Retinal Image Classification for Identification of Cardio Vascular Disease using Forest Graph

A.Rijuvana Begum, S.Purnima
[1]Associate Professor, [2]M.Tech (Communication System), [1]Department of ECE,
[1 2] PRIST University, Thanjavur.

Abstract:

The relationship between changes in retinal vessel morphology and the onset and progression of diseases such as hypertension, coronary heart disease, and stroke has been the subject of several large scale clinical studies. However, the difficulty of quantifying changes in retinal vessels in a sufficiently fast, accurate and repeatable manner has restricted the application of the insights gleaned from these studies to clinical practice. Accurate measurement of vessel diameters on retinal images plays an important part in diagnosing cardiovascular diseases. In this project, a method of vessel diameter measurement has been developed incorporating with a tracking technique. Vessel edges are then more precisely localized using image profiles computed perpendicularly across a spline fit of each detected vessel centerline, so that both local and global changes in vessel diameter can be readily quantified. The retinal vessel network is used to diagnosis of cardiovascular disease. We use the post processing step to identifying the true vessels from for vascular structure segmentation. So we construct the vessel segment graph and formulate the problem of finding optimal forest in the graph. Using image datasets, we show that the diameters output by our algorithm display good agreement with the manual measurements made by independent observers.

Keywords: *Vessel segmentation, Graph, Vascular structure segmentation*

I. INTRODUCTION

Retinal images obtained using Adaptive Optics have the potential to facilitate early detection of retinal pathologies. The retina is the only location where blood vessels can be directly visualized. Increasing technology leading to the development of digital imaging systems over the past two decades has revolutionized fundal imaging. Digital imaging does not still have the resolution of conventional photography; modern digital imaging systems offer very high-resolution images that are sufficient for most clinical scenarios. The retina is the only location where blood vessels can be directly visualized non-invasively in vivo. Increasing technology leading to the development of digital imaging systems over the past two decades has revolutionized fundal imaging. Digital imaging does not still have the resolution of conventional photography; modern digital imaging systems offer very high-resolution images that are sufficient for most clinical scenarios.A method for automatic segmentation of blood vessels in retinal images. The method is based on vessel tracking technique. The key idea of the method is that first a set of seed points (center of vessel cross sections) is extracted. Then, the seed points are connected to establish the vessel skeleton. Finally, the false vessel points are rejected by resorting to a hypothesis-verification based procedure. The major contribution of this work is that we formulate the step of seed point connection in the form of graph-theoretical shortest path problem. The Graph based approach works as follows: it starts from root pixel and follows the adjacent pixels in the line image. When a split is encountered, a local look ahead is done to inspect the directional change of the segments. If they fit the crossover profile, the split is treated as a crossover; otherwise, it is a bifurcation and the tracer will follow both paths. It is greedy because unless a crossover is identified, it will add all the connected pixels to the same vessel. Based on crossover points we can identify the CRAE and CRVE measurements in true blood vessels to predict the cardiovascular diseases with right identification.

II. RELATED WORK

In [1] T.Y.Wong, F. M. A. Islam,R.Klein,B. E.K.Klein,M. F.Cotch,C.Castro, A. R. Sharrett, and E. Shahar . A cross-sectional study comprising 5979 persons aged 45 to 84 years residing in six U.S. communities. Retinal vascular caliber was measured and summarized from digital retinal photographs. Standard cardiovascular risk factors, including biomarkers of inflammation (e.g., high-sensitivity C-reactive protein [hsCRP], interleukin [IL]-6, and plasma fibrinogen) and endothelial dysfunction (e.g., soluble intercellular adhesion molecule [sICAM]-1 [, plasminogen activator inhibitor [PAI]-1) were assessed.

In [3] C. Y.-L. Cheung, Y. Zheng,W. Hsu, M. L. Lee, Q. P. Lau, P. Mitchell, J. J. Wang, R. Klein, and T. Y. Wong. Retinal arteriolar and venular (vascular) tortuosity were quantitatively measured from fundus images using a computer-assisted program. Retinal vascular tortuosity was defined as the integral of the curvature square along the path of the vessel, normalized by the total path length. Data on blood pressure and major cardiovascular disease (CVD) risk factors were collected from all participants.

