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Automatic detection of vascular bifurcations in segmented retinal images using trainable COSFIRE filters

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A R T I C L E I N F O

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A B S T R A C T

Background: The vascular tree observed in a retinal fundus image can provide clues for cardiovascular diseases. Its analysis requires the identification of vessel bifurcations and crossovers.

Methods: We use a set of trainable keypoint detectors that we call Combination Of Shifted FIlter REsponses or COSFIRE filters to automatically detect vascular bifurcations in segmented retinal images. We configure a set of COSFIRE filters that are selective for a number of prototype bifurcations and demonstrate that such filters can be effectively used to detect bifurcations that are similar to the prototypical ones. The automatic configuration of such a filter selects given channels of a bank of Gabor filters and determines certain blur and shift parameters. The response of a COSFIRE filter is computed as the weighted geometric mean of the blurred and shifted responses of the selected Gabor filters. The COSFIRE approach is inspired by the function of a specific type of shape-selective neuron in area V4 of visual cortex.

Results: We ran experiments on three data sets and achieved the following results: (a) a recall of 97.88% at precision of 96.94% on 40 manually segmented images provided in the DRIVE data set, (b) a recall of 97.32% at precision of 96.04% on 20 manually segmented images provided in the STARE data set, and (c) a recall of 97.02% at precision of 96.53% on a set of 10 automatically segmented images obtained from images in the DRIVE data set.

Conclusions: The COSFIRE filters that we use are conceptually simple and easy to implement: the filter output is computed as the weighted geometric mean of blurred and shifted Gabor filter responses. They are versatile keypoint detectors as they can be configured with any given local contour pattern and are subsequently able to detect the same and similar patterns.

1. Introduction

Retinal fundus images provide a unique possibility to take a non-invasive look at the eye and the systemic status of the human body. Besides ocular diseases, such as age-related macular degeneration and glaucoma that are two of the leading causes of blindness, other systemic diseases are also manifested in the retina. Complications of such diseases include diabetic retinopathy from diabetes mellitus (Frank, 2004), hypertension (Tso and Jampol, 1982) and atherosclerosis from cardiovascular disease (Chapman et al., 2002), as well as brain diseases and neuropathies, such as multiple sclerosis (Parisi et al., 1999) and Huntington's disease (Paulus et al., 1993). The retina can thus be considered as a mirror of the health status of a person.

Here we focus on retinal image analysis for the diagnosis of cardiovascular diseases, while for a comprehensive review on retinal image analysis we refer to Abramoff et al. (2010). The vascular geometrical structure in the retina is known to conform to structural principles that are related to certain physical properties (Zamir et al., 1979; Sherman, 1981). For instance, the studies of Murray (1926a,b) revealed that the most efficient blood circulation is achieved when the blood flow is proportional to the cubed power of the vessel's radius; this is known as Murray's law. The branching angle between the two child vessels is also important to optimize the efficiency of the entire vascular network (Zamir et al., 1992).

The analysis of the geometrical structure of the vessel tree is thus important as deviations from the optimal principles may indicate (increased risk of) signs for vascular pathology; a thorough review is given by Patton et al. (2006). The detection of junctions in the vessel tree of a retinal fundus image, commonly referred to as vascular bifurcations and crossovers, is one of the basic steps in this analysis, and it is typically carried out in a time-consuming manual procedure (Chapman et al., 2002). The automation of such a tedious process is thus important to improve the efficiency and to avoid inaccuracies due to human fatigue.

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The existing attempts to automate the detection of retinal vascular bifurcations can be categorized into two classes; geometrical-feature based and model based approaches. The former methods are highly dependent on the segmentation and skeletonization techniques. They also involve extensive local pixel processing and branch point analysis (Martinez-Perez et al., 2002; Chanwimaluang and Guoliang, 2003; Eunhwa and Kyungho, 2006; Bhuiyan et al., 2007; Ardizzone et al., 2008; Aibinu et al., 2010; Calvo et al., 2011). Incomplete bifurcations, which are commonly produced by automatic segmentation techniques, are generally not detected by such skeleton based approaches. On the other hand, model-based approaches are usually more adaptive and have smaller computational complexity that makes them more appropriate for real-time applications (Ali et al., 1999; Shen et al., 2001; Tsai et al., 2004). However, model based approaches suffer from insufficient generalization ability as they are usually unable to model all the features of interest. Consequently, these methods may fail to detect atypical bifurcations.

Besides the diagnosis of pathologies, retinal fundus images have also been used for person verification as the geometrical arrangement of the vascular bifurcations is an effective biometric (Bevilacqua et al., 2009; Ortega et al., 2009). Moreover, vascular bifurcations may also be used as key features to find correspondences between the retinal images of the same eye taken from different views, i.e. for registration of retinal images (Becker et al., 1998; Shen et al., 2003; Tsai et al., 2004; Chen et al., 2011).

