Study Group Learning: Improving Retinal Vessel Segmentation Trained with Noisy Labels

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Abstract. Retinal vessel segmentation from retinal images is an essential task for developing the computer-aided diagnosis system for retinal diseases. Efforts have been made on high-performance deep learning-based approaches to segment the retinal images in an end-to-end manner. However, the acquisition of retinal vessel images and segmentation labels requires onerous work from professional clinicians, which results in smaller training dataset with incomplete labels. As known, data-driven methods suffer from data insufficiency, and the models will easily over-fit the small-scale training data. Such a situation becomes more severe when the training vessel labels are incomplete or incorrect. In this paper, we propose a Study Group Learning (SGL) scheme to improve the robustness of the model trained on noisy labels. Besides, a learned enhancement map provides better visualization than conventional methods as an auxiliary tool for clinicians. Experiments demonstrate that the proposed method further improves the vessel segmentation performance in DRIVE and CHASE_DB1 datasets, especially when the training labels are noisy. Our code is available at https://github.com/SHI-Labs/SGL-Retinal-Vessel-Segmentation.

Keywords: Retinal vessel segmentation · Image enhancement.

1 Introduction

Retinal inspection is an effective approach for the diagnose of multiple retinal diseases including diabetic retinopathy, epiretinal membrane, retinal detachment, retinal tear *etc.*. Among them, retinal vascular disorders which affects retinal blood vessels are usually caused by other medical diseases like atherosclerosis, hypertension, or human blood circulation problems [2]. Those disorders will severely influence human's vision functions and cause obvious symptoms, but can be effectively diagnosed and analyzed by retinal vessel inspection in the collected fundus images. Advanced medical imaging system makes it possible to obtain high-resolution fundus images. However, in practical medical services, visual inspection may still require the involvement and tedious work of neurologists, cardiologists, ophthalmologists, and other experts in retinal vascular diseases. To

release their burden on screening multiple diseased retina from thousands even millions of healthy retinas, an automatic and high-performance Computer-Aided Diagnosis (CAD) system is desirable to conduct pre-screening and other auxiliary works. Specifically for retinal vascular diseases, we expect the system to provide high-quality enhanced images for a better visualization, and reasonable segmentation of the vessel patterns from the complex and noisy images.

Plenty of previous efforts have been made in automatic retinal vessel segmentation. Conventionally, hand-crafted filters [13,14,17,27] like Gabor [14] and Gaussian-based ones [13] are explored to extract features for pixel selection, vessel clustering and segmentation. Recently, data-driven based methods utilize UNet-based model [18] or its variants [11,24,25,28,29] to achieve significant performance compared with traditional methods. Those deep learning methods focus on the design of UNet structures with better feature representation [24,28], or the decouple of structure and textures of retinal images [29]. However, data-driven methods highly suffer from over-fitting issues when the given training data is insufficient. Previously proposed methods cannot overcome the issues of small-scale training data with noisy labels given by the clinicians.

Effectively training networks with noisy labels [21] is a rigid need in industry and an interesting task in academia. Previous research works mostly focus on image classification tasks and develop methodologies like optimizing robust loss functions [4,31], regularizing labels [5,15], or actively selecting samples [7,9] *etc.*. However, noisy pixel-level labels existing in segmentation tasks are not well-studied, especially for medical image processing tasks. Shu *et al.* proposed a LVC-Net [19] to adjust the incorrect pixel-wise labels via a deformable spatial transformation module guided by low-level visual cues. But their method cannot be applied to retinal blood vessel images, because the entire small blood vessels may be mislabeled and cannot be corrected via spatial transformation. Xue *et al.* [26] studied a multi-stage training framework with sample selection for chest X-ray images. They synthesized noisy annotations with image dilation and erosion. However, due to the thickness of blood vessels and less training data compared to other medical image data, neither label synthesis nor sampling procedures are suitable for blood vessel images. Considering the characteristics of blood vessel images, we introduce a novel noisy label synthesis pipeline for retinal vessel images, and propose a Study-Group Learning (SGL) framework to improve the model robustness on noisy labels.

