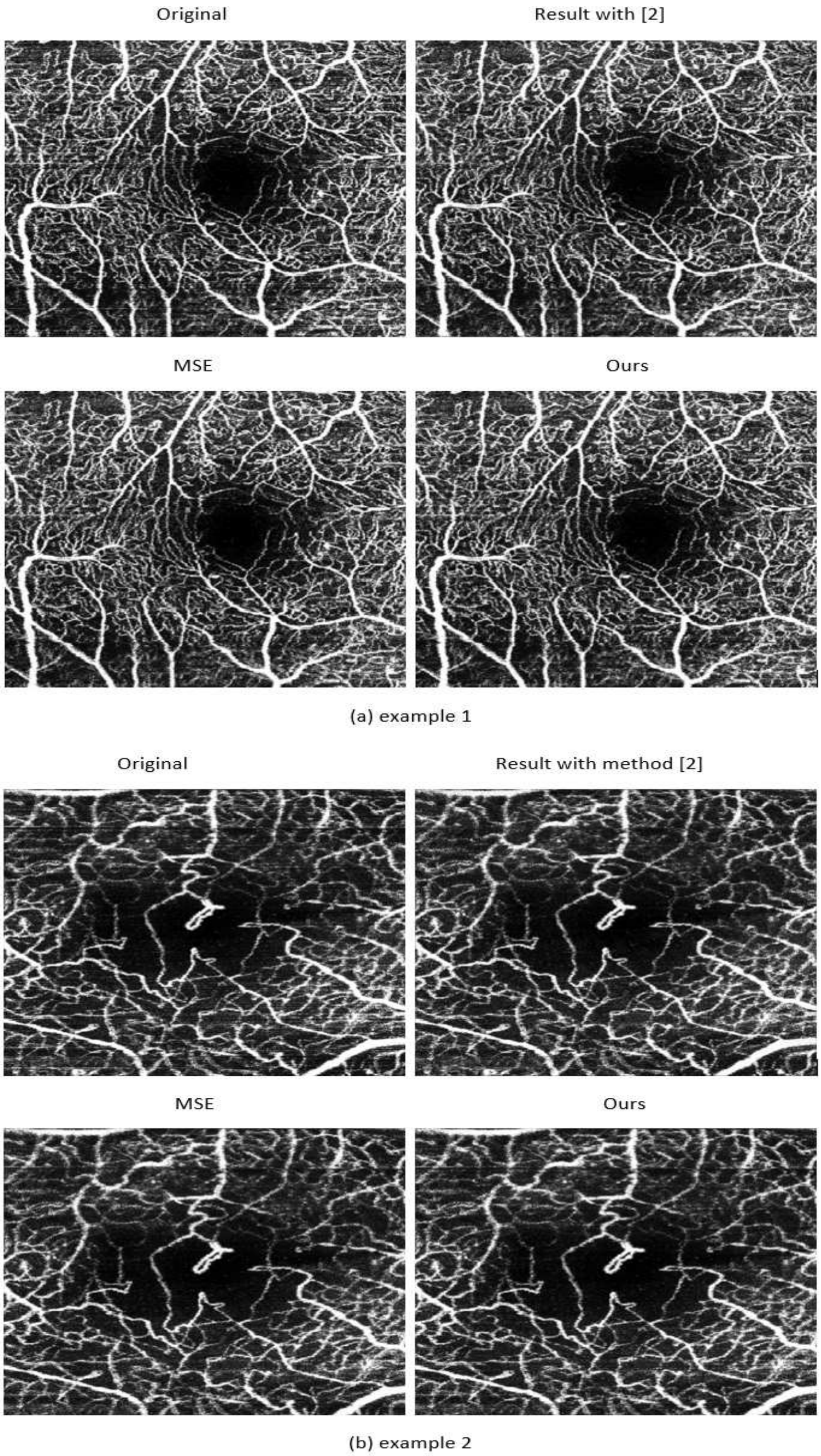

Fig. 2. Image denoising results on OCTA dataset

4.3 Evaluation

Two well-known image quality metrics are used for evaluating the effectiveness of our method, PSNR (peak-signal-to-noise) and SSIM (structural similarity index measure) [7].

With using the predicted image O and the ground truth image I, the PSNR is defined by:

$$PSNR(I,O) = 10log_{10}((255^2)/MSE(I,O)), \tag{3}$$

where MSE is

$$MSE(I,O) = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(I_{ij} - O_{ij})^2. \tag{4}$$

The SSIM is defined by:

$$SSIM(I,O) = l(I,O)c(I,O)s(I,O), \tag{5}$$

where l(I,O),c(I,O),s(I,O) are luminance the comparison, contrast comparison and the structure comparison respectively [18].

Table 1. The performance in terms of image quality.

Methods (60 images)	PSNR ([2] results as reference images)	SSIM([2] results as reference images)
MSE loss	33.09	0.949
Ours	33.29	0.951

4.4 Discussion

Our experimental results in Fig. 2 show our method can preserve detail information and result in improved image quality compared with the original image. Table 1 shows both PSNR and SSIM results calculated across 60 images. Our method has a slightly better performance in terms of both PSNR and SSIM compared with the MSE loss function. However, the ground truth is needed for training with the MSE loss function while it is not necessary to use the ground truth for our method. The introduction of the image decomposition and our proposed deep learning framework enables us to pass both the original image and the learned noise image to our loss function, thus the low rank matrix of the noise and the TV norm of the predicted clean image can be used as regularization terms of our loss function. The combination of our revised network and the image decomposition model can be applied in many applications where no ground truth is available.

5 Conclusion

In this paper, we developed a stripe noise removal method for OCTA images based on our revised U-net, using both the estimated clean image and noise image structure information in constraint terms for our proposed loss function. We compared our approach with a comparable approach using the MSE loss function to verify the effectiveness of our loss function. The experimental results showed that our estimated clean images preserved the image detail information. In addition, both PSNR and SSIM have been used as the evaluation metrics to prove our proposed method is effective in OCTA de-striping without the ground truth during the training process. It is believed our method can be applied in many deep learning applications where ground truth is not available.

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