Retinal Vessel Extraction by Using Visual Cortical Filters

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Abstract— **The change in morphology, diameter, branching pattern and/or tortuosity of retinal blood vessels is an important indicator of various clinical disorders of the eye and the body. In this paper we implement a visual cortical filter which is also called as 2D - Gabor filter in combination with linear model for retinal vessel extraction. By convoluting multiple Gabor filter with the image we try to detect the retinal blood vessels. Here we consider Gabor transformed image as independent variables and the location the vessels as dependent variables. This method is validate graphically and by calculating sensivity and specificity.**

Keywords- cortical filters, sensivity, specificity, Image processing, Image analysis, Ophthalmology

I. INTRODUCTION

Eye disease identification techniques are highly important in the field of ophthalmology. Conventional retinal disease identification techniques are based on manual observation which is highly subjective and prone to error. Hence, the necessity for automated techniques which eliminates the drawback of the conventional techniques is significantly high in the medical field. The accuracy of the automated disease identification techniques should be high. Besides being accurate, the techniques also should possess a quick convergence rate which enables them to be suitable for real - time applications. Based on these two performance measures, several automated techniques are developed and implemented successfully for retinal disease identification. Some of the significant techniques available for the entire automated system. The automated disease identification system is not a single process. This system consists of various modules. The success rate of each and every step is highly important to ensure the high accuracy of the system. The rest of the report is organized as follows: (a) Retinal image database, (b) Image pre - processing, (c) Anatomical structure identification and feature extraction, (d) Optimization techniques, (e) Disease identification.

Certain eye diseases such as choroidal neovascularization and retinal artery occlusion also make changes in the retinal vasculature. As per previous statement, the segmentation of blood vessels in retinal images can be a valuable aid for the detection of diabetic retinopathy and glaucoma diagnosis.

Segmentation of anatomical and pathological structures in ophthalmic images is crucial for the diagnosis and study of ocular diseases. However, manual segmentation is often a time-consuming and subjective process. Retinopathy of prematurity (ROP) or Terry syndrome, previously known as retrolental fibroplasia (RLF), is a disease of the eye affecting prematurely-born babies generally having received intensive neonatal care, in which oxygen therapy is often used and advantageous. ROP is a disorder of the retinal blood vessels that is a major cause of vision loss in premature neonates. It is thought to be caused by disorganized growth of retinalblood vessels which may result in scarring and retinal detachment. ROP can be mild and may resolve spontaneously, but it may lead to blindness in serious cases. As such, all preterm babies are at risk for ROP, and very low birth weight is an additional risk factor. Both oxygen toxicity and relative hypoxia can contribute to the development of ROP. Important features of the disease include increased diameter (dilation) as well as increased tortuosity (wiggliness) of the retinal blood vessels in the portion of the retina centered on the optic nerve (the posterior pole). Increased dilation and tortuosity of the blood vessels in the posterior pole (called pre-plus in intermediate, and plus in severe circumstances) is an important indicator of ROP severity. Plus disease: This term refers to other ocular findings indicative of vascular activity. The most widely recognized feature of plus disease is posterior pole retinal venous dilation and arteriolar tortuosity. Subjective assessment of plus and pre-plus disease leads to poor agreement between examiners [3]. Manual segmentation of retinal images is not only demanding for experts and excessively time-consuming for clinical use, but is also inherently subjective, and different annotators often yield different results [4]. To address these difficulties, different approaches for automated segmentation of retinal vessels have been tried, with varying levels of success. Segmentation methods vary depending on the imaging modality, application domain, method being automatic or semi-automatic, and other specific factors. There is no single segmentation method that can extract vasculature from every medical image modality. While some methods employ pure intensity based pattern recognition techniques such as thresholding followed by connected component analysis [1], [2], some other methods apply explicit vessel models to extract the vessel contours [3], [4], and [5]. Depending on the image quality and the general image artifacts such as noise, some segmentation methods may

