

# Automatic Retinal Vessel Segmentation

Zygmunt L. Szpak and Jules R. Tapamo

School of Computer Science  
University of Kwazulu-Natal  
{szpakz, tapamoj}@ukzn.ac.za

## Abstract

Diabetic Retinopathy is the most common cause of blindness in the working population of the western world and is very common among people who suffer from diabetes. Fortunately, during a clinical examination an ophthalmologist is able to determine the onset of the disease by taking certain features of the retinal vessels of the fundus into account. These features include the narrowing of vessels and their general structure. The clinical examination involves retinal imaging whereby a photo of the back of the inside of the eye is taken. The ophthalmologist then usually digitises the image by manually selecting what parts of the photo constitute vessels, so that certain statistics such as the thickness of the vessels can be calculated by a computer program. Labelling all the vessels however is a tedious and time consuming process. Our work focuses on using image processing techniques in order to develop a computer program that can automatically detect and segment blood vessels in these images, thereby saving the ophthalmologist considerable time. We make use of a fast level set method without solving partial differential equations to extract the contour of the vessels in the retina and overlay the contour over the original input image. This further aids the work of an ophthalmologist because it highlights the vessel structure.

**Keywords:** Fast level-set, Vessel segmentation, Active contours, Retina

## 1. Introduction

The automatic segmentation of blood vessels in retinal fundus images is an active and challenging area of research. Automatic segmentation of retinal vessels is the first step towards the development of an automatic retinal screening system. Such a system is in great demand because common causes of visual impairment such as glaucoma and diabetic retinopathy can often be prevented if they are diagnosed at an early stage. Currently the number of patients that can be screened is limited by the fact that a manual examination by an ophthalmologist is a very time consuming process.

The reason why the automatic segmentation of blood vessels plays such a great role in the development of an automatic retinal screening system is because certain features of the vessels such as the inter-connectivity of the vessels, the thickness and color of the vessels as well as pathologies that appear around the vessels all aid in the diagnosis of diseases. Many algorithms for optic disk detection [1], pathology detection [2] and computer aided screening systems [3] all depend on the extraction of the retinal vessels.

Researchers have approached the problem of automatically segmenting retinal vessels from different angles using a myriad of techniques. The bulk of previous work can be roughly categorized into multi-scale analysis [4], matched filters [5], mathematical morphology schemes [6], adaptive thresholds [7], tracking based approaches [8] and deformable models [9]. In our work we focus on the deformable model approach because in addition to segmenting the retinal vessels we extract the contour of the segmented vessels and overlay the contour over the original image. This aids an ophthalmologist in the diagnosis by highlighting the vessel structure on the original image. It also makes the validation of the segmentation easier since the medical doctor can see the outline of the structures that the algorithm has labelled as being vessel.

The rest of our paper is organized as follows. In section 2 we present a brief overview of vessel extraction methods with focus on deformable models. In section 3 we introduce the fast non partial differential equation based level-set approach developed in [10] and in section 4 we explain how we built the speed function that we used to deform our active contour and achieve a vessel segmentation. We present our final results in section 5 and conclude with a discussion on future work and current limitations in section 6.

## 2. Background

Much has been published on the topic of automatic vessel segmentation and as we have already mentioned, researchers have applied a wide variety of techniques to extract vessels. A good review of vessel segmentation methods can be found in [11] [12] and [13]. Our focus in this paper is on using geometric deformable models to segment retinal vessels. Geometric deformable models work by evolving a curve over time according to three forces: internal forces, external forces and user-defined constraints. The external force is the most important force and is usually synthesized from the image itself. It determines the regions over which the curve will flow very fast and the regions at which the curve will slow down and come to a stop. To segment an image a closed contour has to be placed on the image and then as the curve evolves the area inside the curve is considered to be the segmented region. The curve is evolved over time by embedding it in a higher dimensional scalar function known as the level-set function, and solving partial differential equations that govern the evolution of the curve. A good introduction to the level-set method can be found in [14].

