A HYBRID APPROATCH TO EXTRACT RETINAL USING MATCHED FILTER AND STROKE WIDTH TRANSFORM

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Abstract –

Motivated by the goals of improving detection of low-contrast and narrow vessels and eliminating false detections at non-vascular structures, a new technique is presented for extracting vessels inretinal images. The core of the technique is a new likelihood ratio test that combines matched filter responses, confidence measures and vessel boundary measures. Matched filter responses arederived in scale-space to extract vessels of widely varying widths. A vessel confidence measureis defined as a projection of a vector formed from a normalized pixel neighborhood onto a normalizedideal vessel profile. Vessel boundary measures and associated confidences are computedat potential vessel boundaries. Combined, these responses form a 6-dimensional measurementvector at each pixel.

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INTRODUCTION

The optic nerve is one of the most important organs in the human retina. The central retinal artery and central retinalvein emanate through the optic nerve, supplying the upper layers of the retina with blood. The optic nerve also serves as the conduit for the flow of information from the eye to the brain. Most retinal pathology is local in its early stages, not affecting the entire retina, so that vision impairment is more gradual. In contrast, pathology on or near the nerve can have a more severe effect in early stages, due to the necessity of the nerve for vision

The leading causes of retina-related vision impairment and blindness are diabeticretinopathy, age-related macular degeneration (AMD), and glaucoma. It is believed that halfof all blindness can be prevented [50], in part through periodic screening and early diagnosis.Automated image analysis techniques should play a central role because the huge volume ofimages precludes strictly-manual analysis.Reliable vessel extraction is a prerequisite for subsequent retinal image analysis and processingbecause vessels are the predominant and most stable structures appearing in the images. Manypublished algorithms for optic disc detection [10], image registration [6], change detection [14, 16], pathology detection and quantification, tracking in video sequences, and computer-aided screening systems depend on vessel extraction. The techniques published in the research literature in response tothe importance of retinal vessel extraction may be roughly categorized into methods based onmatched filters [9], adaptive thresholds, intensity edges [5], region growing,statisticalinference, mathematical morphology [16], and Hessian measures [3]. This wide range of techniques closely corresponds to the suite of methods that have beenapplied throughout the medical image analysis literature. Of particular note, the recentliterature has been dominated by Hessian-based methods because of their utility in characterizingthe elongated structure of vessels [3, 11].Several challenges of vessel extraction in retinal images are illustrated by the images shown In Figures 1 and 2. These challenges may be outlined as follows:

• There is a wide range of vessel widths — from less than a pixel to 12 pixels wide in the Example shown.

• Vessels may be low contrast. The central intensity of some vessels differ from the background By as little as 4 grey levels, yet the background noise standard deviation is 2.3 grey Levels. Narrow vessels often have the lowest contrast.

• A variety of structures appears in the images, including the retina boundary, the optic Disc and pathologies. The latter are a particular challenge for automatic vessel extraction Because they may appear as a series of bright spots, sometimes with narrow, darker gaps In between.

• Wider vessels sometimes have a bright strip running down the center (the "central reflex"),Causing a complicated intensity cross-section. Locally, this may be hard to distinguish from Two side-by-side vessels.

Our primary focus in this paper is on techniques needed to solve the first three problems, detecting low-contrast vessels and narrow vessels, while avoiding false responses near pathologiesand other non-vascular structures. The central-reflex, while important, is less of a concern herebecause it typically occurs in larger, more-easily-detected vessels. We will return to this issuemuch later in the paper.

In order to motivate our technical approach, we start by examining the measurements that indicatethe potential presence of a vessel in an image neighborhood. These "vesselness measures", which form the basis of many techniques in the literature, primarily include matched filters, Hessian-based measures, and parallel edge models. The limitations of some of these measuresare illustrated in Figure 2. All common vesselness measures produce substantial responses tonon-vascular structures such as the optic disc and the pathologies. All measures, even those designedto compensate for edge responses [7], produce stronger responses at the boundaryof the retina, near the optic disc, and along central pathological structures than for the thin andlow-contrast vessels. Similar problems also appear in the results of edge-based tracing techniques[5, 13].

The main contribution of this paper is the development of an enhanced vesselness measure that addresses the issues illustrated in Figure 1. Motivated by the apparent effectiveness of thematched filter in highlighting low-contrast and narrow vessels and by recent success in usingmatched filters for retina vessel segmentation [16], we introduce a multi-scale matched filter forvessels, deriving an appropriate normalizing constant to allow combination of responses acrossscales. We then augment the matched filter responses with a new vessel "confidence" measure,analogous to the edge-based measure presented in, that determines how close an image regionis to an ideal vessel profile. Importantly, unlike the matched filter, this measure is independent ofamplitude. To these vessel response and confidence values we add edge detection filter responsesand confidences taken from the boundary of the purported vessel, producing a six degree-of freedom measurement vector at each pixel. Then, we use a learning technique to develop amapping from this vector to a single likelihood ratio that serves as the final "vesselness" measure.

