SCALED GAUSSIAN MATCHED FILTERING ON FLUORESCEIN ANGIOGRAMS OF THE RETINA

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ABSTRACT

Automated analysis of ophthalmic angiography sequences usually requires estimating the positions and appearance changes of blood vessels for computer aided diagnosis. Matched filtering is a standard technique for vessel detection on several types of retinal images, but is ineffective on sequences of fluorescein angiograms largely because that the assumption of Gaussian matched filtering can hardly hold in retinal circulation. In this paper we define a non-linear matched filtering using a scaled Gaussian function, which allows the vessels with varying appearance to be detected and the appearance changes to be extracted. The preliminary experimental results obtained from angiographic pairs and images of a SLO sequence are reported.

1. INTRODUCTION

Detection of known signals transmitted in linear and nonlinear channels is a fundamental problem in signal processing theory with a broad range of applications, e.g., communications, high-energy physics, and biomedical engineering [1-3]. Generally the task of signal or object detection is reliant on the ability of maximising the signal-to-noise ratio (SNR). The classic matched filtering is an optimal filter under the assumptions of Gaussian distribution of additive noise and of the signal to be detected. The signal shape of a Gaussian is used to construct an impulse response, hence the name matched filtering. For many years this has been a standard technique for tackling the detection problem.

Over two decades the matched filtering has been a standard technique for vessel detection from retinal images of several types including fluorescein angiograms (FAs), red-free, and colour fundus images [4-6]. Nowadays it seems still an active research topic in the literature [7]. Vessels are objects with two-sided boundary. "Twin" boundaries of vessel are often assumed to run smoothly or parallel to each other, although their sharpness may vary considerably. A popular detection methodology is to construct matched filters with the Gaussian shape describing vessel cross-sectional profile [6-7]. Figure 1 shows two vessel cross-sections in intensity extracted from two angiographic images. The filter kernel is correlated with each image location to give an estimate of likeness of a local region to a vessel. This filtering repeats at various orientations and the maximum response is retained and thresholded to produce a vessel pattern. Matched filtering can be used not only for detection, but also for measurement of vessel diameters. Clinically width measurement can play a valuable role in the study and diagnosis of several significant diseases (i.e., hypertension and diabetes), since the change in width of vessels within the fundus is believed to be indicative of abnormalities in disease states [8]. It has been suggested that the width control parameter of a Gaussian profile matched-filter is linearly relating to actual vessel width [9].

Retinal photographs of several types are often undergone on single subjects producing stereo pairs or sequential temporal series. Retinal vessels are visible as dark or bright structures relative to the background, i.e., dark in red-free photographic images; bright in many FA images. Since Gaussian profiles of the matched filtering are predefined upward or downward, either bright or dark patterns of vessel can be detected. In practical, negatives of retinal images were generated in order to adapt to profile models [4].

To acquire FA temporal series by a normal ophthalmoscope or angiographic sequences by SLO (Scanning Laser Ophthalmoscope), fluorescent dye injections are required before the angiogram is taken. As dye injections help highlight the vascular tree, the brightness of vessels in an angiographic sequence of SLO images increases from low to a peak, then decreases to original low values [10]. Thus the appearance of vessels in intensity varies significantly in retinal circulation, i.e., changes from upward profiles (see Figure 1 (d)) to downward profiles (see Figure 1 (b)), then back to upward profiles. Gaussian matched filtering in such cases is expected to yield sub-optimal object detection and false alarm performance, since the limitations of filtering are defined by the assumptions under which its optimality can be achieved. We are aware that in many applications, extending the classic matched filtering by approximating non-Gaussian distribution functions (e.g., the mixture Gaussian model as used in [11]) for signal detection is possible. It is therefore interesting to devise non-linear matched filtering for vessel extraction on angiographic pairs and sequences.

Apart from matched filtering, there is still a wide literature in retinal vessel detection. However few attentions have been given to extracting vessel appearance variations. By contrast, it is of great clinical and theoretical interest to understand how vessel appearance evolves in SLO sequences acquired in retinal circulation [10], [12].

We introduce a scaled Gaussian distribution function, which has been shown promising in natural image denoising [13], into the matched filtering in the next section. Then, we

discuss the phase invariance of scaled Gaussian distributions, which can be sought for by utilising phase congruency and can be used to initialise matched filtering. We proceed to applying the proposed algorithm to estimating vessel positions and appearance changes. In Section 3, we present some preliminary experimental results obtained from FA pairs and sequences.