Even though geometric deformable models have been used in many medical images to segment regions of interest, they have so far performed quite poorly in segmenting retinal vessels. The greatest challenge in segmenting retinal vessels lies in the segmentation of thin vessels. This is because some ves-

sels are only one pixel thick and they may vary from the background by as little as four gray-levels [15]. As a result of this it is very difficult to build an accurate speed field such that the contour is attracted to the thin vessels. Typically the contour leaks into the background as the speeds defined over the thin vessel and the background are too similar. In [16] the authors attempt to address the problem by incorporating a soft shape prior (used-defined constraint) into the evolution of the contour. They present promising results where some leakages are successfully contained. A different approach to preventing contour leakages and detecting vessels with poor contrast is introduced in [17]. The authors extract edge information including orientation and clearness to aid in the evolution of the contour based on weighted local variance. They show that their method is suitable for segmenting vessels that have blurry and low contrast boundaries. However both of the above approaches are still fairly computationally expensive.

In our work we focus on incorporating a fast non partial differential equation based deformable model for the segmentation of retinal vessels. We follow this route since to our knowledge no one has as yet attempted to use a fast non-PDE based deformable model to segment retinal vessels and we find the computational complexity of the model particularly appealing.

### 3. A fast level-set method without solving PDEs

One of the main drawbacks of using geometric deformable models is the computational burden of solving the partial differential equations that govern the evolution of the curve. The fast level set method without solving PDEs proposed in [10] takes advantage of the fact that for image segmentation we are usually less interested in knowing precisely how the curve evolves at each iteration but are more concerned with the final segmentation. In their proposed framework a curve  $C$  is represented implicitly as the zero level-set of a higher dimensional scalar function which is defined over a fixed grid. The function used in this method has a negative value inside the curve and a positive value outside the curve. This resembles the traditional level-set method. Their method assumes that the grid is sampled uniformly and that the sampling interval is one. This means that we can simply consider the pixels of the image as being the points on the grid. With this implicit representation two lists of neighboring grid points (pixels)  $L_{In}$  and  $L_{Out}$  are defined for a curve  $C$  as,

$$L_{In} = \{x | \phi(x) < 0 \text{ and } \exists y \in N(x), \phi(y) > 0\} \quad (1)$$

$$L_{Out} = \{x | \phi(x) > 0 \text{ and } \exists y \in N(x), \phi(y) < 0\} \quad (2)$$

where  $N(x)$  is a discrete neighborhood of  $x$  defines as,

$$N(x) = \{y \in D | \sum_{k=1}^k |y_k - x_k| = 1\}, \quad \forall x \in D \quad (3)$$

and  $\phi$  is the level set function.

Following this definition, a list of neighboring grid points that lie inside the curve  $C$  is given by  $L_{In}$  and a list of neighboring grid points that lie outside the curve  $C$  is given by  $L_{Out}$ . By considering these two lists of points, one can implicitly determine where the curve  $C$  is. This means that to evolve the

curve one can do so by updating the two lists  $L_{In}$  and  $L_{Out}$  using simple operations such as insertions and deletions. The decision of inserting or deleting a point from either  $L_{In}$  or  $L_{Out}$  depends on the sign of the speed function at that point.

The method can be implemented using an array for the level-set function  $\phi$ , another array for the speed function  $F$  and two lists for  $L_{In}$  and  $L_{Out}$ . Pixels which are not in  $L_{In}$  or  $L_{Out}$  are classified as interior or exterior points depending on whether they lie inside or outside the curve respectively. With this in mind, the level-set function  $\phi$  can be approximated to a signed distance function as follows,

$$\phi(x) = \begin{cases} 3 & \text{if } x \text{ is outside } C \text{ and } x \notin L_{Out} \\ 1 & \text{if } x \in L_{Out} \\ -1 & \text{if } x \in L_{In} \\ -3 & \text{if } x \text{ is inside } C \text{ and } x \notin L_{In} \end{cases} \quad (4)$$

To understand the details of the algorithm, two procedures have to be defined:  $switch\_in(x)$  and  $switch\_out(x)$ . The procedure  $switch\_in(x)$  for a point  $x \in L_{Out}$  is defined as follows:

1. Delete  $x$  from  $L_{Out}$  and add it to  $L_{In}$ . Set  $\phi(x) = -1$
2.  $\forall y \in N(x)$  satisfying  $\phi(y) = 3$ , add  $y$  to  $L_{Out}$  and set  $\phi(y) = 1$ .

By applying the  $switch\_in(x)$  procedure to any point in  $L_{Out}$ , the boundary is moved outward by one grid point at that location. On the other hand applying the  $switch\_out(x)$  procedure at a point in  $L_{In}$ , the boundary is moved inward by one grid point at that location. The procedure  $switch\_out(x)$  for a point  $x \in L_{In}$  is defined as follows:

1. Delete  $x$  from  $L_{In}$  and add it to  $L_{Out}$ . Set  $\phi(x) = 1$
2.  $\forall y \in N(x)$  satisfying  $\phi(y) = -3$ , add  $y$  to  $L_{In}$  and set  $\phi(y) = -1$ .

