# Impact of ICA-Based Image Enhancement Technique on Retinal Blood Vessels Segmentation

Course: CSM433 - Digital Image Processing

Under the guidance of

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Implementation Report

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### **Abstract**

Retinal blood vessel can prove to be markers for certain key ailments such as diabetic retinopathy, agerelated macular degeneration, etc. So, automatic segmentation of blood vessels can better assist in diagnosis of these diseases and has been studied by many researchers.

In this study, the authors proposed an automatic retinal vessel segmentation method, for quick and accurate segmentation of blood vessels is retinal fundus images.

A retinal fundus image contains varying low contrasts, which undermine the performance of the segmentation process. The proposed method was based on Independent component analysis (ICA), which is used in Image Processing largely for noise removal.

The authors achieved improvements over previously reported state-of-the-art methods on the publicly available database DRIVE. In case of the DRIVE database, a segmentation accuracy of around 96% was achieved.

### **Dataset**

### **DRIVE (Digital Retinal Images for Vessel Extraction)**

This publicly available dataset consists of 20 pairs of images of the following form: -

- 1. Retinal fundus images that have the blood vessels visible.
- 2. Binary masks, representing their ground truth segmentation masks.

We need to segment out the blood vessels from these fundus images, and compare the segmentation results to the ground truth segmentation masks.

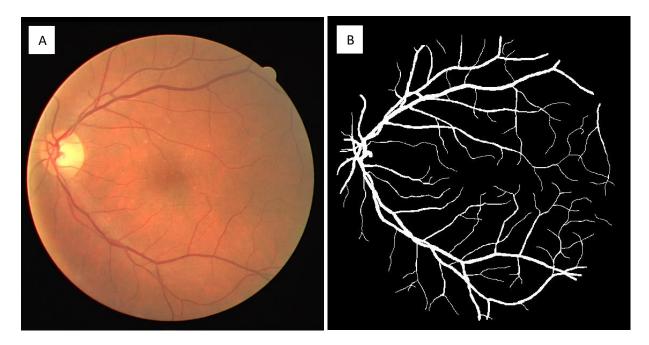


Figure 1: (A) Retinal Fundus Image (B) Ground Truth Segmentation Mask

### **About ICA (main work)**

The independent component analysis (ICA) is a statistical computation method for linear transformation of signals and images that separate the statistically dependent mixture of signals or images into its components. Each component is statistically linearly independent of each other.

ICA defines a generative model for the observed multivariate data, which is typically given as a large database of samples. In the model, the data variables are assumed to be linear mixtures of some unknown latent variables, and the mixing system is also unknown. The latent variables are assumed non-gaussian and mutually independent, and they are called the independent components of the observed data. These independent components, also called sources or factors, can be found by ICA.

ICA is superficially related to principal component analysis and factor analysis. ICA is a much more powerful technique, however, capable of finding the underlying factors or sources when these classic methods fail completely.

### Why use ICA?

The natural pigments present in our retina are macular, hemoglobin and melanin. Retinal pigments give us a good idea of how to modeling the retinal fundus, according to the similar properties shared by the retinal pigment and color fundus images. These include, for example, a retinal image containing the distribution of melanin, hemoglobin and macular pigment (similar color retinal fundus images contained red, green and blue channels). These three retinal pigments are linearly independent, and similarly, retinal color channels are also linearly independent. This is why ICA performs well with retinal fundus images.

The red channel contains most of the luminance information as well as a lot of noise; the green channel has the least noise, and the blue channel has shadows as well as noise.

### **Proposed Algorithm**

The proposed ICA-based vessel enhancement algorithm comprises of the following 6 stages: -

#### Stage 1 - Non-uniform background removal

The input image consists of 3 channels, RGB. Each of the channels face the issue of uneven background illumination. We deal with this issue in the first stage. Morphological tactics are implemented to overcome uneven illumination from each channel of the retinal color fundus image.

#### Stage 2 - Contrast Enhancement (using ICA)

The contrast of blood vessels is not uniform throughout the fundus images. The proposed ICA enhancement is applied to the output of each color channel of the previous image to obtain well-contrasted images.

#### Stage 3 - PCA-based color to grayscale conversion method

The output of stage 2 is a 3-channel image (corresponding to RGB). This stage handles conversion of a color image into a grayscale (single channel) image, using PCA technique. The PCA color-to-grey conversion method implemented for retinal images achieves well-contrasted grayscale images.

The following 3 steps are the post-processing steps.

### Stage 4 - Second-Order Multi-Scale Laplacian of Gaussian Detector

The coherence of blood-vessels in the grayscale image needs to be further boosted. This is done using an LoG detector, which is based on the second-order detector scale normalization parameters named  $\alpha$  and  $\beta$ .

### Stage 5 - Anisotropic Diffusion Filtering

Even after scale normalization, the uneven intensity of vessels still exists along with some broken ridges. So, to tackle with this problem, and to remove the noise, anisotropic oriented diffusion filtering is applied in this stage.