require image pre-processing prior to the segmentation algorithm [6], [7]. On the other hand, some methods apply post-processing to overcome the problems arising from over segmentation we divide vessel segmentation algorithms and techniques into six main categories: (1) Parallel Multiscale Feature Extraction and Region Growing, (2) a hybrid filtering, (3) Ridge-Based Vessel Segmentation, (4)artificial intelligence based approaches, (5)neural network based approaches, and (6) miscellaneous tubelike object detection approaches. Pattern recognition techniques are further divided into seven categories: (1) multiscaleapproaches, (2) skeleton based approaches, (3) region growing approaches, (4) ridge- based approaches, (5) differential geometry-based approaches, (6) matching filters approaches, and (7) mathematical morphology schemes. Model-based approaches are also further divided into four categories: (1) deformable models, (2) parametric models, (3) template matching approaches, and (4) generalized cylinders approaches. Sometimes multiple techniques are used together to solve different segmentation problems. However, the usual method for diagnosing ROP is the indirect ophthalmoscope (IO). More recently, Video Indirect Ophthalmoscopy (VIO), in which the physician wears a head-mounted video camera during IO evaluations, has emerged as an economical and convenient method for capturing digital retinal images during ROP examinations. In contrast to RetCam, however, VIO data is often of low quality, fraught with reflections from the IO lens, motion blur, low resolution, and sensor noise. A previous study reported that only 24% of randomly selected video sequences can be utilized for semi-automated evaluation of retinal vessel morphology in ROP.

II. PROPOSED WORK

In this paper we present Retinal vessel segmentation algorithms which are fundamental component of automatic retinal disease screening systems .This paper will demonstrate how Gabor transform and generalized linear model can be used for detection of retinal vessels in images. Specifically, we will attempt to detect the retinal vessels from a 'training image'; by first, convoluting multiple Gabor filters with the image. A GLM will be determined using the Gabor transformed images as features (the independent variables), and the locations of the vessels as the outcome (the dependent variable). We will term this method for detecting vessels as Gabor + GLM. The Gabor + GLM will be validated by how well it detects retinal vessels in a 'testing image'. Finally, we will calculate the sensitivity, the specificity; plot the ROC curve, and the corresponding area under the curve.

A. Visual cortical filter

Gabor filter is a Gaussian envelope modulated by a complex sinusoid. This filter, developed by Dennis Gabor, resembles visual cortical filters and has been shown to be useful in computer vision, e.g. edge detection and pattern discrimination.For a 2D gabor filter, the shape of the filter can be varied by altering the size of the envolope with 'sigma', the direction of the sinusoid with 'theta', and the frequency of the sinusoid with 'F'.

Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave.Simple cells in the visual cortex of mammalian brains can be modeled by Gabor functions.Thus, image analysis with Gabor filters is thought to be similar to perception in the human visual system.

A set of Gabor filters with different frequencies and orientations may be helpful for extracting useful features from an image. Gabor filters have been widely used in pattern analysis applications.Forexample; it has been used to study the directionality distribution inside the porous spongy trabecular bone in the spine.

Gabor filters are directly related to Gabor wavelets, since they can be designed for a number of dilations and rotations. However, in general, expansion is not applied for Gabor wavelets, since this requires computation of bi-orthogonal wavelets, which may be very time-consuming. Therefore, usually, a filter bank consisting of Gabor filters with various scales and rotations is created. The filters are convolved with the signal, resulting in a so-called Gabor space. This process is closely related to processes in the primary visual cortex.Jones and Palmer showed that the real part of the complex Gabor function is a good fit to the receptive field weight functions found in simple cells in a cat's striate cortex.

B. Gaussian Linear Model

Gaussian process is a stochastic process whose realizations consist of random values associated with every point in a range of times (or of space) such that each such random variable has a normal distribution. Moreover, every finite collection of those random variables has a multivariate normal distribution. The concept of Gaussian processes is named after Carl Friedrich Gauss because it is based on the notion of the normal distributionwhich is often called the Gaussian distribution. In fact, one way of thinking of a Gaussian process is as an infinite-dimensional generalization of the multivariate normal distribution.Gaussian processes are important in statistical modelling because of properties inherited from the normal. For example, if a random process is modelled as a Gaussian process, the distributions of various derived quantities can be obtained explicitly. Such quantities include: the average value of the process over a range of times; the error in estimating the average using sample values at a small set of times.