To evolve the curve at every iteration the speed of all points in  $L_{Out}$  and  $L_{In}$  is computed and the sign of the speed is stored in the speed array  $F$ . Thereafter all the points in  $L_{Out}$  are scanned and the  $switch\_in(x)$  procedure is applied to a point if  $F > 0$ . This takes care of all the points on the curve with a positive speed and moves them outward by one grid point. After this scan, some of the points in  $L_{In}$  become interior points due to the newly added inside neighboring grid points and so they are removed from  $L_{In}$ . The points in  $L_{In}$  are then scanned and a  $switch\_out(x)$  procedure is applied to a point if  $F < 0$ . This takes care of all the points on the curve with a negative speed and moves them inward by one grid point. After this scan, some of the points in  $L_{Out}$  will become exterior points and so they are removed from  $L_{Out}$ . Finally a stopping condition is checked and if it is satisfied the evolution of the curve stops, otherwise the iterative process continues. A more thorough discussion on the algorithm including some test results can be found in [18].

### 4. Building a speed field

From our investigation it is clear that the evolution of the curve depends primarily on the speed field that is defined over the image that we are trying to segment. A point on the curve either moves outwards or inwards depending on the speed that is defined for it. In order to extract the contour of the vessels we need to ensure then that the speed field will resemble our final segmentation of the vessel structure. In the next section we will describe the process that we followed to build our speed field.



Figure 1: *Extracted Green Channel of the Image Before Laplacian Filter.*

#### 4.1. Extracting the green channel for maximum contrast

Our first step was to enhance the contrast between the vessel structure and the background. The green channel of the image usually contains the best contrast between the vessel structure and the background [19]. For this reason we extracted the green channel for all our input images and used them in the subsequent steps (see Fig. 1).

#### 4.2. Sharpening the image

We sharpened the image to enhance the appearance of edges which represent vessels. We used an unsharp mask which is the process of subtracting a blurred version of the image from the image itself.

#### 4.3. Detecting edges

A ‘Laplacian of Gaussians’ filter was applied to the image to detect edges (see Fig. 2). The laplacian highlights gray-level discontinuities in an image and deemphasizes regions with slow varying gray levels, however it is also very sensitive to noise. The ‘Laplacian of Gaussians’ filter reduces the response to noise by smoothing the laplacian convolution mask. The 2D ‘Laplacian of Gaussians’ function centered on zero and with a standard deviation of  $\sigma$  has the form:

$$LoG(x, y) = -\frac{1}{\pi\sigma^4} \left[ 1 - \frac{x^2 + y^2}{2\sigma^2} \right] \exp^{-\frac{x^2 + y^2}{2\sigma^2}} \quad (5)$$

#### 4.4. Thresholding the edge response

To determine what gray values represent the background and what gray values represent the vessels that we are trying to segment, we made use of a mixture of gaussian threshold algorithm. The mixture of gaussian threshold algorithm assumes that the foreground and the background can be modelled by two

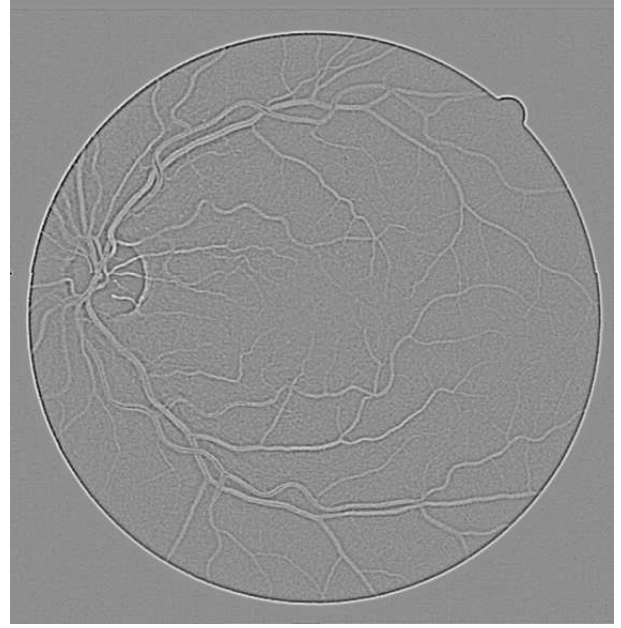


Figure 2: *Resulting Image After the Laplacian Filter is Applied.*

gaussian distributions and it calculates the threshold as the intersection of these two distributions (see Fig. 5). We compared this automatic thresholding algorithm to automatic thresholding based on the entropy of the histogram [20] and the Otsu thresholding [21] technique and found in our experiments that it performed best on our images. A more detailed explanation of the mixture of gaussians threshold algorithm can be found in [22].