In [4] C. Y.-L. Cheung, W. T. Tay, P. Mitchell, J. J. Wang, W. Hsu, M. L. Lee, Q. P. Lau, A. L. Zhu, R. Klein, S. M. Saw, and T. Y. Wong. Retinal photographs from the Singapore Malay Eye Study, a population-based cross-sectional study of 3280 (78.7% response) persons aged 40-80 years, were analyzed. Quantitative changes in the retinal vasculature (branching angle, vascular tortuosity, fractal dimension, and vascular caliber) were measured using a semi-automated computer-based program. Qualitative signs, including focal arteriolar narrowing (FAN), arteriovenous nicking (AVN), opacification of the arteriolar wall (OAW), and retinopathy (e.g., microaneurysms, retinal hemorrhages), were assessed from photographs by trained technicians. After excluding persons with diabetes and ungradable photographs, 1913 persons provided data for this analysis.

III . SUPPORT VECTOR MACHINE (SVM)

Support Vector Machines are based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between a set of objects having different class memberships. A schematic example is shown in the illustration below. In this example, the objects belong either to class GREEN or RED. The separating line defines a boundary on the right side of which all objects are GREEN and to the left of which all objects are RED. Any new object falling to the right is labeled, i.e., classified, as GREEN.

The above is a classic example of a linear classifier, i.e., a classifier that separates a set of objects into their respective groups with a line. Most classification tasks, however, are not that simple, and often more complex structures are needed in order to make an optimal separation, i.e., correctly classify new objects on the basis of the examples that are available. This situation is depicted in the illustration below. Compared to the previous schematic, it is clear that a full separation of the GREEN and RED objects would require a curve. Classification tasks based on drawing separating lines to distinguish between objects of different class memberships are known as hyperplane classifiers. Support Vector Machines are particularly suited to handle such tasks.

Advantages:

1. By introducing the kernel, SVMs gain flexibility in the choice of the form of the threshold separatingsolvent from insolvent companies, which needs not be linear and even needs not have the same functionalform for all data, since its function is non-parametric and operates locally.
2. As a consequence theycan work with financial ratios, which show a non-monotone relation tothe score and to the probabilityof default, or which are non-linearly dependent and this without needing any specific work on eachnon-monotone variable.

Disadvantage:

1. SVMs cannot represent the score of all companies as a simple parametric function of the financialratios, since its dimension may be very high.
2. It is neither a linear combination of single financial ratios nor has it another simple functional form. The weights of the financial ratios are not constant.

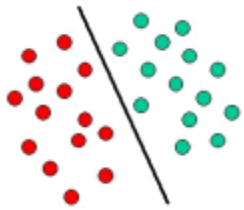

Figure 1: Example of SVM

IV . EXTREME LEARNING MACHINE (ELM)

ELM works for the generalized single hidden layer feed forward networks but the hidden layer in ELM need not be tuned. Such SLFNs include but are not limited to support vector machine, polynomial network, RBF networks and the conventional feed forward neural networks. Different from the tenet in neural networks that all the hidden nodes in SLFNs need to ne tuned, ELM learning theory shows that the hidden nodes/ neurons of generalized feed forward networks needn't be tuned and these the hidden nodes/ neurons of generalized feed forward networks needn't be tuned and these hidden nodes/ neurons of generalized feed forward networks needn't be tuned and these hidden nodes/ neurons can be randomly generated. All the hidden node parameters are independent from the target functions or the training datasets. ELM theories conjecture that this randomness may be true to biological learning in animal brains. Although in theory all the parameters

of ELMs can be analytically determined instead of being tuned, for the sake of efficiency, in real applications the output weights of ELMs may be determined in different ways.

Advantages:

1. Ease of use, Faster Learning Speed
2. Higher generalization performance suitable for many nonlinear activation function and kernel functions.

