CLASSIFICATION OF NORMAL AND ABNORMAL RETINAL IMAGES USING NEURAL NETWORKS

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***Abstract*—Measurements of retinal blood vessel morphology have been shown to be related to the risk of cardiovascular diseases. The wrong identification of vessels may result in a large variation of these measurements, leading to a wrong clinical diagnosis In this paper, address of the problem identifying true vessels as a post processing step to vascular structure classification. These model classified vascular structure as a vessel classify graph and formulate the problem of identifying vessels as one of finding the optimal forest in the graph given a set of constraints.**

***Index Terms*—Ophthalmology, optimal vessel forest, retinal image analysis, simultaneous vessel identification, vascular structure.**

I. INTRODUCTION

Image Processing is a technique to enhance raw images received from cameras/sensors placed on satellites, space probes and aircrafts or pictures taken in normal day-to-day life for various applications. Image processing involves changing the nature of an image in order to either improve its pictorial information for human interpretation and also for autonomous machine perception. Image processing involves using a computer to change the nature of a digital image. It is necessary to realize that these two aspects represent two separate but equally important aspects of image processing. The processing element is a computer. The output of the processing may be a display, created for the human visual system. RETINAL image[3] provides a snapshot of what is happening inside the human body. In particular, the state of the retinal vessels has been shown to reflect the cardiovascular condition of the body. Measurements to quantify retinal vascular structure and properties have shown to provide good diagnostic capabilities for the risk of cardiovascular diseases. For example, the central retinal artery equivalent (CRAE) and the central retinal vein equivalent (CRVE) are measurements of the diameters of the six largest arteries and veins in the retinal image, respectively.

II. FUNDUS IMAGE

The **fundus** of the eye is the interior surface of the eye, opposite the lens, and includes the retina, optic disc, macula and fovea, and posterior pole. The fundus can be examined by ophthalmoscope and/or fundus photography. The term fundus may also be inclusive of Bruch's membrane and the choroid. The color of the fundus varies both between and within species. The retina of the primates is blue, green, yellow, orange, and red; only the human fundus is red. The main abnormal features of diabetic retinopathy are exudates and blot hemorrhages. The detection of OD, blood vessels and exudates will be introduced. The eye's fundus is the only part of the human body where the microcirculation can be observed direct.

Figure 1.1 Fundus Image

III. CLASSIFICATION

Classification[1] is a key to analyze the numerical properties of various image features and organizes data into categories. Classification algorithms typically employ two phases of processing: training and testing. In the initial training phase, characteristic properties of typical image features

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are isolated and, based on these, a unique description of each classification category, i.e. training class, is created. In the subsequent testing phase, these feature-space partitions are used to classify image features. Classification[1] includes image sensors, image preprocessing, object detection, object segmentation, feature extraction[4] and object classification. Classification system[1] consists of database that contains predefined patterns that compares with detected object to classify in to proper category. Image classification is an important and challenging task in various application domains, including biomedical imaging, biometry, vehicle navigation, industrial visual inspection, robot navigation, and remote sensing.

Retinal images[2] are widely used by ophthalmologists and primary care physicians for screening of epidemic eye diseases, because they are direct and no harm. From the retinal image, an ophthalmologist can observe (detect) whether the patient has the eye diseases such as cataract, glaucoma, and diabetic retinopathy. At the same time, changes in the retinal vascular such as vessel width, tortuosity, and branching angle are important indicators for predicting hypertension and cardiovascular diseases. Based on the clearness degree of the retina image, ophthalmologist can find out the current condition of the patient and predict the visual acuity after phacoemulsification. Hence a careful analysis of such a data is hardly possible. In the medical context, the problem arises while making the medical decision when the state of the patient has to be assigned to the initially known class. In most of the cases, the boundaries between the different normal and abnormal classes are not straightforward which further add to the complexity. These classifications problems are specific in the case of ophthalmologic applications. In ophthalmology, eye fundus examinations are highly preferred for classifying the retinal images and follow-up of the development of the eye disease. But the problem of classification lies in the huge amount of examinations which has to be performed by the specialists to detect the normal and abnormal images. The blood vessels are extracted and the true vessels are identified using Kirsch Edge Detection and Graph Tracer in the existing system. From the identified true blood vessels, a system based on artificial neural network[2] is proposed to overcome the problem of retinal image classification. The classifier building procedure includes three parts: feature extraction, feature selection and classifier construction. According to the analysis of retinal image, the statistical and textural message of the image are extracted as classification features. The classifier is constructed by back propagation neural network[2] which has three layers. Based on the clearness degree of the retinal image, the retinal images are classified into normal and abnormal classes. The initial evaluation results have great potential to improve diagnosis efficiency of the ophthalmologist and reduce the physical and economic burden of the patients and society.