A Gaussian process can be used as a prior probability distribution over functions in Bayesian inference. Given any set of N points in the desired domain of your functions, take a multivariate Gaussian whose covariance matrix parameter is

theGram matrix of your N points with some desired kernel, and sample from that Gaussian.Inference of continuous values with a Gaussian process prior is known as Gaussian process regression, or kriging; extending Gaussian process regression to multiple target variables is known as co-kriging. As such, Gaussian processes are useful as a powerful non-linear interpolation tool. Additionally, Gaussian process regression can be extended to address learning tasks both in a supervised (e.g. probabilistic classification) and an unsupervised (e.g. manifold learning) learning framework.

III. GABOR AND GLM

We will import an image of the retina and an image indicating where the vessels are in the image. The images will be halved and used as training and testing images.

The next step is to perform multiple Gabor transforms with varying Gabor filters to the training image, and use the transformed images as features.

We now will generate a GLM using the features extracted above and also the location of the vessels in the training image.Now that we have generated a GLM from the training image, we will test how well Gabor+GLM performs by feeding the features of the testing image to the GLM which process is clearly shown in fig 1

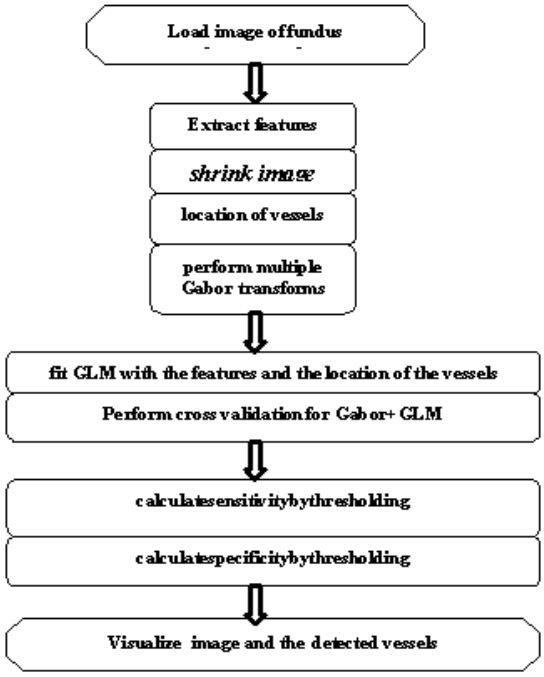


Fig.1Flow chart showing proposed model

IV. RESULTS

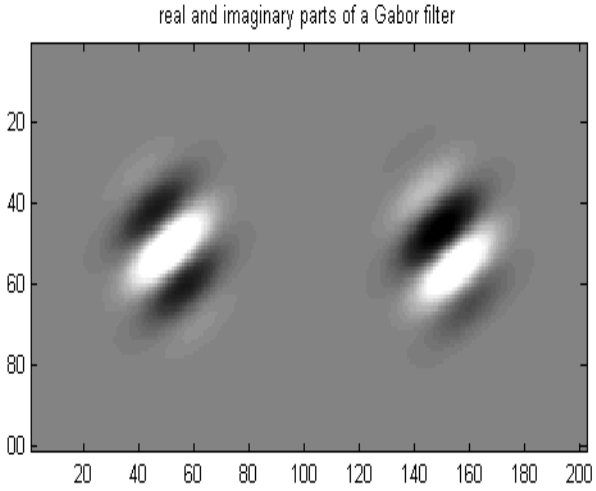


Fig. 2For a 2D gabor filter, the shape of the filter can be varied by altering the size of the envolope with 'sigma', the direction of the sinusoid with 'theta', and the frequency of the sinusoid with 'F'. above displays the real and imaginary part of a gaborfilter.real and imaginary parts of gabor filter