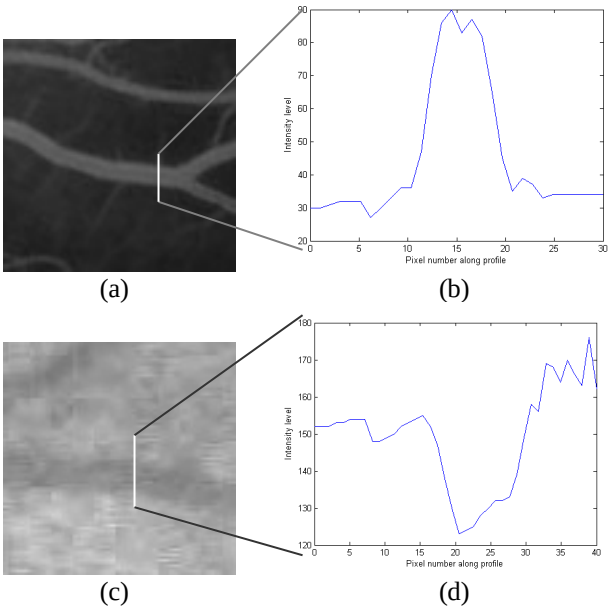


Figure 1 – The cross-section of a bright vessel (a) and its profile in intensity (b); the cross-section of a dark vessel (c) and its profile in intensity (d). The image patches (a) and (c) were cropped from two angiographic images respectively.

2. METHODOLOGY

2.1 Concept of Scaled Gaussian Matched Filtering

Let us consider that a random vector A can be approximated by the product of a zero-mean Gaussian vector H and an independent positive scalar random variable γ:

$$\mathrm{A} \stackrel{d}{=} \gamma \mathrm{H}, \qquad (1)$$

where $\stackrel{d}{=}$ indicates equality in distribution [13]. Suppose the amplitudes of A are corrupted by additive noise:

$$\mathrm{Y} = \mathrm{A} + W_n,$$

where W_n is zero-mean Gaussian noise; Y is the observed vector. Without loss of generality, the vector Y is expressed as follows:

$$\mathrm{Y} = \pm\gamma\mathrm{H} + W_n, \qquad (2)$$

where "+" or "-" is dependent on upward or downward signals (i.e., bright or dark object relative to background). As an approximation, H and W_n are assumed to be decorrelated.

Classic matched filters constructed with Gaussian can be viewed as a special case where the multiplier takes the value 1.0. Rather than a Gaussian shaped function, the object to be detected is characterised by the product of an independent scalar random variable γ and a Gaussian function H. Apparently a scaled Gaussian vector is a real even signal. Using the Fourier transform we can readily see that the vector is also a zero-phase signal. The phase of a downward zero-phase signal is zero for all frequency components contained within the signal, and the phase of upward is π. That is, the phase is invariant with respect to the signal magnitude (i.e., the multiplier).

Our observation partly motivates us to locate scaled Gaussian signals by exploiting Fourier phase information. To this end, the Kovesi phase congruency model of feature detection [14] is utilised. Specifically the Fourier series expansion of a 1-D signal is

$$I(x) = \sum_n A_n \cos(\phi_n(x)),$$

where ϕ_n is the phase offset of the n$^{\text{th}}$ component of the expansion, and A_n is the amplitude. Kovesi proposed to use the following function for feature detection [14]:

$$PC(x) = \frac{\sum_n \lfloor A_n(x)(\cos(\phi_n(x) - \bar{\phi}(x)) - |\sin(\phi_n(x) - \bar{\phi}(x))|) - S \rfloor}{\sum_n A_n(x) + \varepsilon},$$

where $\overline{\phi(x)}$ is a weighted mean phase angle of all the Fourier terms at the point (x) being considered; the term S is a noise threshold; ε is a small constant for avoiding division by zero. The symbol $\lfloor \cdot \rfloor$ denotes that the enclosed quantity is equal to itself when its value is positive, and zero otherwise. This function has been shown effective in edge detection [14-15]. Herein we extend it for zero-phase signal detection by replacing the item $\overline{\phi(x)}$ with a specific phase ϕ_s ($\phi_s = 0$ or π). We have

$$PC(x, \phi_s) = \frac{\sum_n \lfloor A_n(x)(\cos(\phi_n(x) - \phi_s) - |\sin(\phi_n(x) - \phi_s)|) - S \rfloor}{\sum_n A_n(x) + \varepsilon}. \qquad (3)$$

The derived function is to calculate the alignment degree of the phases of all frequency components with ϕ_s, $\phi_s = 0$ for a downward signal and $\phi_s = \pi$ for upward. It gives a normalised measure of the alignment degree, so as to be invariant to the signal magnitude.

