ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

An ISO 3297: 2007 Certified Organization
Vol. 5, Special Issue 4, March 2016

National Conference on Signal Processing, Instrumentation and Communication Engineering (SPICE' 16)

Organized by

Dept. of ECE, Mar Baselios Institute of Technology & Science (MBITS), Kothamangalam, Kerala-686693, India

A Review on Retinal Vessel Segmentation Using Supervised Classifiers

Mini.V[1], Jinto Chacko [2]

PG Student [Applied Electronics], Dept. of ECE, Nehru College of Engineering, Pampady, Kerala, India[1]

Asst. Professor, Dept. of ECE, Nehru College of Engineering, Pampady, Thrissur, Kerala, India [2]

ABSTRACT: In this paper various supervised classification techniques for retinal vessel segmentation is discussed. The segmentation of blood vessels in retinal images support early detection, diagnosis and for better treatment. By analysis of retinal images leads to decrease in complication levels. The relationship between changes in retinal vessels and the onset, gives detection of different systematic diseases such as Hypertension, Stroke, Diabetes, Arteriosclerosis, and Cardiovascular diseases and retinal diseases like Glaucoma, Cataract, Retinitis pigmentosa, Macular pucker, Retinal detachment, Branch retinal vein occlusion(BRVO), Branch retinal artery occlusion(BRAO), Central retinal vein occlusion(CRVO), and Central retinal artery occlusion(CRAO).

KEYWORDS: Classification, Fundus, Vessel Segmentation

I. INTRODUCTION

Vessel segmentation in retinal images focus particularly for the detection of small vessels. Fundus image analysis is widely used in medical field for diagnosis of vascular and non-vascular diseases. The inspection of vasculature may reveal early signs of diabetes, hypertension, cardiovascular diseases, stroke, and other eye diseases. By enhancing retinal images and vessels in it, is an easy task with different clinical applications. In this paper gives a review on retinal vessel segmentation using different supervised classifiers for vessel segmentation. Images evaluated based on available database. As the green channel of retinal images present largest contrast between vessels and background. Retinal colour images convert into gray scale images, by keeping green channels discarding other channels. Vessels in retinal images appear darker than background and intensity of vessels higher than background. The review of retinal vessel segmentation using different supervised classifiers based on inverted gray scale images.

II. DATASETS

Fundus images in ophthalmology plays an important role in medical diagnosis. Retina is the only one blood circulation system that can measure directly. By the analysis of retinal vasculature structure early detection, diagnosis and treatment is possible. Retinal images are available as three public datasets, DRIVE, STARE and VAMPIRE. Different supervised classifiers are used for segmentation with the analysis of images in three datasets [1]-[5].

DRIVE (Digital Retinal Images for Vessel Extraction) consists of a total of 40 colour retinal images, obtained in the course of a diabetic retinopathy screening program in the Netherlands. The images were acquired using a Canon CR5 non-mydriatic 3-CCD camera (Canon, Tokyo, Japan) with a 45 degree field of view. Each image resolution is 768×584 pixels. The set of 40 images was divided into a test and a training set, each containing 20 images.

STARE (Structured Analysis of the Retina) contains 20 colour retinal images, 10 of which show evidence of pathology. The digitized slides were captured by a TopCon TRV-50 fundus camera (Topcon, Tokyo, Japan), and the photos were digitized to 605×700 pixels.

VAMPIRE comprises eight ultra-wide field of view retinal angiographic images acquired with an OPTOS P200C camera (Optos PLC, Dunfermline, UK). Four of the images are from an AMD retina, while the other four are from a healthy retina. Each image has a size of 3900×3072 pixels.