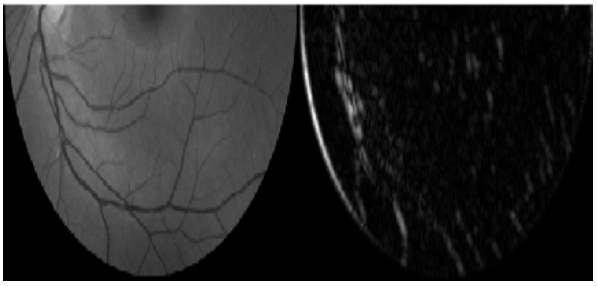
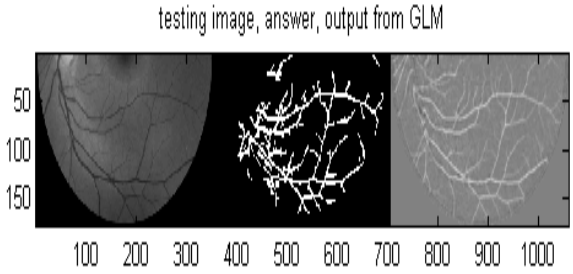
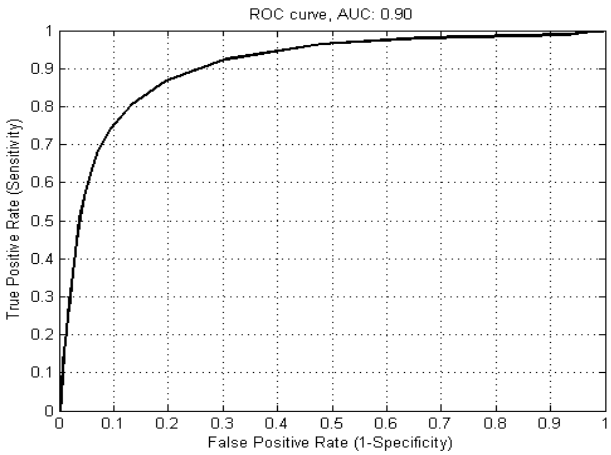


Fig. 3*The above figure shows extracting features*

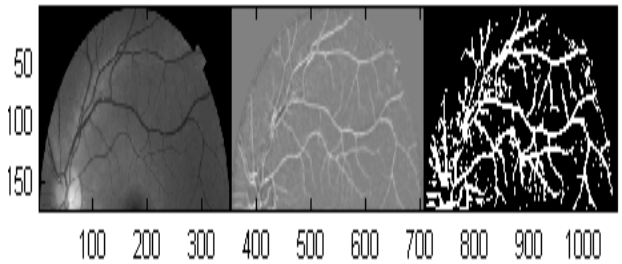
Byperforming multiple Gabor transforms with varying Gabor filters to the training image, and uses the transformed images as features.Gabor transformed image



Above figure shows GLM using the features extracted above and also the location of the vessels in the training image.



From the above we can see how well it compares to the actual locations of the vessels. Since the 'Ctest' ranges from 0 to 1, we can assess the GLM by selecting multiple thresholds and determine the sensitivity and specificity at varying threshold levels. With multiple sensitivity and specificity values, we can then generate a ROC curve, calculate its area under the curve and also select an optimal threshold which maximizes Youden's index.multiple sensitivity and specificity value



From the above figure we can see from the ROC curve, by training half of the retinal image, the Gabor+GLM was able to detect the other half of the image with a satisfactory performance (area under the curve of 0.90).original output of proposed model

V. CONCLUSION

Now that we have the output 'Ctest' from the GLM using the features extracted from the testing image, we can see how well it compares to the actual locations of the vessels. Since the 'Ctest' ranges from 0 to 1, we can assess the GLM by selecting multiple thresholds and determine the sensitivity and specificity at varying threshold levels. With multiple sensitivity and specificity values, we can then generate a ROC curve, calculate its area under the curve and also select an optimal threshold which maximizes Youden's With the optimal threshold, we will now visualize the testing image, the output image from the GLM, along with the thresholded output image.As you can see from the ROC curve, by training half of the retinal image, the Gabor+GLM was able to detect the other half of the image with a satisfactory performance (area under the curve of 0.90).

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[2] In [3], Miguel et al. presented multi-scale feature extraction and region growing algorithm for retinal blood vessels segmentation. This implementation allowed a faster processing of these images and was based on a data partitioning.

[3] In [4] [10], different methods for blood vessel detection and segmentation are presented.

[4] Staal [14] et al. proposed a pixel feature based method that additionally analyzed the vessels as elongated structures. The edge - based methods can be further classified into window -based and tracking - based methods. Window- based method estimates a match at each pixel against the pixel's surrounding window. In order to trace the vessels, the tracking approach makes use of local image properties from an initial point.

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