a) CLASSIFICATION OF RETINAL IMAGE FOR AUTOMATIC CATARACT DETECTION

Cataract is one of the most common diseases that might cause blindness. Previous research shows that cataract occupies almost 50% in severe visually impairments. Considering the fact that retinal image is one of the most important medical references that help to diagnose the cataract, this paper proposes to use a neural network[2] classifier for automatic cataract detection based on the classification of retinal images. The classifier building procedure includes three parts: preprocessing, feature extraction, and classifier construction. In the pre-processing part, an improved Top-bottom has transformation is proposed to enhance the contrast between the foreground and the object, and a trilateral filter is used to decrease the noise in the image. BP neutral network[3] classifier is proposed for the automatic cataract detection based on the retinal images classification. The classifying procedure mainly includes pre-processing, feature extraction and classification three parts. The pre-processing can improve the quality of the retinal image, and make it better for subsequent processes. Improved Top-bottom hat transformation and a trilateral filter is used to enhance the quality of the retinal image. Feature extraction is necessary before classification because it can discriminate different classes. Based on the experimental comparison, luminance and the texture message of the image is selected as the features for the classifier building. Finally, the neutral network classifier [3] is constructed. Based on the clearness degree of the retinal images, the patients' cataracts are classified into normal, mild, medium or severe ones. The method proved in this paper has great potential to improve the efficiency of the ophthalmologist to diagnose and reduce the physical and economic burden of the patients and society.

b) NEURAL COMPUTING BASED ABNORMALITY DETECTION IN RETINAL OPTICAL IMAGES

Automated eye disease identification systems facilitate the ophthalmologists in accurate diagnosis and treatment planning. In this paper, an automated system

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based on artificial neural network[2] is proposed for eye disease classification. Abnormal retinal images from four different classes namely non-proliferative diabetic retinopathy , Central retinal vein occlusion , Choroidal neo vascularisation membrane and central serous retinopathy are used in this work. A suitable feature set is extracted from the pre-processed images and fed to the classifier, Classification of the four eye diseases is performed using the supervised neural network namely back propagation neural network. Experimental results show promising results for the back propagation neural network as a disease classifier. The results are compared with the statistical classifier namely minimum distance classifier to justify the superior nature of neural network based classification.

c) FEATURE EXTRACTION

Feature Extraction[4] is a special form of dimentionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (e.g. the same measurement in both feet and meters) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.Feature extraction[4] involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which overfits the training sample and generalizes poorly to new samples. Feature extraction[4] is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. The features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

d) FEATURE SELECTION

Feature Selection[7] is the process of selecting a subset of relevant features for use in model construction. The central assumption when using a feature selection technique is that the datacontains many redundant or irrelevant features. Redundant features are those which provide no more information than the currently selected features, and irrelevant features provide no useful information in any context. Feature selection techniques are a subset of the more general field of feature extraction. Feature extraction [6]creates new features from functions of the original features, whereas feature selection returns a subset of the features. The main benefits of feature selection include improved model interpretability, shorter training times, enhanced generalization by reducing overfitting.
Feature selection[5] techniques are often used in domains where there are many features and comparatively few samples. A feature selection algorithm can be seen as the combination of a search technique for proposing new feature subsets, along with an evaluation measure which scores the different feature subsets. The simplest algorithm is to test each possible subset of features finding the one which minimizes the error rate. This is an exhaustive search of the space, and is computationally intractable for all but the smallest of feature sets.