Once scaled Gaussian signals are detected, the multiplier is sought by minimising the Euclidean distance between the scaled Gaussian function and data with high phase alignment, using the Levenberg-Marquardt algorithm. We have an initial estimator for the multiplier:

$$\gamma(\mathrm{Y}) = \frac{\mathrm{Y}^T\mathrm{Y}}{N} - \sigma_\omega^2, \qquad (4)$$

where N is the dimensionality of vectors A, H, W_n, and Y. An estimate of the multiplier is adjusted based on the initial estimator (4) until the minimum distance is approximated.

2.2 Vessel Extraction

Herein vessel cross-sections in intensity are modelled by a scaled Gaussian function - the product of an independent scalar random variable (γ) and a Gaussian shaped function (H). The scalar variable implies in the appearance of a vessel being observed. Hence the values of γ extracted from the same cross-section across an angiographic sequence, reflect the interval variation of vessel brightness induced by dye injection.

Vessel detection is achieved by assessing the alignment of Phases zero and π. The computation of applying the derived function of phase alignment on 2-D images follows the implementation of the Kovesi phase congruency model. We apply the function on data from oriented 2-D log-Gabor wavelets. Empirically we chose six orientations with four resolution levels increasing the wavelength by 0.2 octave. In the scale of filter support, a resultant image is a map of the alignment degree on an input image. The region with high alignment is sought to coincide with vascular structures to be detected.

The multiplier is optimally obtained by maximising the cross-correlation of a local vessel detection and a scaled Gaussian. Specifically, the optimisation step repeats at 24 different orientations, and the value corresponding to the maximum cross-correlation is taken. A notorious problem for many vessel detection methodologies is that, some vessel segments show a central light reflex due to certain imaging or pathologic conditions. In such cases, the phase invariance of any cross-section in intensity is expected to retain, but it would be difficult to approximate optimal values of the multiplier. As a first approximation, for a upward signal its Fourier components with zero phase are not taken into the optimisation, and for a downward signal its Fourier components with π phase are discarded.

In contrast to the classical filtering, the scaled Gaussian matched filtering technique is expected to be capable of estimating the positions and appearance changes of blood vessels. Briefly we give a summary of algorithm:

- Apply (3) on each FA image producing a phase alignment map;
- Apply thresholding on the phase alignment producing a detection map;
- Perform optimisation to find optimal values of the multiplier.

3. EXPERIMENTS

A pair of cropped FA images acquired from the same subject at different time are given in Figures 2(a) and 2(c), and their zero-phase detection results are given in Figures 2(b) and 2(d) respectively. In the original FA images, the central light reflex is obvious on some vessel segments. The alignment degrees shown in Figure 2(b) and 2(d) take values between 0 and 1. From the results we readily observe that high alignment degrees of local Fourier components are detected coinciding with the positions of the vasculature trees. Observation of the result in Figure 2(b) also supports that high alignment degrees retain even if the central light reflex is present.

For the purpose of comparison, the classical matched filtering technique ([6] and [7]) was applied to the image shown in Figure 2(a). Its detection result and our detection result are given in Figures 3(a) and 3(b) respectively. We notice here that, unlike the Gaussian matched filtering where the large vessel segments are partially detected, the proposed algorithm extracts the large vessel segments in the original image and the diameters of the detections show good agreement with visual inspections.