#### 4.5. Connected component analysis

After thresholding our edge response (see Fig. 3) we make use of connected component analysis to remove small components from our speed field and the large circular disk component which does not constitute a vessel. We also fill any holes that appear in the connected components. An example of our final speed field for an input image can be found in Fig. 4. Black regions constitute a fixed negative speed and white regions constitute a fixed positive speed. We use this binary speed field to flow our active contour over the input image to extract the final vessel contours.

## 5. Results

Since we are using a binary speed field, the accuracy of the final contour depends entirely on the speed field. This means that to validate the results of our extracted contour we can consider the speed field as being our segmented vessels and we can compare it against a ground truth segmentation for a particular test image. We made use of the DRIVE database [23] which has been established to facilitate comparative studies on segmentation of blood vessels in retinal images. The database contains gold standard manual segmentations done by an expert in the field against which we compared our results. We tested our algorithm on all twenty images and achieved the following results:

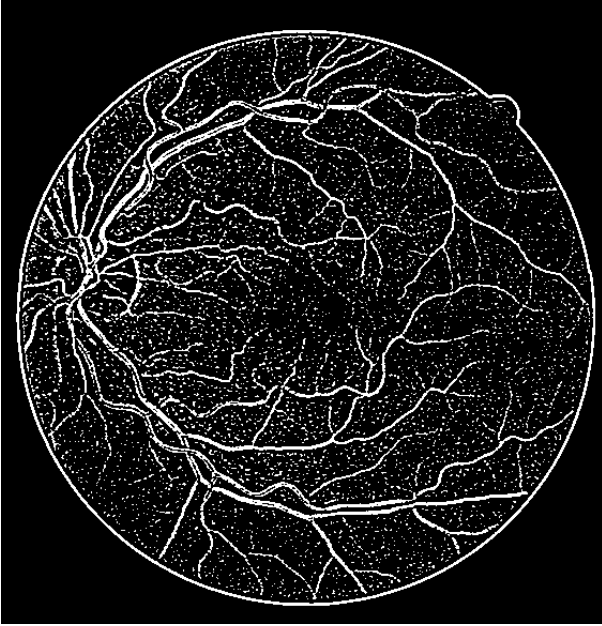


Figure 3: *Resulting Image After Thresholding on Edge Response.*

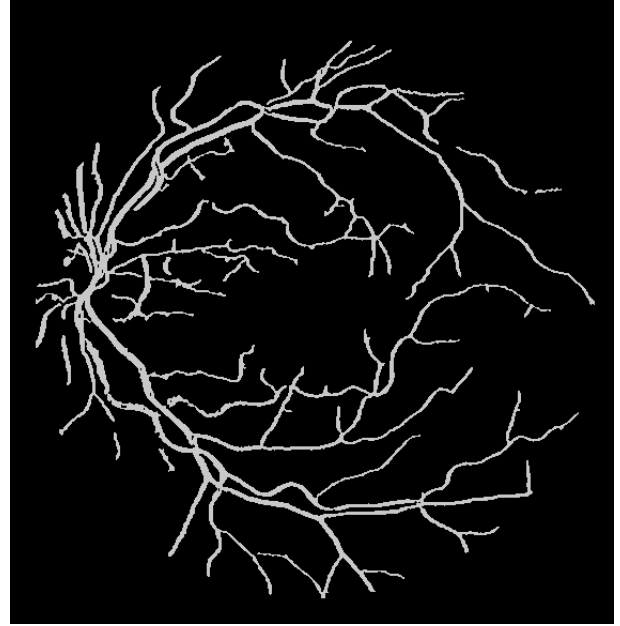


Figure 4: *Resulting Speed Field After Connected Component Manipulation.*

Table 1: Vessel Segmentation Results

Method	Average Accuracy
Human Observer	0.9473
Staal [23]	0.9442
Niemeijer [24]	0.9416
Zana [25]	0.9377
<b>Our Approach</b>	<b>0.9299</b>
Jiang [26]	0.9212
Martinez-Perez [27]	0.9181
Chaudhuri [28]	0.8773
All Background	0.8727

- The highest accuracy of our algorithm was 0.944 with a sensitivity of 0.678 and a specificity of 0.975.
- The lowest accuracy of our algorithm was 0.887 with a sensitivity of 0.755 and a specificity of 0.905.