DRIVE and STARE datasets are available easily but VAMPIRE is not available because they having angiographic images.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

An ISO 3297: 2007 Certified Organization Vol. 5, Special Issue 4, March 2016

National Conference on Signal Processing, Instrumentation and Communication Engineering (SPICE' 16)

Organized by

Dept. of ECE, Mar Baselios Institute of Technology & Science (MBITS), Kothamangalam, Kerala-686693, India

III. SUPERVISED CLASSIFIERS

AdaBoost **is** a machine learning meta-algorithm. They can be used in conjunction with many other types of learning algorithms to improve their performance. The output of the other learning algorithms ('weak learners') is combined into a weighted sum that represents the final output of the boosted classifier. AdaBoost is adaptive in the sense that subsequent weak learners are tweaked in favour of those instances misclassified by previous classifiers. AdaBoost is sensitive to noisy data and outliers. In some problems, however, it can be less susceptible to the over fitting problem than other learning algorithms. The individual learners can be weak, but as long as the performance of each one is slightly better than random guessing. The final strong classifier is a weighted combination of weak classifiers. A threshold is applied to the output to decide class [4].

K-Nearest Neighbours algorithm (k-NN) is a non-parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression. In k-NN classification, the output is a class membership. An object is classified by a majority vote of its neighbours, with the object being assigned to the class most common among its k nearest neighbours (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbour. K-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The k-NN algorithm is among the simplest of all machine learning algorithms. Both for classification and regression, it can be useful to assign weight to the contributions of the neighbours, so that the nearer neighbours contribute more to the average than the more distant ones...A shortcoming of the k-NN algorithm is that it is sensitive to the local structure of the data. The algorithm has nothing to do with and is not to be confused with k-means, another popular machine learning technique [1].

Conditional Random Fields (CRF) is mainly used to reduce energy minimization problem in segmentation. CRFs are essentially a way of combining the advantages of discriminative classification and graphical modelling. Images are mapped into graphs; each pixel considered as a node, nodes are connected to edges of the neighbours. By connecting through neighbour pixel improves accuracy. CRFs widely used in applications like text processing, bio informatics, and computer vision. Early applications of CRFs used linear chains; recent applications of CRFs have also used graphical structures [5].

Support Vector Machine (SVM) is based on the concept of decision planes that defines decision boundaries. A decision plane is one that separates between a set of objects having different class membership. In the case of a linear classifier uses separating line between two classes, any new object falling either to one class. Most classification tasks are not simple; more complex structures are needed in order to make optimal separation. SVM Classify new objects (test cases) on the basis of the example that are available (train cases).SVM is a classifier method that perform classification tasks by constructing hyper planes in a multidimensional space that separates cases of different class labels. The process of rearranging objects is known as mapping. Original objects mapped, rearranged using a set of mathematical function known as kernels.SVM support both regression and classification tasks [3].

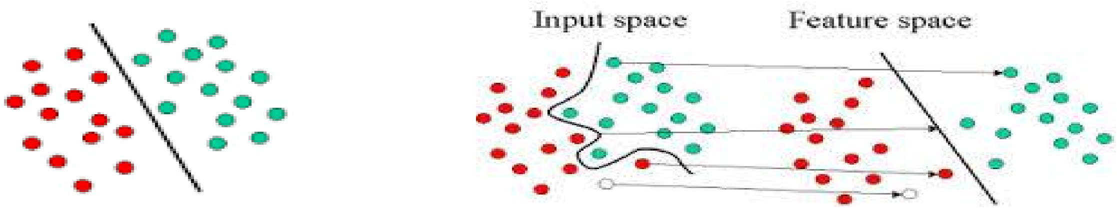

Fig 1. (a) Linear Classifier and (b) Hyper plane Classifier

Artificial Neural Network (ANN) Neural network have received much attention for their successful application in pattern recognition. Once a neural network has been configured, it forms an appropriate internal feature extractors and classifiers based on training examples. Neural networks consist of a set of interconnected neurons which operates together to perform a particular task. Each neuron is associated with its weight. In training phase, network uses training set to update weights of its neuron in order to reduce network error. After the training phase, trained network is used for classification. The representation internally distributed across the network as a series of independent weights has many advantages: noise immunity, pattern generalization and interpolation capability [2].