Disadvantages:

1. Usually different learning algorithms used in different SLFNs architectures.
2. Some parameters have to be tuned manually.
3. Over fitting.

V. LINEAR DISCRIMINANT ANALYSIS (LDA)

Linear Discriminant Analysis (LDA) is a classification method originally developed in 1936 by R. A. Fisher. It is simple, mathematically robust and often produces models whose accuracy is as good as more complex methods. Linear discriminant analysis (LDA) and the related Fisher's linear discriminant are methods used in statistics, pattern recognition and machine learning to find a linear combination of features which characterizes or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier, or, more commonly, for dimensionality reduction before later classification.

LDA is closely related to ANOVA (analysis of variance) and regression analysis, which also attempt to express one dependent variable as a linear combination of other features or measurements. However, ANOVA uses categorical independent variables and a continuous dependent variable, whereas discriminant analysis has continuous independent variables and a categorical dependent variable. Logistic regression and probit regression are more similar to LDA, as they also explain a categorical variable by the values of continuous independent variables. These other methods are preferable in applications where it is not reasonable to assume that the independent variables are normally distributed, which is a fundamental assumption of the LDA method.

LDA is also closely related to principal component analysis (PCA) and factor analysis in that they both look for linear combinations of variables which best explain the data. LDA explicitly attempts to model the difference between the classes of data. PCA on the other hand does not take into account any difference in class, and factor analysis builds the feature combinations based on differences rather than similarities. Discriminant analysis is also different from factor analysis in that it is not an interdependence technique: a distinction between independent variables and dependent variables (also called criterion variables) must be made.

LDA works when the measurements made on independent variables for each observation are continuous quantities. When dealing with categorical independent variables, the equivalent technique is discriminant correspondence analysis.

Advantages:

1. Multiple dependent variables
2. Reduced error rates
3. Easier interpretation of Between-group Differences: each discriminant function measures something unique and different.

Disadvantages:

1. Interpretation of the discriminant functions: mystical like identifying factors in a factor analysis
2. Each discriminant function formed is distributed normally in each group being compared.
3. Each discriminant function is assumed to show approximately equal variances in each group.

VI. ARTERY/VEIN CLASSIFICATION USING GRAPH BASED APPROACH

The goal of blood vessel tracking is to find and stores all vessels, and each vessel will be labeled with a number. Identification and measurement of blood vessels in retinal images could allow quantitative evaluation of clinical features, which may allow early diagnosis and effective monitoring of therapies in retinopathy. A new system is proposed for the automatic extraction of the vascular structure in retinal images, based on a Graph based approach algorithm. After processing pixels on a grid of rows and columns to determine a set of starting points (seeds), the tracking procedure starts. It moves along the vessel by analyzing subsequent vessel cross sections (lines perpendicular to the vessel direction), and extracting the vessel center, caliber and direction. Vessel structures such as retinal vasculature are important features for computer-aided diagnosis. In this project, a probabilistic tracking method is proposed to detect blood vessels in retinal images. During the tracking process, vessel edge points are detected iteratively using local grey level statistics and vessel's continuity properties.

Tracking begins with the located starting, together with initial estimates for the Gaussian model coefficients. The algorithm compares the model to a cross-sectional intensity profile through the image, local to each candidate vessel point, from this a new set of model coefficients are computed. In practice the cross-sections are two-dimensional to improve the accuracy of the estimate. The algorithm then steps to the next candidate point based on the estimated orientation and width of the blood vessel. This process is carried out iteratively until some ending criterion is met. When tracking stops because of a critical area, e.g. low contrast, bifurcation or crossing, a "Tracing technique" module is run. It grows and analyzes crossovers around the critical points, allowing the exploration of the vessel structure beyond the critical areas. After tracking the vessels, identified segments are identified by optimal forest. Finally bifurcations and crossings are identified analyzing vessel end points with respect to the vessel structure. Numerical evaluation of the performances of the system compared to human expert is reported.