### Stage 6 - Flood-Filled Morphological Reconstruction

The final stage involves binarization of the result of stage 5. Since some intensity differences still exist along the length of the vessels, and so, flood-filled morphological reconstruction is applied to carefully chosen seed points in the image. After this, the binary segmentation output is obtained.

# Results

### 1. Final Output

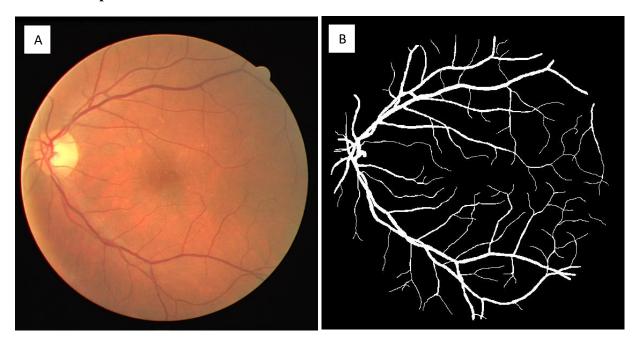


Figure 2: (A) Input Image (Retinal Fundus). (B) Ground Truth Segmentation Mask

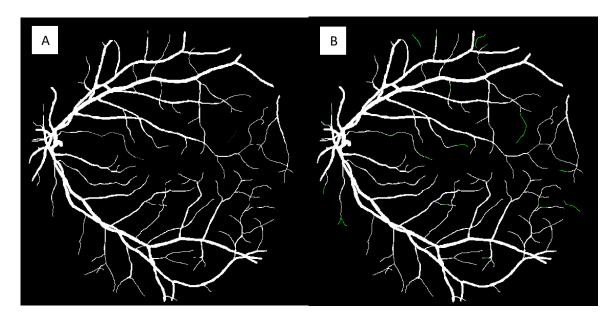


Figure 3: (A) Output Generated by Proposed Algorithm. (B) Superposition of Generated Output on Mask

### 2. Step-By-Step Output

### 2.1 Stage-1

#### Red Channel

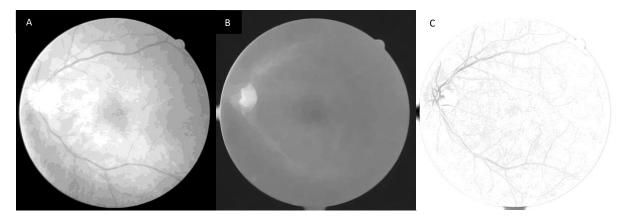


Figure 4: (A) Input Image. (B) Background Image. (C) Background-removed Output

#### Green Channel

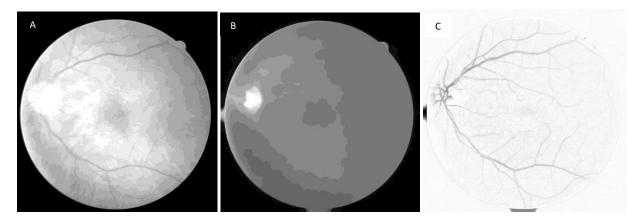


Figure 5: (A) Input Image. (B) Background Image. (C) Background-removed Output

#### Blue Channel

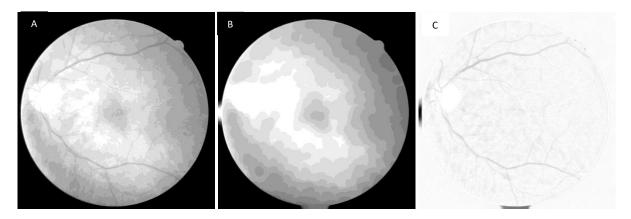


Figure 6: (A) Input Image. (B) Background Image. (C) Background-removed Output

### **2.2 Stage-2**

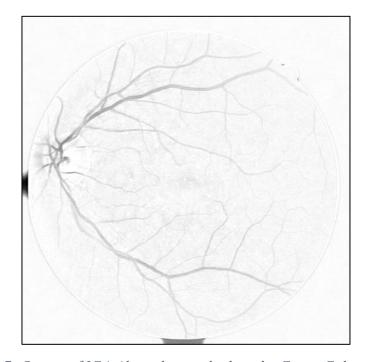


Figure 7: Output of ICA Algorithm applied on the Green Color Channel

### **2.3 Stage-3**

Results showing conversion of RGB image to YCbCr image (using conventional transfer function)