In this paper, we mainly study the two main practical problems for retinal vessel segmentation task. First, we explore the deeply unsupervised learned enhancement of the original retinal images compared with traditional contrast adjustment methods like CLAHE [16]. Second, suppose the ground truth segmentation labels given by the clinicians are incomplete and noisy, which yields missing annotations of some vessel segments, we study the effective learning scheme to improve the robustness of the model while training on noisy labels. Therefore, the contributions can be summarized in the following aspects.

– First, to better visualize the retinal image and understand the model, we design the network to output the learned enhancement map. Compared with
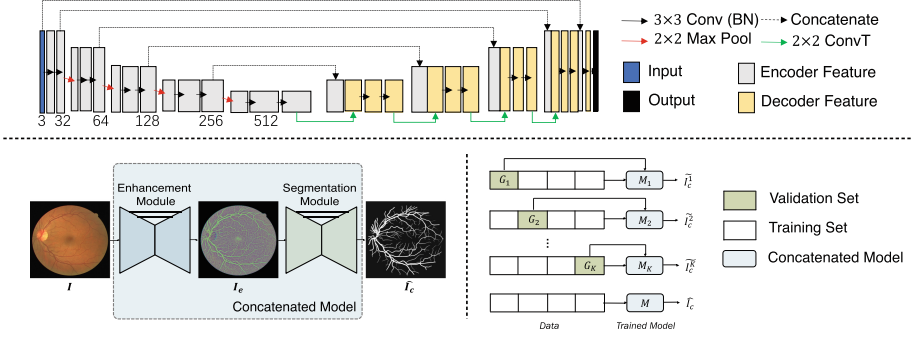
Fig. 1. Baseline model structure and the proposed Study Group Learning (SGL) scheme. The baseline network is a concatenated UNet consisting of an enhancement module and a segmentation module. The three-channel enhancement map I_e is obtained from the bottleneck structure. The SGL is inspired by the cross-validation training scheme and knowledge distillation idea. We first split the whole training set G into K subsets $\{G_k\}$ and feed the model M_k with G_k. The obtained estimation $\tilde{I}_c^k$ of G_k is utilized as the pseudo labels for joint optimization.

other baselines, the high-contrast learned map are better visually plausible, and provides an additional auxiliary tool to aid clinicians for visual inspection or manual segmentation.

– Second, we design a pipeline to manipulate vessel segmentation labels. Given a complete annotations, the proposed approach simulates to automatically erase some vessel segments.

– Third, we propose a Study Group Learning (SGL) framework to improve the generalization ability of the learned model, and better address the missing annotation problems in the training set. The model achieves a more robust performance even some of the vessel pixels are mislabeled.

2   Methodology

2.1   Model Structure

The proposed baseline model structure is illustrated in Fig. 1. We utilize the concatenated UNet consisting of the enhancement and segmentation modules to learn both the enhancement and the segmentation map. Different from previous works, we do not pre-process the retinal images, but directly utilize the raw captured images to preserve the entire information. Specifically, given a three-channel raw retinal image I as the input, we aim to process the image by enhancing its contrast and highlighting the vessel structures in I_e, and estimate the segmentation map $\hat{I}_c$ of the vessels matched with the ground truth segmentation map I_c given by professional clinicians. Notice that I_e preserves the maximum image contents including the vessel structures and retinal textures. It

helps the clinicians to inspect the segmentation results $\hat{I}_c$ and better explains the learned model.

During testing, we enhance the raw image and infer the segmentation maps from unseen retinal images. To cope with noisy labels in vessel segmentation datasets, we propose and follow a Study Group Learning (SGL) scheme to train the baseline model, which is explained in the following subsections.