Advantages:

1. Efficient post processing step for tracking cross over points.
2. Advanced approach for vessel structure segmentation.
3. Measurements are correlated with hypertension, coronary heart disease, and stroke

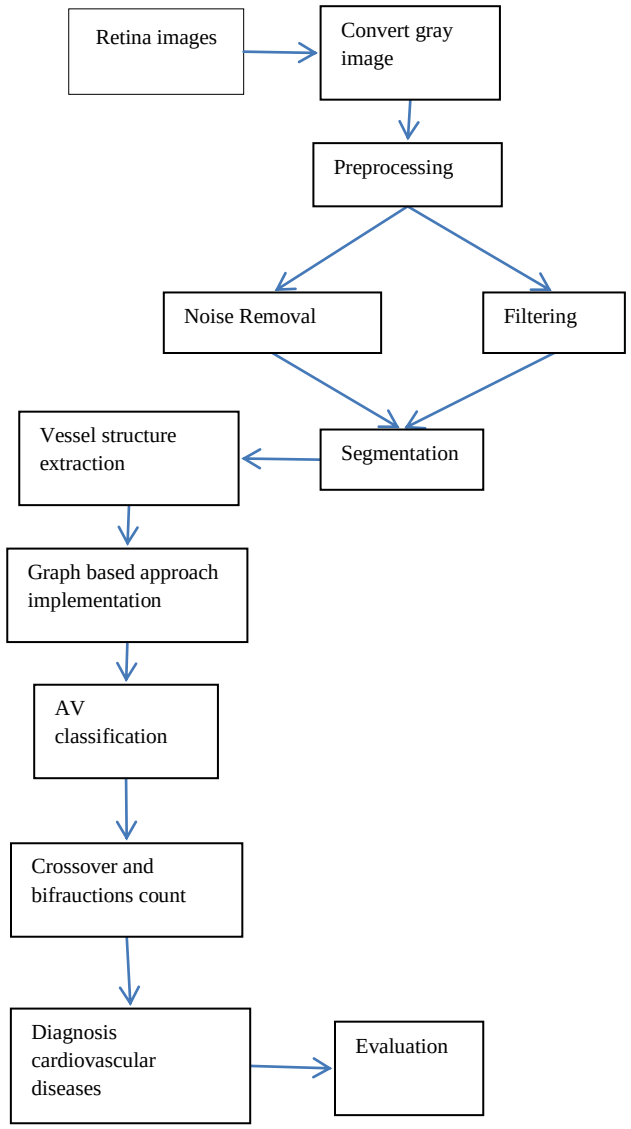

Figure 2: System architecture for proposed

VII. COMPARISON

In comparison between the SVM, LDA, ELM and the graph based proposed approach was compared to find which produce the good result.