An example of the kind of results we achieved can be found in Fig.6-9

On average only about 12.3% of pixels in one retinal image in the DRIVE database are vessels [23], so it is possible to achieve an accuracy of approximately 0.87% over the entire test-set, just by naively labelling every pixel in the retinal image as being part of the background. This means that finding a good measure to evaluate the segmentation result is difficult. The current accepted norm is to use sensitivity and specificity as we have done.

Our method compares favorably with other published algorithms displayed in Table 1, achieving the second best segmentation result of the non-supervised methods. The best segmentation result was achieved by a human observer who received limited training from an expert. The second and third best results were achieved by Staal et al [23] and Niemeijer et al [24] respectively. Both used supervised pixel classification methods which were trained on the DRIVE training set.

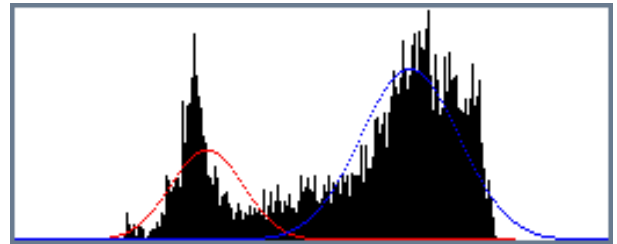


Figure 5: *The Mixture of Gaussians Algorithm Sets the Threshold at the Intersection of the two Gaussian Distributions.*

## 6. Limitations and future work

One of the main challenges in this field of research remains the extraction of thin vessel structures. Currently our algorithm still fails to identify many of these thin vessels, especially in noisy images. However one of the positive aspects of our approach is that it very rarely results in an over-segmentation of the vessel structures. This means that most of the pixels that are labelled as being vessels are in fact vessels. To address the challenge of thin vessel segmentation we propose separating the problem of detecting thin and thick vessels. Our algorithm already detects thick vessels with very good accuracy and we suggest using the knowledge that thin vessels branch off thick vessels to incorporate a shape prior tailored to very thin vessels and letting it flow from a few select points of the thick vessels' contours.

## 7. Conclusions

We have successfully incorporated the fast level set method without solving PDE's to extract the contour of vessels in retinal fundus images. We have demonstrated how a binary speed field for the fast level set method could be built, and we have tested our algorithm on a publicly available database with promising results. By overlapping the extracted contour over the color reti-