This gives a measure at each pixel which may be used either for segmentation of vessel pixelsor for identifying the centerline vessel pixels and vessel widths, when used in combination withnon-maximum suppression. We focus on the latter because the measures are designed to havemaximum response along the centerline of the vessel, and because this provides a more compact,geometric description of the vessels than segmentation alone.

Matched Filters

Working from a linear filtering perspective, let the input function (image) be f(x) and let the Filter be s(x). Then the output is

$$h(\mathbf{x}) = \int_{-\infty}^{\infty} s(\mathbf{x} - \mathbf{x}') f(\mathbf{x}') d\mathbf{x}'$$

The optimal filter (maximizing the signal-to-noise ratio) is known as the matched filter and itsshape can be obtained by reversing the shape of the detecting signal. In this way, the filter'sshape is matched to the signal's shape.Chaudhuri [9] et al. used a matched filter to detect vessels in retinal images. The filtergives maximum response when its orientation and shape is the same as the intensity profile. Vessels are modeled as piecewise linear segments with Gaussian cross sections. Twelve Gaussiantemplates at different orientations and a single scale are used. In Hoover's vessel segmentationalgorithm [16] a piece of the blood vessel network is hypothesized by probing an area of thematched-filter response image and while doing so the threshold on the matched filter is iterativelydecreased.

Gang [15] proposes amplitude-modified second-order differential of Gaussian filter to detectvessels at scales that match their widths. This is achieved by change of amplitude which isnecessary so that responses can be combined over scales.Steerable filters are introduced in [12] and extended in. In particular, Freeman [12]shows an example of applying steerable filters to vessel enhancement. The second derivativeof the Gaussian (G2) along any direction is expressed as a combination of the derivativesat orientations 0, 60, and 120 degrees. The G2 filter is steered adaptively along direction ofdominant vessel orientation. The result is less noisy than the output of an isotropic filter of the same frequency pass band [12]. It is computed at a single scale.The main disadvantage of matched filters is their computational cost. They are usuallyimplemented as a convolution of an image with a set of oriented segments, which is especiallyexpensive when computed at multiple scales. We will return to this issue in Sections 6 and 7.

The Stroke Width Transform

The SWT value of each pixel is roughly the width of the stroke that contains the pixel. A stroke is defined as a part of the image that forms a band of constant width. In the first step, we find the edges of the input image by means of the edge detection method. Then, the gradient direction dp of each edge pixel p is determined. A ray starting from p with the direction of dp is considered and followed until it meets another edge pixel q. If the gradient direction dq at edge pixel q is approximately opposite to dp, the distance value of p and q is assigned to all the pixels that lie on the ray. SWT of a sample image is computed and shown in Fig. 1.