2.2   Study Group Learning (SGL) Scheme

Tasks like retinal vessel segmentation faces the problem of small-scale dataset and incorrect or incomplete vessel annotations. These two practical problems will make the deeply trained model very easily over-fitting the training set. The severe over-fitting problem does harm to the generalization ability and robustness of the model to unseen testing data. In addition to conventional data augmentation approaches like image transformation and random warping, we propose to alternate the training scheme. Inspired by K-fold cross-validation scheme and knowledge distillation [8] approaches, we propose the K-fold Study Group Learning (SGL) to better cope with noisy labels in small datasets, especially for the retinal vessel segmentation task.

The pipeline is illustrated in Fig. 1. Specifically, we first randomly and averagely split the whole training set (G, I_c) into K subsets $\{(G_k, I_{ck})\}$, where $k \in [1, K]$. Like the cross-validation scheme, we train totally K models $\{M_k\}$. For each M_k, we train it on $(G \backslash G_k, I_c \backslash I_{ck})$ using pixel-wise binary cross entropy loss. After optimizing the model set $\{M_k\}$ as $\{M_k^*\}$, we infer the estimated segmentation label $\tilde{I}_{ck}$ of G_k as the pseudo label, where

$$\tilde{I}_{ck} = M_k^*(G_k), k \in [1, K]. \tag{1}$$

Finally, we train a model M from scratch by jointly optimizing the ground truth vessel labels I_c and the obtained pseudo label set $\tilde{I}_c = \bigcup_{k=1}^{K} \tilde{I}_{ck}$ as,

$$\mathcal{L}_{SGL} = CE(\hat{I}_c, I_c) + \lambda CE(\hat{I}_c, \tilde{I}_c), \tag{2}$$

where $\hat{I}_c = M(G)$, CE is the cross entropy loss, and $\lambda = 1$.

Intuitively, we name the proposed learning scheme as Study Group Learning (SGL) because each model M_k trained with partial training set can be regarded as a 'Study Group'. The final model M is a process of group discussion by merging and fusing the knowledge from different study groups. Theoretically, the second term in Eq. 2 can be regarded as a regularization to avoid over-fitting the ground-truth labels, especially when the given labels contain some noises and possibly incorrect annotations. Figure 2 shows one example of such cases. In this example, we set $K = 2$, and the inference of the training samples I from M_1 and M_2 are shown in the right two columns, where I is in the training set of M_1 but not in the training partition of M_2. M_1 highly overfits the given labels of I by ignoring multiple thin and ambiguous vessels. However, if not trained on I, M_2 can infer some of the ignored vessels as the pseudo labels. While combining these two labels, the final model M can intuitively learn better representation and become more generalized.

<div align="center">Retinal Image Input   Enhanced Image   Overfitting the Ground Truth Map   Pseudo Label</div>
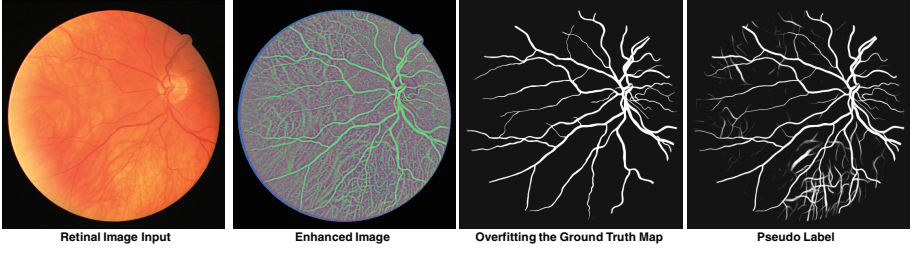
Fig. 2. Inference results on one training example. Clinicians may only label some salient vessels while ignoring the ambiguous ones. The model trained on the entire set will overfit the ground truth annotations. However, inference results from the model trained on the subset can serve as the pseudo label for model regularization purpose.