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

An ISO 3297: 2007 Certified Organization Vol. 5, Special Issue 4, March 2016

National Conference on Signal Processing, Instrumentation and Communication Engineering (SPICE' 16)

Organized by

Dept. of ECE, Mar Baselios Institute of Technology & Science (MBITS), Kothamangalam, Kerala-686693, India

An ANN is created by combining artificial neurons into a structure containing three layers. The first layer consists of neurons that are responsible for a face image sample. The second layer is a hidden layer which allows an ANN to perform the error reduction necessary to successfully achieve the desired output. The final layer is the output layer wherein the number of neurons in this layer is determined by the size of the set of desired outputs, with each possible output being represented by a separate neuron. Any network must be trained in order to perform a particular task.

In training process, training data set is presented to the network and network's weights are updated in order to minimize errors in the output of the network. Back propagation neural network uses back propagation algorithm for training the network. The principal advantages of Back propagation are simplicity and reasonable speed. The feed-forward path is trained using the standard back propagation algorithm, until the feed-forward path is trained. The feedback path must be taught to produce different signals depending on the initial output from the feed-forward algorithm. The feedback signals will vary depending on the stability of the sample input. The training of the feedback path is conducted using a set of pairs consist of two face images. The use of these pairs facilitates the adjustment of the weights in the feedback path. The training phase is complete as soon as the feed-forward and feedback paths both have been trained.

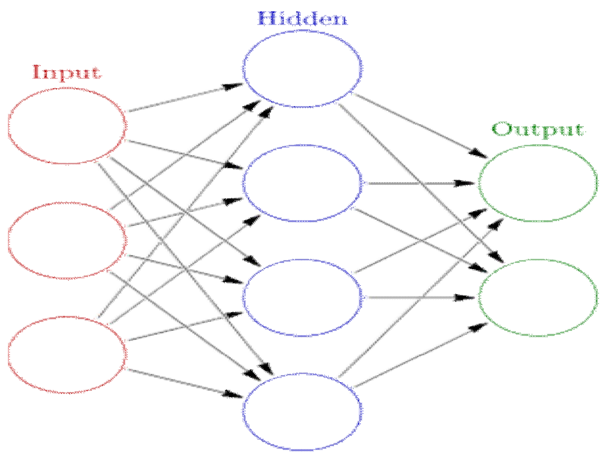

Fig 2. Structure of Artificial Neural Network

IV. EXPERIMENTAL EVALUATION

FABC is a method for automated segmentation in retinal images by classifying pixels as vessel or non vessel. DRIVE dataset images are used, 20 images for training and 20 other for testing. In all images789914 pixel samples are chosen to train classifier. ROC curves are represented by plotting true positive fractions versus false positive fractions.TPF is called sensitivity, i.e. dividing number of pixels correctly classified as vessel pixel by total number of vessel pixel in the segmentation. The area under ROC curve (A_z) measures ability to classify vessel and non vessel. The accuracy (Acc) is the fraction of pixels correctly classified at specific threshold and observer agreement taken as kappa. The classification performance of FABC better than comparison methods [4]. FABC depends upon shape and structural information. The drawback of method is do not consider broken vessels and bend multiple vessels, and computation time is more.

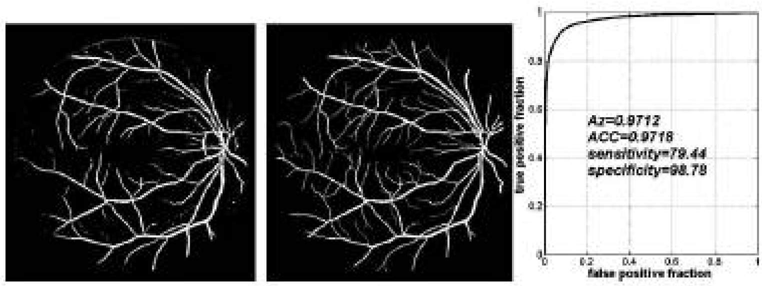

Fig 3. (a) FABC Segmentation (b) Gold standard segmentation and (c) ROC curve

KNN classifiers available by K neighbours of which n are labelled as vessel the posterior probability for part of vessel is approximated as

