Automatic Methods for Vessel Segmentation in Fundus Images

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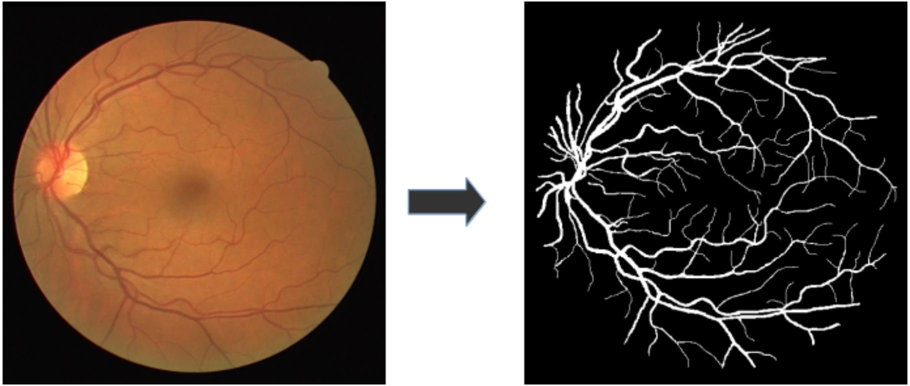
Overview

Retinal Vessel Segmentation

Automatic methods for Retinal Vessel Segmentaion in Fundus Images

Task



Challenges and Limitations

- False vessel detections
- Varying vessel width
- Merging of close vessels
- Bifurcation of vessels
- Merging of close vessels
- Presence of other structures like hemorrhage spots, exudates and lesions.

Challenges

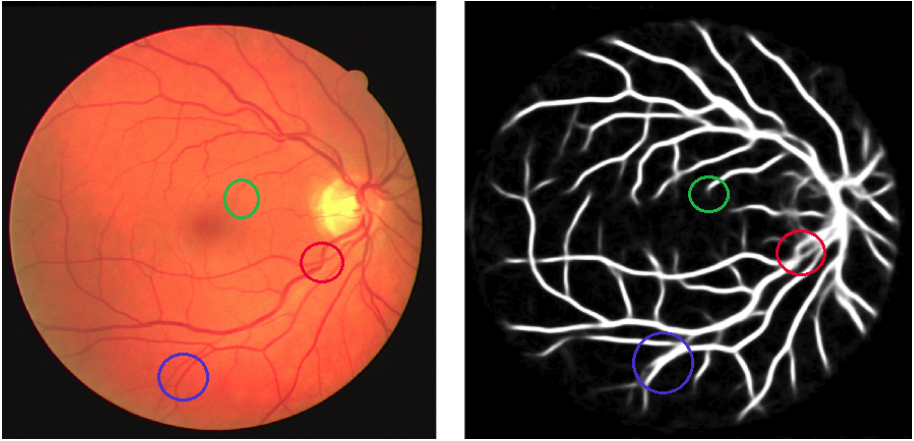
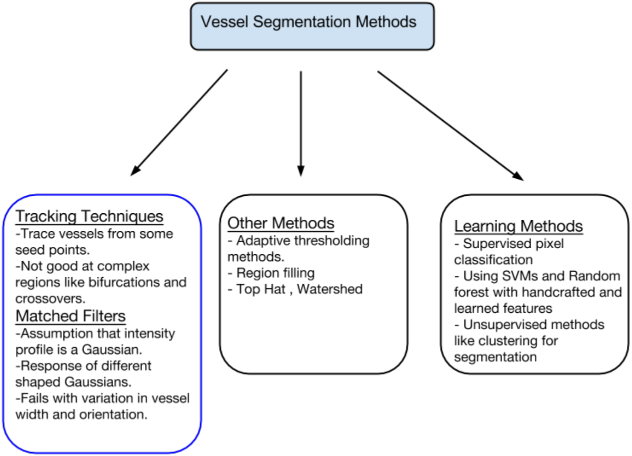
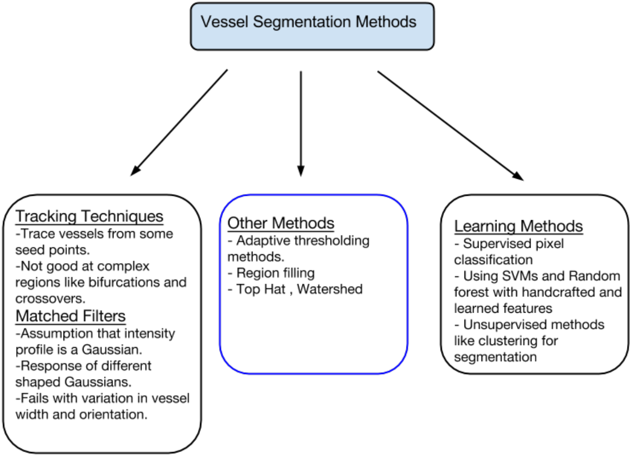