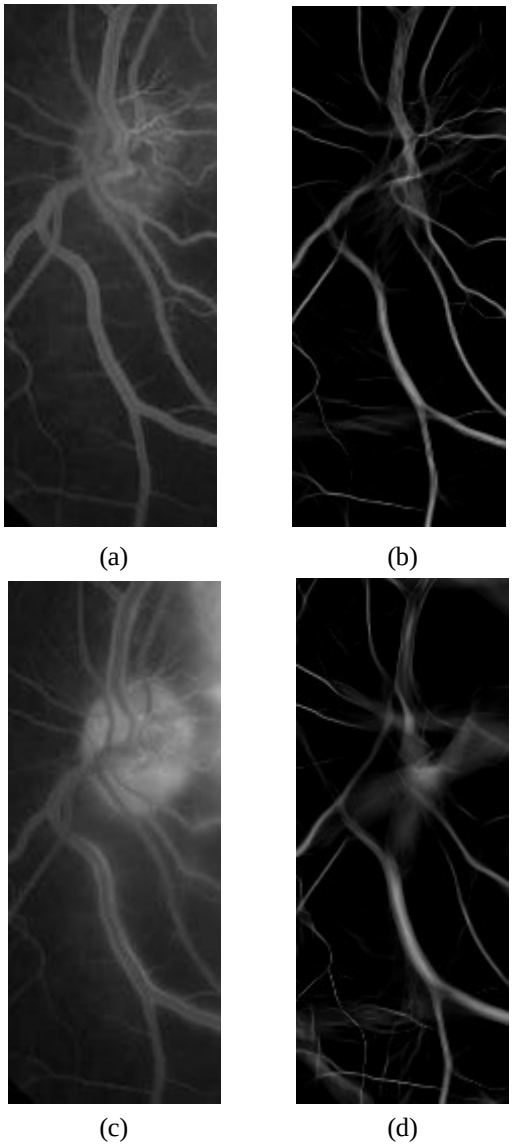
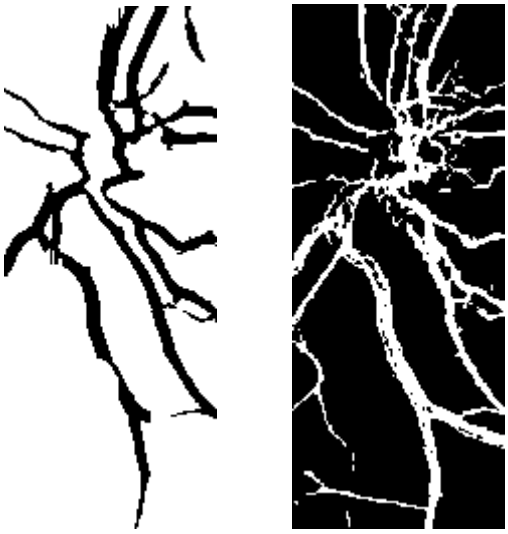


Figure 2 – FA images (a) and (c) acquired from one subject at different time; and their detection results (b) and (d) of zero phase.

Careful observation of the original image in Figure 2(c) shows that a few vessel segments are dark relative to the surrounding background, while others are bright. In the presence

of both dark and bright vessels, it is necessary to look for both zero phase and π phase. Figure 4 shows the corresponding detection result of π phase. Further study on fusing detection results of zero and π phases is needed.