e) BACK PROPAGATION NEURAL NETWORK

The selected features are fed into the constructed neural network[5] to train it to identify the seven universal facial expressions. The architecture is a 3-layer back propagation neural network. The back propagation algorithm [1] basically replicates its input to its output via a narrow conduit of hidden units. The hidden units extract regularities from the inputs because they are completely connected to the inputs. Every network was trained to give the maximum value of 1 for exact abnormal retinal image and 0 for normal retinal image. The input vectors of the network represented by $X = [x_1, x_2,...,x_l]^T$. The output layers are denoted by $Y = [y_1 , y_2,..., y_k]^T$. The optimization model is formulated as X:h --> Y. The output dataset of each layer of the network is denoted by $y^j_1 \ldots y^j_{k\_1}, y^j_k$), $j= 1, 2\ldots k -1, k$, where k -1 corresponds to the total hidden layers and k represents the total output layers. To denote the target datasets and its additive white noise by $(t^1, t^2,\ldots t^K)$ andg $= (e^1, e^2,..., e^K)$, respectively. The variable K represents the total patterns of the network. The corresponding vectors of the hidden units are denoted by $V = (v_1, v_2,..., v_{k\_1})$.The sigmoid activation function $h = (h_1, h_2,..., h_k)$ of each layer is $h_1, h_2,..., h_{k\_1}$. The weights of the network are updated by $w_1, w_2,..., w_k$. The training epochs are 1000 and the target of error is 0.001.The process of training [2] involves weight initialization, calculation of the activation unit, adjustment, weight adaptation, and testing for convergence of the network. Assuming v_{ji} represents the weight between the j^{th} hidden unit and i^{th} input unit; and w_{kj} represents the weight between the k^{th} output and the j^{th} hidden unit.

IV. GRAPH TRACER IMPLEMENTATION

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To identify vessels [7] and represent them in the form of binary trees for subsequent vessel measurements. It has two main steps: 1) identify crossovers, and 2) search for the optimal forest (set of vessel trees).The details of tracing algorithm, Graph Tracer[7]. The input is the segment graph GP with n root segments given in S_{root} . Initialize the global variables and call the recursive procedure Trace. F[1. .n] corresponds to the initial forest of n vessels. R[1. .n] denotes a fringe stack for each vessel. F_{min} and c_{min} record the minimum cost forest and its corresponding cost. In Trace, if F satisfies all constraints and cannot be grown further, update F_{min} if cost(F) < c_{min}. Otherwise, it may prune descendant forests grown from F with the lower bound $LB_{cost(F)}$. The outer loop orders each vessel T [1, n] for growth. T ranges from the current index i to n, ensuring that Trace does not enumerate duplicate forests. Each vessel's fringe stack, R[T], stores its current leaf nodes to be grown. R[T] is used in conjunction with the loop to enumerate vessels in a depth-first traversal order. A subprocedure FindChildren returns pairs (s_l, s_r) of possible children for the current fringe node s_T . If only one child is to be added, set s_r = 0. FindChildren eliminates many combinations using the constraints presented.

The blood vessels are extracted and the true vessels are identified using Kirsch Edge Detection and Graph Tracer in the existing system. From the identified true blood vessels, a system based on artificial neural network is proposed to overcome the problem of retinal image classification. The classifier building procedure includes three parts: feature extraction, feature selection and classifier construction. According to the analysis of retinal image, the statistical and textural message of the image are extracted as classification features. The classifier is constructed by back propagation neural network which has three layers. Based on the clearness degree of the retinal image, the retinal images are classified into normal and abnormal classes. The initial evaluation results have great potential to improve diagnosis efficiency of the ophthalmologist and reduce the physical and economic burden of the patients and society.Misclassification probability tends to increase with the number of features and classifier structure is more difficult to interpret. Feature selection tries to avoid these problems by choosing the subset of the extracted features that is most useful for a specific problem. Feature analysis for classification is based on the discriminatory power of features. Traditional feature selection methods are classifier-driven, they rely on the results that a particular classifier obtains for different subsets of features. On the other hand, classifier independent feature analysis is more adequate for medical image analysis. It gathers information concerning the structure of the data rather than the requirements for a particular classifier. Logistic Regression is a classifier-independent method commonly used for feature selection. It analyzes the relationship between a dichotomous dependent variable (the class of an object) and several independent variables (the extracted features)