Table 1: Fscore result comparison table

Methods	Fscore
SVM	54%
ELM	67%
LDA	34%
Proposed	89%

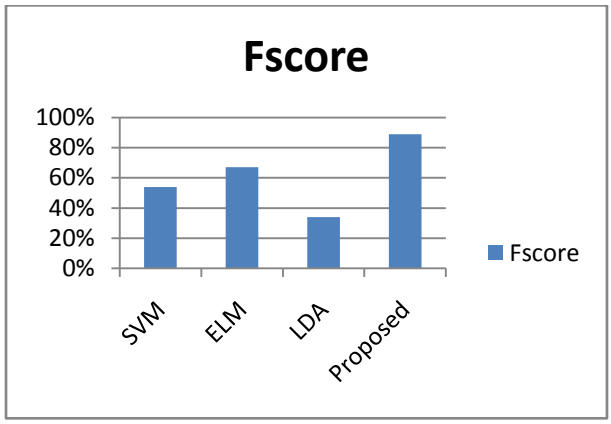

Figure 7: Fscore Comparison of algorithm

VIII. CONCLUSION

We conclude that, our proposed system implemented successfully with accurate identification of true vessels to obtain correct retinal ophthalmology measurements. And we implement the post processing step to vessel segmentation. This step is used to track all true vessels and find the optimal forest. We can overcome wrong diagnosis of crossovers by using simultaneous identification of blood vessels from retina. The final goal of the proposed method is to make easier the early detection of diseases related to the blood vessels of retina. Its main advantage is the full automation of the algorithm since it does not require any intervention by clinicians, which releases necessary resources (specialists) and reduces the consultation time; hence its use in primary care is facilitated. In future we extend new approach for the automatic detection of the optic disc. First, it is focused on the use of a new grey image as input obtained through LDA which combines the most significant information of the three RGB components. Secondly, several operations based on mathematical morphology are implemented with the aim of locating the OD. In future we extend new approach for the automatic detection of the optic disc. First, it is focused on the use of a new grey image as input obtained through LDA which combines the most significant information of the three RGB components. Secondly, several operations based on elliptic curve fitting methods are implemented with the aim of locating the OD.

References

[1] T.Y.Wong, F. M. A. Islam,R.Klein,B. E.K.Klein,M. F.Cotch,C.Castro, A. R. Sharrett, and E. Shahar, "Retinal vascular caliber, cardiovascular risk factors, and inflammation: The multi-ethnic study of atherosclerosis (MESA)," Invest Ophthalm. Vis. Sci., vol. 47, no. 6, pp. 2341–2350, 2006.

[2] K. McGeechan, G. Liew, P. Macaskill, L. Irwig, R. Klein, B. E. K. Klein, J. J. Wang, P. Mitchell, J. R. Vingerling, P. T. V. M. Dejong, J. C. M. Witteman,M.M. B. Breteler, J. Shaw, P. Zimmet, and T. Y.Wong, "Metaanalysis: Retinal vessel caliber and risk for coronary heart disease," Ann.Intern. Med., vol. 151, no. 6, pp. 404–413, 2009.

[3] C. Y.-L. Cheung, Y. Zheng,W. Hsu, M. L. Lee, Q. P. Lau, P. Mitchell, J. J. Wang, R. Klein, and T. Y. Wong, "Retinal vascular tortuosity, blood pressure, and cardiovascular risk factors," Ophthalmology, vol. 118, pp. 812– 818, 2011.

[4] C. Y.-L. Cheung, W. T. Tay, P. Mitchell, J. J. Wang, W. Hsu, M. L. Lee, Q. P. Lau, A. L. Zhu, R. Klein, S. M. Saw, and T. Y. Wong, "Quantitative and qualitative retinal microvascular characteristics and blood pressure," J. Hypertens, vol. 29, no. 7, pp. 1380–1391, 2011.

[5] Y. Tolias and S. Panas, "A fuzzy vessel tracking algorithm for retinal images based on fuzzy clustering," IEEE Trans. Med. Imag., vol. 17, no. 2, pp. 263–273, Apr. 1998.

[6] H. Li, W. Hsu, M. L. Lee, and T. Y. Wong, "Automatic grading of retinal vessel caliber," IEEE Trans. Biomed. Eng., vol. 52, no. 7, pp. 1352–1355, Jul. 2005.

[7] E. Grisan, A. Pesce, A. Giani, M. Foracchia, and A. Ruggeri, "A new tracking system for the robust extraction of retinal vessel structure," in Proc. IEEE Eng. Med. Biol. Soc., Sep. 2004, vol. 1, pp. 1620–1623.

[8] Y.Yin,M.Adel, M. Guillaume, and S. Bourennane, "Aprobabilistic based method for tracking vessels in retinal images," in Proc. IEEE Int. Conf.Image Process., Sep. 2010, pp. 4081–4084.

[9] M. Martinez-Perez, A. Highes, A. Stanton, S. Thorn, N. Chapman, A. Bharath, and K. Parker, "Retinal vascular tree morphology: A semiautomatic quantification," IEEE Trans. Biomed. Eng., vol. 49, no. 8, pp. 912–917, Aug. 2002.

[10] H. Azegrouz and E. Trucco, "Max-min central vein detection in retinal fundus images," in Proc. IEEE Int. Conf. Image Process., Oct. 2006, pp. 1925–1928.