2.3   Vessel Label Erasing

Annotating the retinal vessels requires the involvement of professional clinicians, and the process of manual labeling is onerous, which reveals one of the reasons why public retinal vessel databases are always small-scale or partially-labeled. It is also common that some labels of thinner vessels are missing due to the annotators' errors. To resemble this practical situation in industry, we propose to synthesize an incomplete map I_c^r by erasing some labeled vessel segments I_r from the ground truth segmentation map $I_c = I_c^r \cup I_r$, where r is the removal ratio. The process is illustrated in Fig. 3.

To generate I_c^r, we first compute and approximate the skeleton of I_c using the method proposed by Zhang *et al.*[30] followed by a skeleton tracing approach [1]. This algorithm converts the binary segmentation map into a set of polylines $L_c = \{l_i\}_c$, where $i \in [1, M]$ and each l_i is stored as an array of coordinates *i.e.* $l_i = \{p_d\}$. The geometric polylines and their spatial relationship represent the topological skeleton of the annotated vessels. We utilize it to locate the vessel center lines, and roughly compute the thickness of the vessels.

Second, to compute and rank the thickness of each vessel segment, we redraw the polylines with larger width t on a black canvas to form the complete mask M_c^t. Notice that t is the least value which makes M_c^t cover the entire vessel regions in I_c. For each l_i, the corresponding pixel regions covered by the drawing lines of width t is denoted by l_i^t, then the thickness s_i of the vessel segment is measured by $s_i = \frac{\|I_r \cap l_i^t\|}{\|l_i^t\|}$. We rank the polylines according to their thickness s_i, and include the thickest vessels in order in the partial set $L_c^r = \{l_j\}$, where $j \in [1, N]$ and $N \leq M$. In L_c^r, we include the top-r thick vessels. Finally, we form the selected mask M_r^t from L_c^r, and the synthetic segmentation mask ablating some of the thin vessels with ratio r can be computed by $I_c^r = M_r^t \odot I_c$. Figure 3 shows one example of I_c^r where r is from 1 to 0.3. Adding a small portions of thin vessels helps the model maintain the ability of segmenting smaller objects. Therefore, we also randomly select 50% of thin vessels in the set and add them to L_c^r.

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[1] skeleton-tracing: https://github.com/LingDong-/skeleton-tracing.
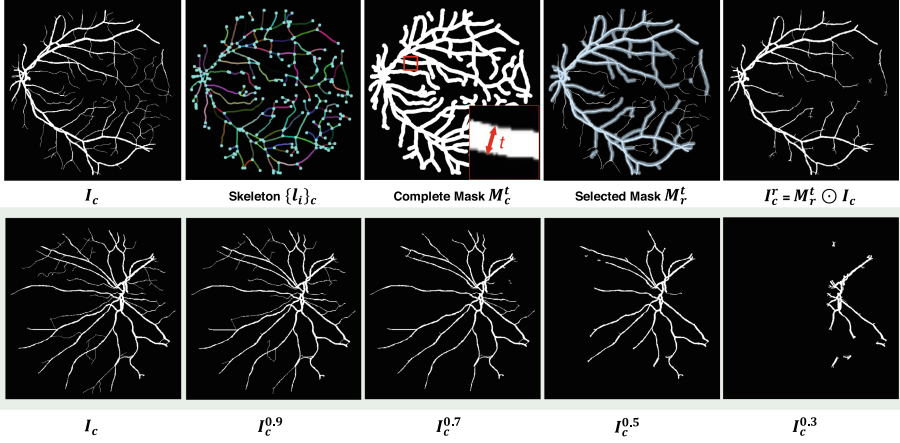
Fig. 3. Vessel label erasing process. Given the complete label map I_c, we compute the skeleton of the vessels, and dilate the vessel skeleton to mask by drawing the polylines with width t. We then rank the vessel segments by their approximated thickness, and include the thick vessels according to ratio r. The second row shows one instance of label erasing with r from 1 to 0.3.