V. EXPECTED RESULTS

The validation of the method has been carried out on a public database: DRIVE, HRF. From DRIVE database 25 images and from HRF database 15 images are used for the training process. In the existing system the blood vessels are extracted using Krisch Edge Detector and the true vessels are identified using Graph Tracer. From the identified true vessels, 23 features are extracted and 15 features are selected using Fast Correlation Based Filter to speed up the classification of normal and abnormal retinal images by Back Propagation Neural Network.

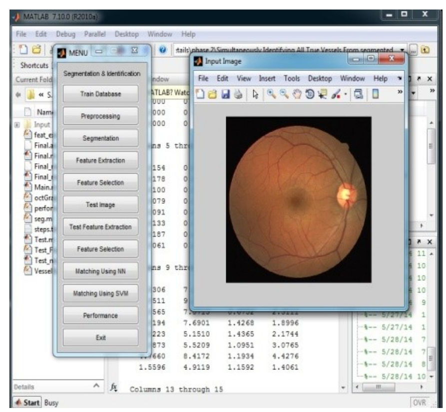

Figure 1.1 Input Image

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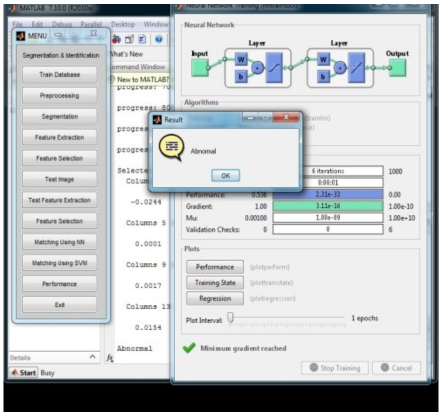

Figure 1.2 Back Propagation Neural network Classification

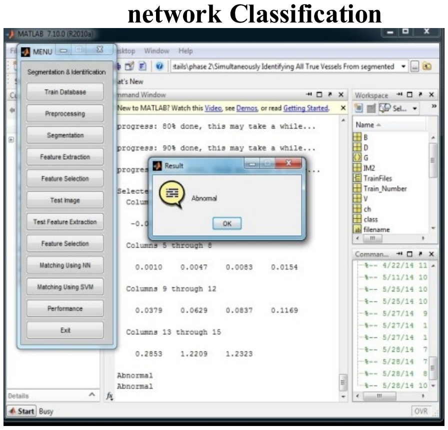

Figure 1.3 Support Vector Machine Classification

The performances of the BPN classification is compared with the Support Vector Machine. During the comparison the accuracy of BPN classification is higher(90%) than the SVM's accuracy(74%).

VI. CONCLUSION

The eye diseases mainly contribute to blindness and often cannot be remedied because the patients are diagnosed too late with the diseases. In this work, the neural network classifier is developed as an diagnostic tool to aid physician in the classification of normal and abnormal retinal images. It is based on the clearness degree of the retinal image. The classifier consists of feature extraction, feature selection and classification three parts. The images used for training is taken from the DRIVE and HRF database. The feature set consists of gray scale features, shape features and texture features. Totally 23 features are extracted from the true vessels which have been identified in the existing system. Then 15 features are selected and ranked using fast correlation filter inorder to speed up the BPN classification. The experimental results show that the BPN classifier is approximately more efficient than the SVM classifiers. The accuracy achieved depends on various factors such as the parameters used and the feature set.

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