We use the COSFIRE (Combination Of Shifted FIlter REsponses) filters, which we have introduced elsewhere (Azzopardi et al., 2012a), for the detection of bifurcations in segmented retinal images. COSFIRE filters are trainable keypoint detection operators, which are selective for given local patterns that consist of combinations of contour segments. These operators are inspired by the properties of some neurons in area V4 of visual cortex, which are selective for parts of (curved) contours or for combinations of line segments (Pasupathy and Connor, 1999, 2002). In this work we focus on one application and provide more elaborate experiments to demonstrate the robustness and generalization capability of the COSFIRE filters.

The response of a COSFIRE filter in a given point is computed as a function of the shifted responses of simpler filters. Using shifted responses of simpler filters – Gabor filters in the concerned application – corresponds to combining their respective supports at different locations to obtain a more sophisticated filter with a bigger support. The specific function that we use here to combine the responses of simpler filters is weighted geometric mean, essentially multiplication, which has specific advantages regarding shape recognition.

Two-dimensional (2D) Gabor filters (Daugman et al., 1985) that we use as input to our COSFIRE filters have been extensively used to detect oriented structures (lines and/or edges) in many computer vision applications, including retinal image analysis. For instance, these filters have been found effective in detecting signs of glaucoma (Bodis-Wollner and Brannan, 1997; Sun et al., 2006; Muramatsu et al., 2009) detecting the optic nerve head of the retina (Rangayyan et al., 2010), and mostly for the segmentation of the vessel tree in retinal fundus images (Soares et al., 2006; Li, 2006; Usman Akram et al., 2009; Moin et al., 2010; Xiaojun Du et al., 2010; Yavuz et al., 2010, 2011; Fraz et al., 2011; Selvathi et al., 2011). Apart from Gabor filters, other state-of-the-art methods have also been found effective for the segmentation of the vessel tree (Chauduri et al., 1989; Jiang and Mojon, 2003; Staal et al., 2004; Niemeijer et al., 2004; Mendonca and Campilho, 2006; Ricci and Perfetti, 2007).

The rest of the paper is organized as follows: In Section 2 we present our method and demonstrate how it can be used to detect retinal vessel features. In Section 3, we evaluate the effectiveness of the COSFIRE filters on manually and automatically segmented retinal images from the DRIVE and STARE data sets. In Section 4 we provide a discussion of some aspects of our approach and finally we draw conclusions in Section 5.

2. Method

A COSFIRE filter for the detection of local combinations of lines is conceptually simple and straightforward to implement: it requires the application of selected Gabor filters, blurring of their responses, shifting the blurred responses by specific, different vectors, and multiplying the shifted responses. The questions of which Gabor filters to use, how much to blur them and how far to shift them are answered in a filter configuration process in which a local pattern of interest that defines a keypoint is automatically analyzed. The configured COSFIRE filter can then detect the same and similar patterns.

2.1. Overview

In Fig. 1a we illustrate a typical vascular bifurcation encircled in a segmented retinal fundus image.[1] We use this feature as a prototype bifurcation, which is shown enlarged in Fig. 1b, to automatically configure a COSFIRE filter that will respond to the same and similar bifurcations.

The three ellipses shown in Fig. 1b represent the dominant orientations in the neighborhood of the specified point of interest. We detect such orientations by Gabor filters. The central circle represents the overlapping support of a group of such filters. The response of a COSFIRE filter is computed by combining the responses of the concerned Gabor filters by a weighted geometric mean. The preferred orientations of these filters and the locations at which we take their responses are determined by automatically analyzing the local prototype pattern used for the configuration of the concerned COSFIRE filter. Consequently, the COSFIRE filter is selective for the presented local spatial arrangement of lines of specific orientations and widths. Taking the responses of Gabor filters at different locations around a point can be implemented by shifting the responses of these Gabor filters by different vectors before using them for the pixel-wise evaluation of a function which gives the COSFIRE filter output.

Such a design is inspired by electrophysiological evidence that some neurons in area V4 of visual cortex are selective for moderately complex stimuli, such as curvatures, that receive inputs from a group of orientation-selective cells in areas V1 and V2 (Pasupathy and Connor, 1999, 2001, 2002). Moreover, in a psychophysical experiment, Gheorghiu and Kingdom, 2009 show that curved contour parts are likely detected by a nonlinear operation that combines the responses of afferent orientation-selective filters by multiplication. Since a COSFIRE filter makes use of such multiplication, it produces a response only when all its afferent inputs from Gabor filters are stimulated; i.e. all constituent parts (in this case lines) of a vascular bifurcation are present.

In the following sections we explain the automatic configuration process of a COSFIRE filter that will be selective for the prototype bifurcation shown in Fig. 1b. The configuration process determines which responses of which Gabor filters in which locations need to be combined in order to obtain the output of the filter.

2.2. Detection of dominant orientations by 2D Gabor filters

We build the COSFIRE filter using as input the responses of 2D Gabor filters, which are known to serve as line and edge detectors.

[1] The image used in this example is named 40_manual1.gif in the DRIVE data set (Staal et al., 2004).