3 Experiments

3.1 Dataset and Implementation

DRIVE: The Digital Retinal Images for Vessel Extraction (DRIVE) [23] dataset consists of 40 images of size 565×584. The training and testing set are fixed, and the ground truth manual annotations are given. We do not resize the image to alternate the resolution or change the Aspect-Ratio.

CHASE_DB1: [3] It consists of 28 retinal images of size 999×960. For a fair comparison with previous methods, we use the first 20 images for training, and the remaining 8 images for testing.

While training the model, we randomly crop the images into 256×256 patches, and apply data augmentation including horizontal and vertical flip, rotation, transpose, and random elastic warping [20]. We train the model using Adam (0.9, 0.999) with learning rate 10^{-4} and batch size 16. We train it for 30 epochs separately for each M_k to generate pseudo label sets, and train for another 20 epochs using the pseudo and ground truth labels. While testing, suppose the image size is $W \times H$, we zero-pad the input image to size $(2^4 \times m, 2^4 \times m)$, where $2^4 \times m > \max(W, H) > 2^4 \times (m - 1)$, and crop the estimated map accordingly. Specifically, m is 37 for DRIVE and 63 for CHASE_DB1 dataset. It makes the arbitrary-sized inputs adaptive to the UNet structure with four down-sampling layers, and retain the original resolution and aspect-ratio of the image. We mask out the non-retinal area in DRIVE, and compute the metrics on the entire image. More details can be found in our code.
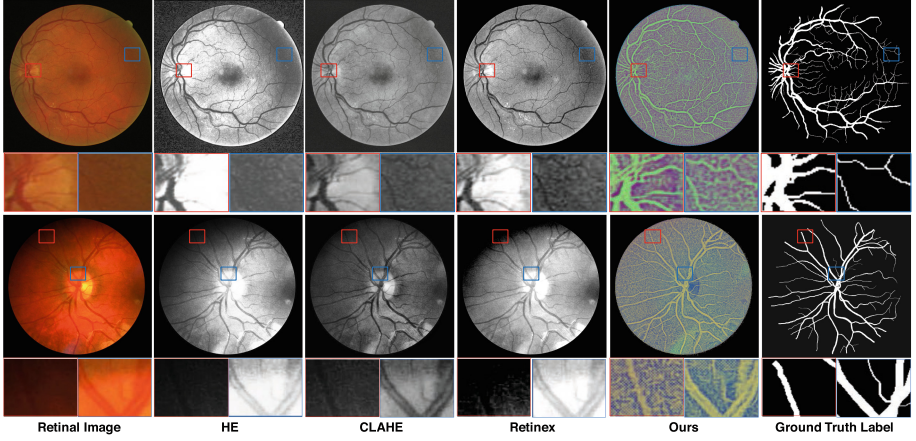
Fig. 4. The learned enhancement map I_e compared with other baseline methods including Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE) [16], and Single-scale Retinex [32]. The learned map demonstrates a better contrast and intensity, enhancing the vessel information for a better identifiable visualization for clinicians. Top row is from DRIVE dataset and the bottom row is from CHASE_DB1 dataset. Zooming in for better visualization.
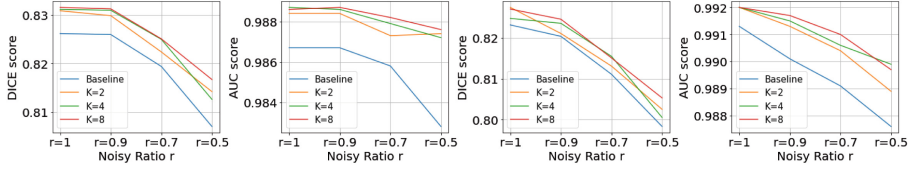

Fig. 5. The performance of the model in the simulated training set with label noise ratio $r = [1, 0.9, 0.7, 0.5]$. The proposed SGL learning scheme overall improves the robustness in all K. Left two columns: DICE and AUC scores on DRIVE. Right two columns: on CHASE_DB1 dataset.