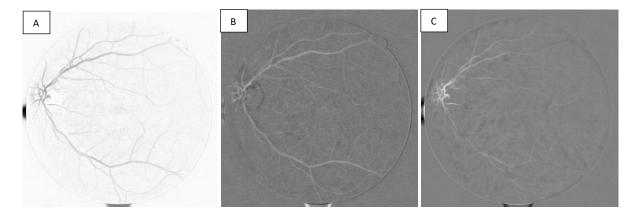


Figure 8: (A) Y-Channel (B) Cb-Image (C) Cr-Image

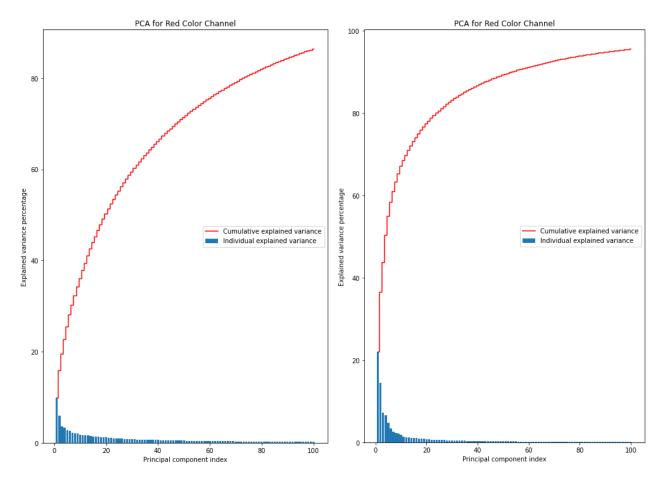


Figure 9: PCA Curves for Red Channel

### Contrast Enhancement Observed by Using PCA for Color-to-Grayscale Conversion

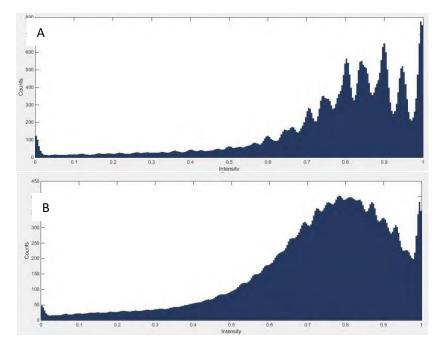


Figure 10: (A) Histogram of ICA Green Channel Image. (B) Histogram of PCA Grayscale Image

### **2.4 Stage-4**

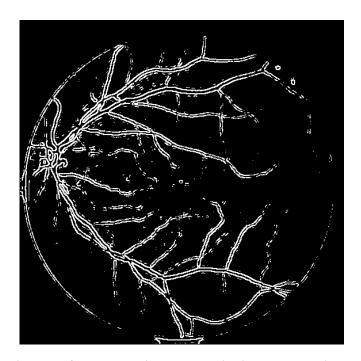


Figure 11: Output of Laplacian of Gaussian detector applied on Grayscale Image generated at Stage-3

### **2.5 Stage-5**

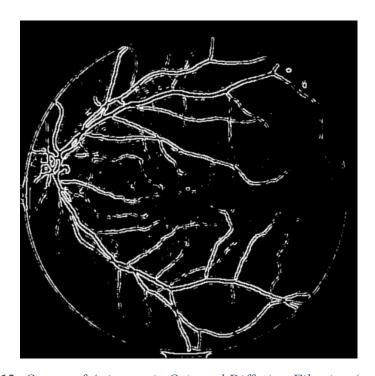


Figure 12: Output of Anisotropic Oriented Diffusion Filtering (n\_iter = 2)

### 2.6 Stage-6



Figure 13: Localized Seed Points selected randomly from output of Stage-5

### 2.7 Final Output

It is obtained after performing Morphological Reconstruction on Flood-Filled Algorithm's output, with marker as previous image, and mask as output of Stage-5

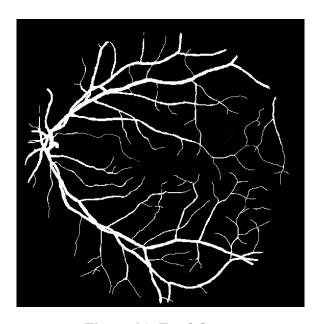


Figure 14: Final Output

# 3. Comparative Study

	DRIVE		
METHODS	Sensitivity	Specificity	Accuracy
Supervised Methods			
Steal et al	-	-	0.946
Soares et al	-	-	0.946
Lupascu et al	0.720	-	0.959
Orlando et al	0.785	0.967	-
Liskkowski	-	-	0.949
<b>Unsupervised Methods</b>			
Mendoca et al	0.734	0.976	0.945
Matinez-Perez et al	0.724	0.965	0.934
Palomera-Perez et al	0.66	0.961	0.922
Nguyen et al	-	-	0.940
Xiaoxia Yin et al	-	-	0.947
Zhao et al (PR Method)	0.682	0.867	0.853
Zhao et al (IUWT Method)	0.716	0.978	0.944
Zhao et al (IPACHI Method)	0.742	0.982	0.954
Soomro et al	0.713	0.968	0.941
Khan et al	0.734	0.967	0.951
Soomro et al	0.753	0.976	0.943
Proposed Method	0.752	0.976	0.953

# References

Soomro, T.A., Khan, T.M., Khan, M.A., Gao, J., Paul, M. and Zheng, L., 2018. Impact of ICA-based image enhancement technique on retinal blood vessels segmentation. IEEE Access, 6, pp.3524-3538.

....and their references