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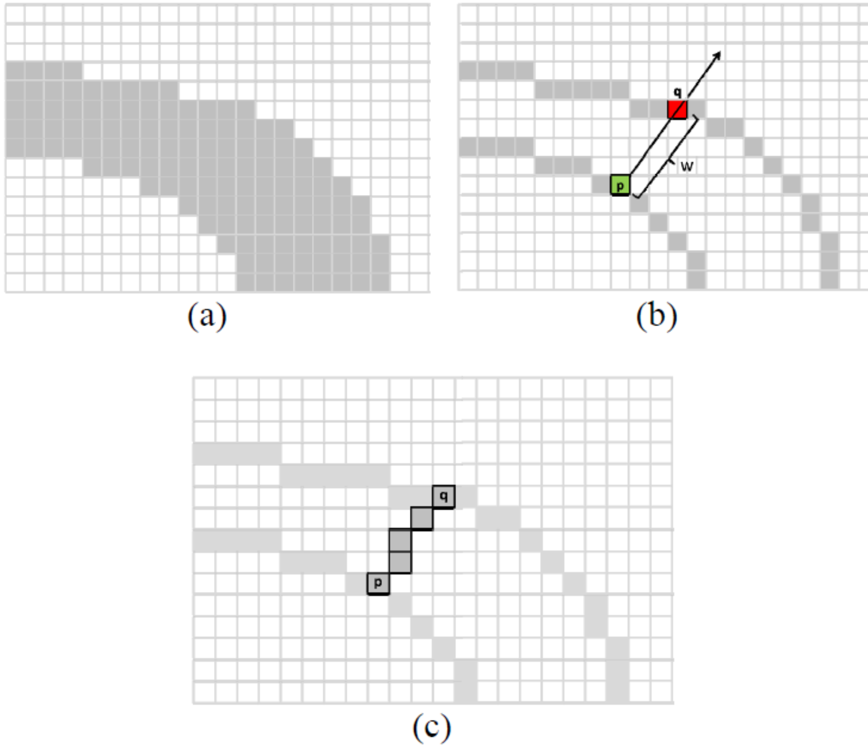
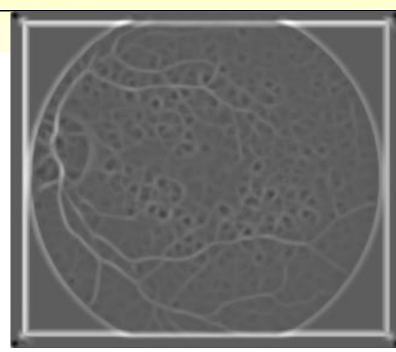
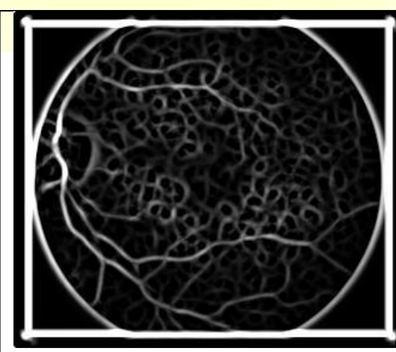
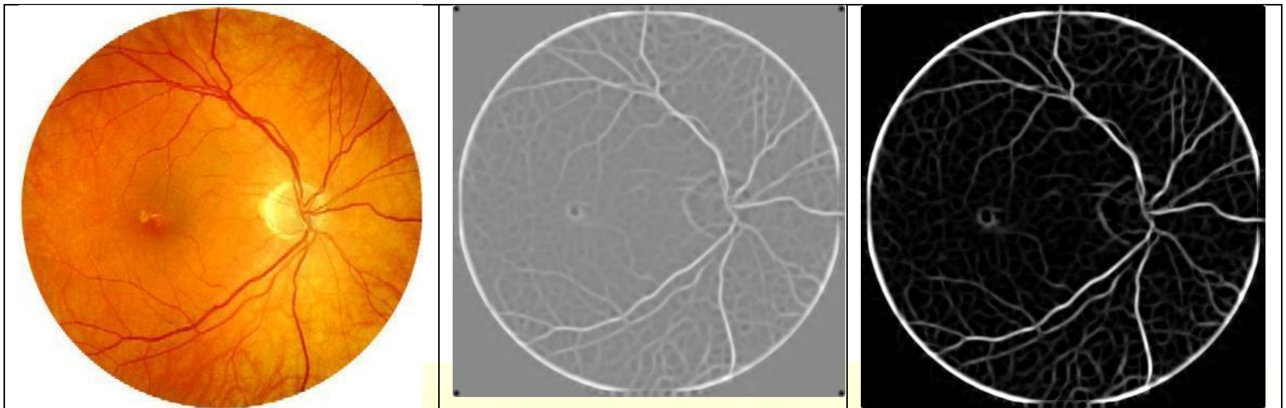


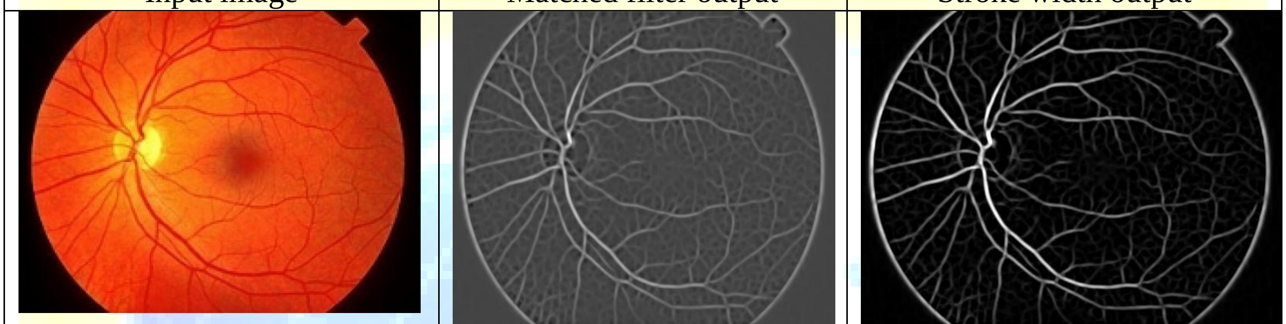
Neighboring pixels are grouped together and form CCs if they have similar stroke width values. The traditional CC algorithm is not performed on a binary mask but on the SWT values with a different connection criterion. In the CC algorithm, 4-neighboring pixels are considered. Adjacent pixels are grouped if the ratio of their stroke width values is higher than 0.3 and lower than 3. Features of the produced CCs are used to find text candidates.

Experimental Results

		
Input image	Matched filter output	Stroke width output



Input image | Matched filter output | Stroke width output



Input image | Matched filter output | Stroke width output

Figure 2

Conclusion

We have presented novel methods to automatically locate the optic nerve in a retinal image. Our methods use the matched filter and stroke width transform based techniques to extract the blood vessel network. Each component is designed to help address the problemof detecting narrow and low-contrast vessels, while avoiding responses to other retinal image structures. In particular, the elongated template of the matched filter tends to preserve vessels that are only a pixel wide (and typically low-contrast), whereas isotropic measures such as the Hessian tend to substantially blur these structures. The edge responses are useful in distinguishing between offset edges near pathologies and true vessels.

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