Figure: In blue, merging of close vessels, in red poor segmentation at crossover, and in green, poor segmentation of thin vessels

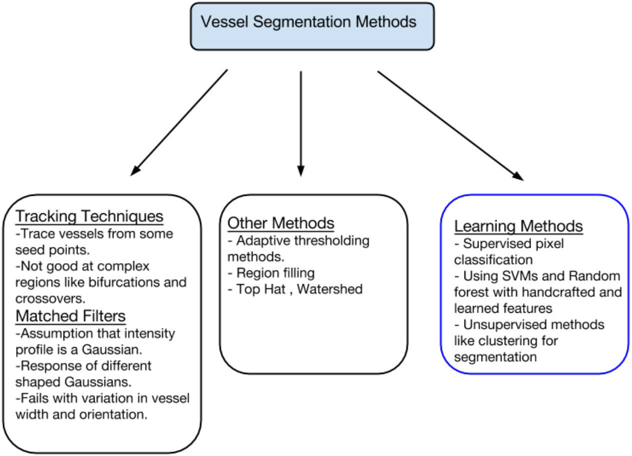
Related Work



Related Work



Related Work



Related Work

Now, we talk about four of the recent advancements in the vessel segmentation methods, to have a comparison with our approach

- Structured Forests for Fast Edge Detection (SE) [Dollar et al]
- Accurate and Efficient Linear Structure Segmentation by leveraging Ad Hoc Features with learned Filters (CS) [Rigamonti et al]
- Filter Learning for Linear Structure Segmentation (DL) [R.Rigamonti]
- Neural Network Nearest Neighbor Fields for Image Transforms (N4) [Ganin et al]

Structured Forests

- Exploits the presenece of structures like edges, T-junctions in small local image patches.
- Trains structured forests over these local image patches and their segmentation maps.
- Learns multiple edge maps, which are aggregated to obtain final edge map.

Structured Forests

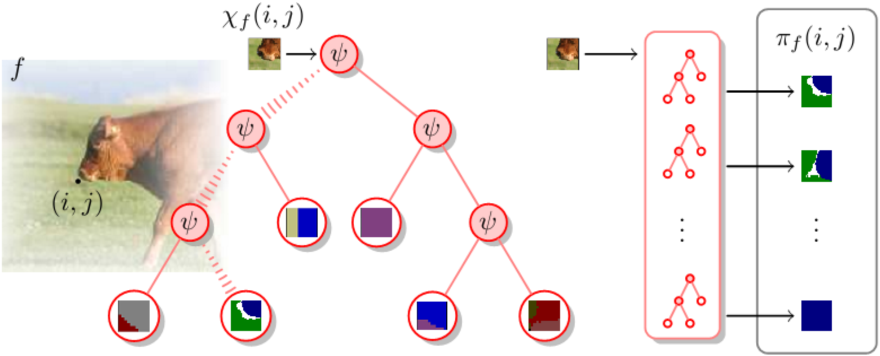
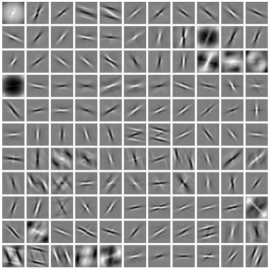


Figure: An example of Structured Random forests for image segmentation (https://pdollar.wordpress.com/2013/03/08/structured-random-forests/)

Filter Learning for Linear Structure Segmentation

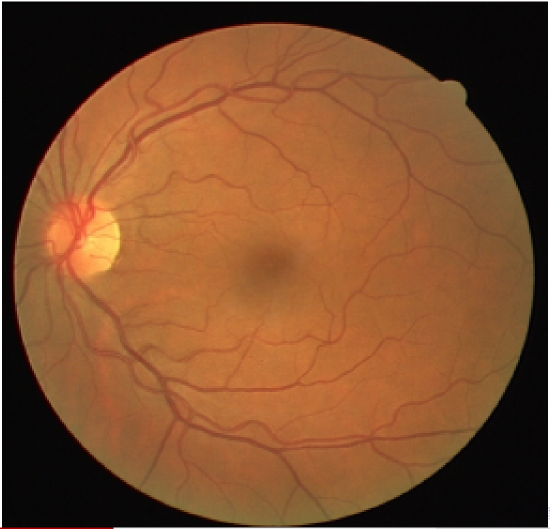
- Learns a filter bank from a set of representative training images in a sparse convolution coding way.
- Features maps are computed by convolving the filters with the images.
- A random forest classifier is trained to classify each image location as lying on a linear structure or background.