3.2 Learned Retinal Image Enhancement

We learn the enhanced map of the original input images by supervising the model on the manual segmentation labels. We extract the bottleneck 3-channel output which can be visualized in a better contrast level. We compare the learned enhancement of the retinal images with other baseline methods including Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE) [16], and Retinex [32].

Figure 4 shows one example of the visual comparison. Traditional methods like HE, CLAHE and Retinex cannot achieve a uniform contrast level both locally and globally. The cropped patches are from either a brighter or darker regions of the image, making the vessel pixels hard to parse accurately by the inspector. However, the learned map in the fifth column demonstrates a better

Table 1. Comparison with other baseline methods on DRIVE dataset.

Method	Year	Sensitivity	Specificity	DICE	Accuracy	AUC
R2U-Net [1]	2018	0.7792	0.9813	0.8171	0.9556	0.9784
LadderNet [33]	2018	0.7856	0.9810	0.8202	0.9561	0.9793
IterNet [12]	2020	0.7791	0.9831	0.8218	0.9574	0.9813
SA-UNet [6]	2020	0.8212	0.9840	0.8263	0.9698	0.9864
BEFD-UNet [28]	2020	0.8215	**0.9845**	0.8267	0.9701	0.9867
Our Baseline	2021	0.8341	0.9827	0.8262	0.9695	0.9867
Our SGL (K=8)	2021	**0.8380**	0.9834	**0.8316**	**0.9705**	**0.9886**

Table 2. Comparison with other baseline methods on CHASE_DB1 dataset.

Method	Year	Sensitivity	Specificity	DICE	Accuracy	AUC
UNet [12]	2018	0.7840	0.9880	0.7994	0.9752	0.9870
DUNet [10]	2019	0.7858	0.9880	0.8000	0.9752	0.9887
IterNet [12]	2020	0.7969	0.9881	0.8072	0.9760	0.9899
SA-UNet [6]	2020	0.8573	0.9835	0.8153	0.9755	0.9905
Our Baseline	2021	0.8502	**0.9854**	0.8232	0.9769	0.9913
Our SGL (K=8)	2021	**0.8690**	0.9843	**0.8271**	**0.9771**	**0.9920**

contrast and intensity level, enhancing the vessel information for a better identifiable visualization for clinicians, especially for the dark regions in CHASE_DB1 images. It highlights the vessel regions while preserving the textures.

In summary, compared with CLAHE, the learned map has three advantages: first, the region of interests can be better highlighted. It aggregates the information from RGB channels and extracts the features relevant to the vessels, while CLAHE only uses grayscale inputs. Second, no saturation artifacts exist like CLAHE. Third, it helps us interpret the segmentation errors to debug the system. In real applications, the obtained enhancement images can be combined with other enhancement methods for a better visual inspection or labelling.

3.3   Study Group Learning

Table 1 and 2 illustrate the effectiveness of the proposed SGL scheme. Compared with previous works, the proposed learning scheme can boost the DICE score [22] and other evaluation metrics by a large margin. Figure 5 shows the DICE and Area Under the Receiver Operating Characteristic (ROC) Curve (AUC) of the model in the simulated training set with label noise ratio $r = [1, 0.9, 0.7, 0.5]$, where $r = 1$ represents the original training set. As shown in the figure, erasing some vessel labels in the training set will drastically degrade the system performance, while the SGL learning scheme overall improves the robustness on both datasets. Besides, a better sensitivity indicates the model is able to

extract more thin vessels and boundary pixels. More results can be found in the supplementary material (click here to open).

4   Conclusions

In this paper, we studied the learning-based retinal vessel segmentation model trained with noisy labels. Specifically, we designed the pipeline of synthesizing noisy labels, and proposed a Study Group Learning (SGL) scheme boosting the performance of model trained with imperfect labels. Besides, the learned enhanced images as a side product made the model explainable and helped the clinicians for visual inspection. We still discovered the gap between models trained with different levels of noisy labels, leaving for future work to further improve the model sensitivity.

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