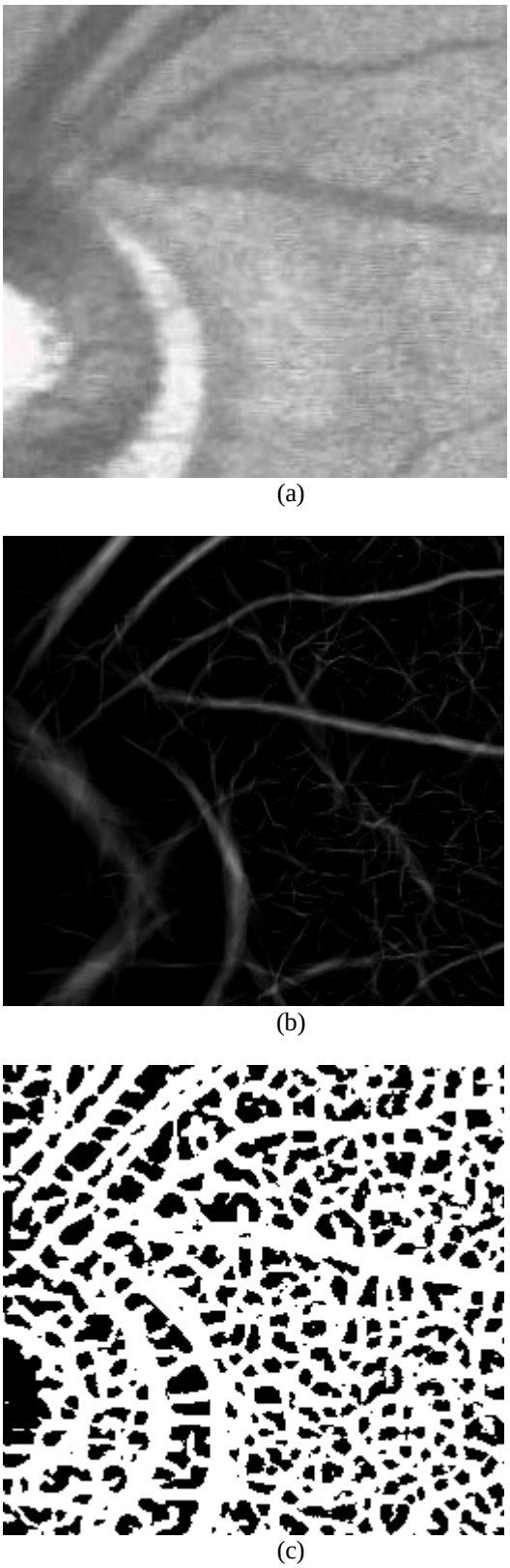
A cropped original SLO image is given in Figure 5(a), and the detection result of zero-phase is given in Figure 5(b). For the purpose of comparison, the classical matched filtering ([6] and [7]) was applied to the same image, and the corresponding filtered image is given in Figure 5(c). We notice here that the classical matched filtering is ineffective, largely because that the SLO image is fairly noisy. By contrast, the result of zero-phase detection delineates the vasculature tree. We may conclude that the method of zero-phase detection is noise-robust.



(a) (b)

Figure 3 – Gaussian matched filtering result (a) and Scaled Gaussian matched filtering result (b) on the image of Figure 2(a).

Figure 4 – Detection result of π phase on the image of Figure 2(c).



(a)

(b)

(c)

Figure 5 – A cropped SLO image (a) and the detection result of zero phase (b). The corresponding detection result (c) of the Gaussian matched filtering.

The scaled Gaussian matched filtering was performed on the cross-section illustrated in Figure 1(c), across angiographic images of a SLO sequence. The material of this experiment includes 35 images in time order taken from the frames of the sequence. These images have been registered beforehand. In this work a universal threshold value (0.38) on phase alignment was used. The values of the multiplier obtained were recorded and illustrated in Figure 6, reflecting the dye filling progress. We can see the proposed technique provides an interface to illustrate the dye filling progress, i.e., the time to peak. We expect to extend the interface to a powerful visualisation tool.

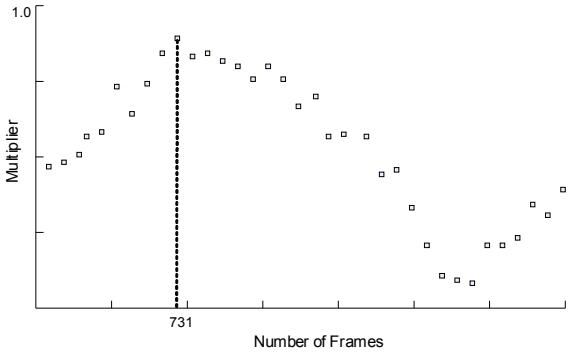


Figure 6 – The values of the multiplier at the cross-section as shown in Figure 1(c), and calculated from a SLO sequence.

4. DISCUSSION

We have presented a new non-linear matched filtering technique for the understanding of FA pairs and sequences. The novelty of this work is that a scaled Gaussian function for modelling the distribution of signals is proposed to reinforce the matched filtering, and the phase invariance of scaled Gaussian is utilised for the detection purpose. The proposed algorithm technique retains the advantage of the popular matched filtering, and may have gained the following strengths attractive for retinal image sequences:

- dark and bright vessels with varying appearance can be detected;
- appearance changes can be extracted;
- noise-robustness;
- minimal operator intervention partly thanks to phase congruency.

Additionally, the proposed algorithm may be useful for vessel detection on colour fundus images, since the filter kernel used is based on the one which has been shown effective on colour fundus images. It is interesting to further investigate this. Presently we are investigating on how to utilise the aperture of a scaled Gaussian for wide measurement, and expect to extend it to the images where both dark and bright vessels are present simultaneously. The driving application is super-resolution of angiographic images of a SLO sequence acquired during retinal circulation.

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