Ad Hoc Features and Learned Filters

- Linear filters are learned by modeling the distribution of image representatives.
- Filters are learned in a convolutional sparse learning model.
- Features maps are computed using the learned filters and other hand crafted features are computed.
- A random forest classifier is trained to classify each image location as lying on a linear structure or background.

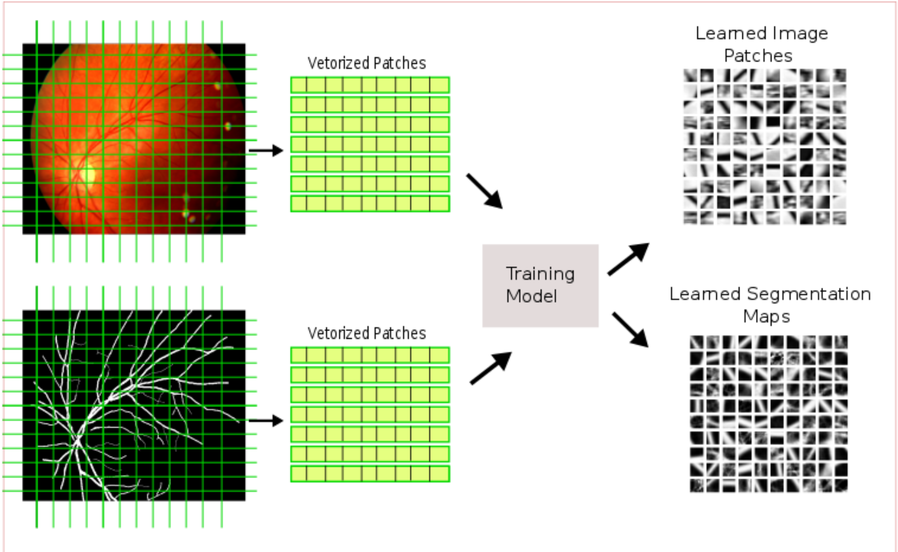
Neural Network Nearest Neighbor Fields for Image Transforms



Architecture

- We approach the problem in a patch based framework
- In a patch based framework, we extract patches around each pixel taken at centre, and make individual predictions for each patch.
- Using image patches and their corresponding segmentation masks, we learn a dictionary of individual patches mapped to the segmentation masks.
- This learned dictionary is then used to make predictions by matching the new patches to the dictionary.
- Segmentation map is reconstructred from the patches.

Architecture



Architecture

We propose two different models to learn these dictionaries:

- k-means clustering model for local structure dictionary learning.
- Sparse Coding dictionary of local structures.

Clustering Model

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Clustering Model

- Learn local structures like edges and straight lines.
- Image patches are clustered using K-means to find common local structures withing all the image patches.
- Each of these clusters are assigned segmentation maps, obtained by averaging the segmentation maps of all the patches within a cluster.
- A dictionary is made of these clustered structures and segmentation maps.

Dictionary using Clustering model

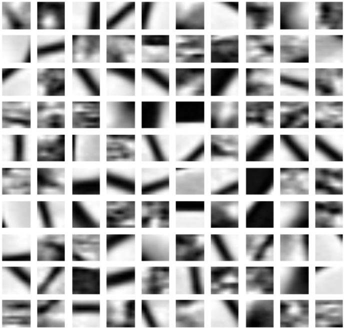


Figure: Learned cluster centers.

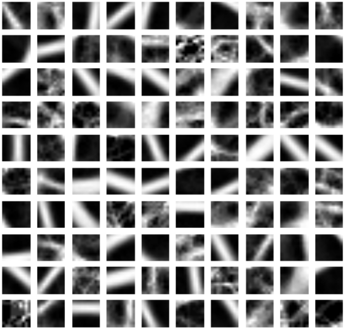


Figure: Segmentation maps for learned clusters.