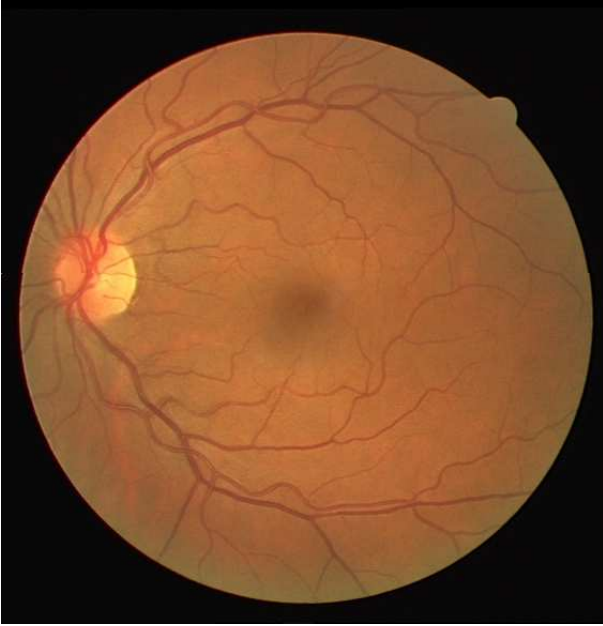


Figure 6: *Original Retinal Fundus Image.*

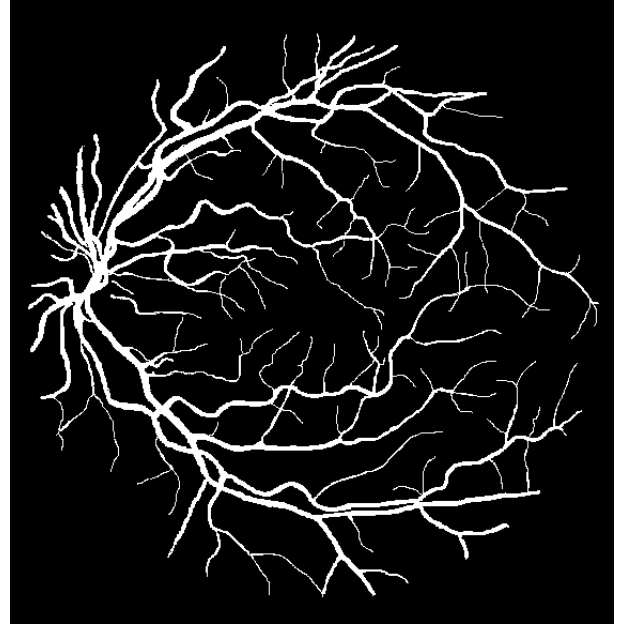


Figure 8: *Gold Standard Ground Truth Segmentation.*

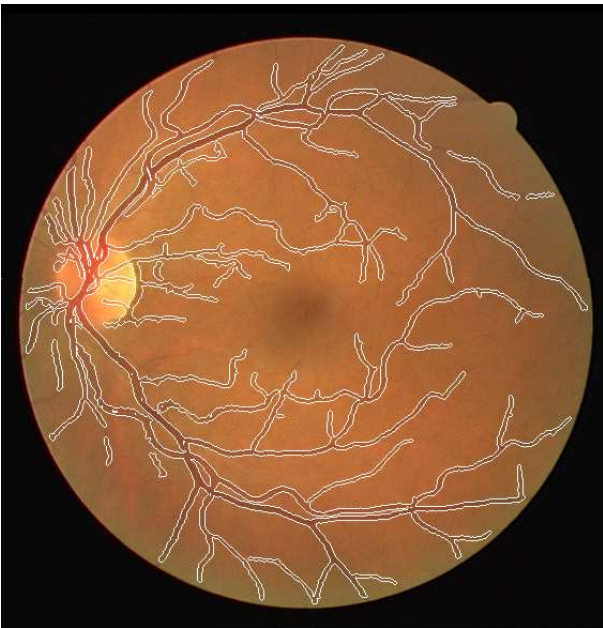


Figure 7: *Final Extracted Contour Overlayed Over the Original Image.*

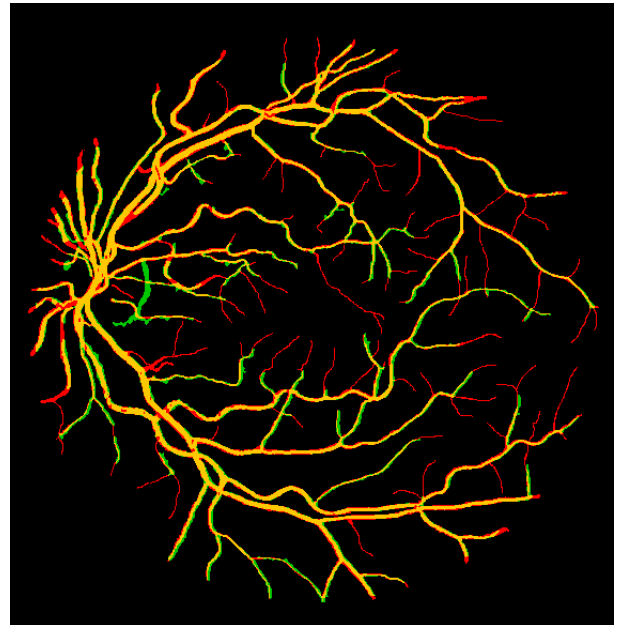


Figure 9: *Our Segmentation Overlayed Over the Ground Truth. (Yellow regions indicate a perfect match, red regions indicate vessels that have been missed and green regions indicate pixels that have been incorrectly labelled as vessels.)*

nal fundus image we aid an ophthalmologist by highlighting the vessels, and our speed field which represents a vessel segmentation can be considered as the first step towards an automatic retinal vessel screening system.

## 8. Acknowledgements

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