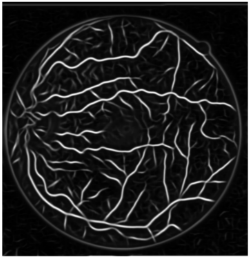
Parameters

There are two important parameters to our patch based Clustering model.

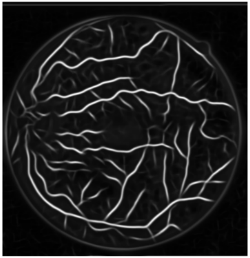
- Patch Size: The size of the patch extracted around each pixel.
- K : Number of clusters to be learned.

Effect of Patch Size

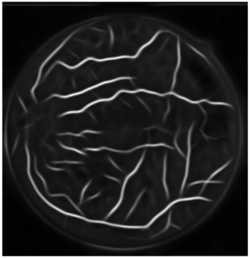
(a) patch size (10,10)



(b) patch size (15,15)

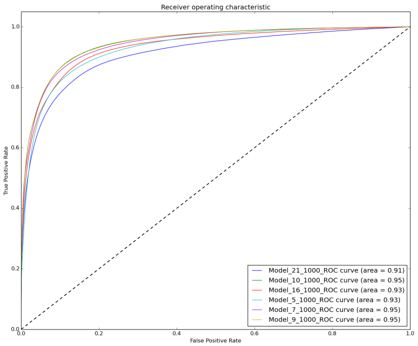


(c) patch size (21,21)



(d) patch size (33,33)

Effect of Patch Size



Effect of Cluster Size

(a) K=50

(b) K=100

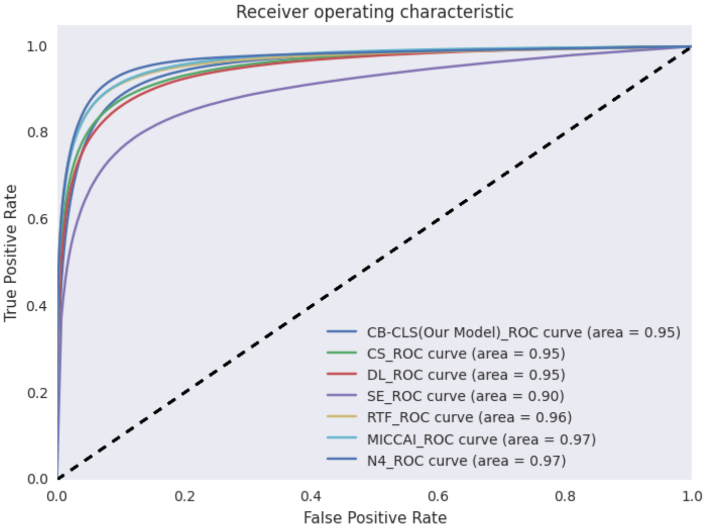
(c) K=250

(d) K=500

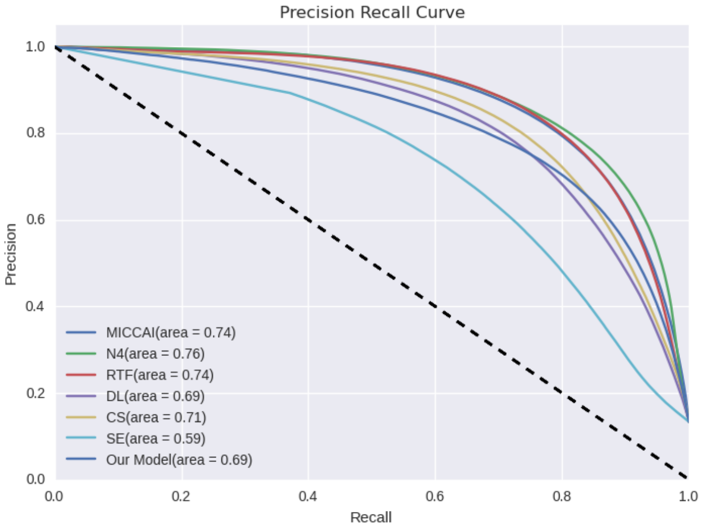
Evaluation on DRIVE dataset

We train our model on the DRIVE train set with K=1000 and patch size (10,10) and test on DRIVE test.
We report the results in terms of Area under curve (AUC) for the ROC and PRC curve.

Receiver operating characteristics



Precision Recall Curve



Best and Worst Case

We look into the best case and worst case image prediction on the DRIVE dataset.