$$P\text{ (vessel)} = n / k$$

Area under the curve (A_z) which is a single measure to quantify behaviour of the system, 1 for perfect system. The random classification in system make straight line through origin with slope 1 and A_z=0.5 in ROC curve. Convex set of features, a part of vessel can verify from non - vessels by their local appearance. The profile information is collected by sampling every point K in a convex set from green plane of image. All the experiments for PBM calculated by extracting ridges. Paired-t-tests on the A_z values for images shows PBM better than rule based methods [1]. By selecting features for convex set regions, extracting features for area under ROC curve for different rule based model and accuracy calculated for rule based method, PBM method. Accuracy of PBM is better than any other method. Mainly two types of errors occur over and under segmentation of vessels and missing or erroneous detection of vessel branches. PBM takes around 15 minutes for segmentation, most of the time spent for classification. KNN classifiers are sensitive to scaling between different features, in all experiments, each feature is normalised independently to zero mean and unit variance.

Table I. Accuracy and Area under ROC curve values for different methods

Criterion	Method	Database	
		Utrecht	Hoover
A_z	Hoover		0.7590
	Jiang	0.9327	0.9298
	PBM	0.9520	0.9614
Accuracy	2nd obs.	0.9473	0.9351
	Hoover		0.9275
	Jiang	0.8911	0.9009
	PBM	0.9441	0.9516
	Most likely class	0.8727	0.8958

The reduction of energy in segmentation with the help of fully connected conditional random fields. Fully connected CRFs each node is assumed to be a neighbour of every other and model take into accounts not only neighbouring information but also long term interaction between pixels, so process is expensive. The evaluation process carried out in terms of sensitivity (Se) and Specificity (Sp) and three stages of evaluation is done with help of ground truth labelling, human observer labelling and CRF segmentation [5]. Fully connected CRF segmentation achieves best results. CRFs having poor performance in the presence of thin branching structures, sensitivity reflects estimation of vessel pixels in fundus image analysis.

Support vector machine uses radial projection and semi supervised self training method. Radial projection to detect narrow blood vessels with low contrast. The projected curve of pixel displays prominent peaks, to distinguish between vessels and background. The performance evaluation with accuracy, sensitivity and specificity. The detection of thin and wide vessels, thin vessel segments contain few pixel which contribute a little to sensitivity but crucial in accurate analysis of retinopathy. The main disadvantage is some pathological regions, optic disc border; several spots are still falsely detected as vessels [3]. Some of narrow vessels are over estimated due to noise to overcome choosing new features to differentiate between vessels and abnormal tissue, noisy spots removed radial suppression method.

Artificial neural network employed in the area of medicine and eye fundus analysis. ANN is widely used in retinopathy but minimal pre-processing, so the small blood vessels are difficult to detect. By finding accuracy exact position of vessels and edges detected. The active contour models avoid confusion between edges and haemorrhages. Main regions of fundus image detect once data from these regions analysed for abnormality [2]. This algorithm used to reduce risk, particularly for disease progression stages. Neural network can be used for analysis of fundus images and any number of diseases can detect, stages of diseases can be detected.

V. CONCLUSION

Retinal vessel segmentation plays an important role in medical image analysis. For vessel segmentation different rule based methods and supervised classifiers are used. The primary objective to detect vessel and non vessel pixels, edges and ridge. The evaluation process is based on the selected features. In supervised segmentation process artificial neural

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

An ISO 3297: 2007 Certified Organization Vol. 5, Special Issue 4, March 2016

National Conference on Signal Processing, Instrumentation and Communication Engineering (SPICE' 16)

Organized by

Dept. of ECE, Mar Baselios Institute of Technology & Science (MBITS), Kothamangalam, Kerala-686693, India

network is used to reduce level of risk, number of diseases and stages of diseases are detected. Major limitation of supervised method always needs a help of an operator throughout the process.

REFERENCES

[1] Joes Staal, Michael D Abramoff, Meindert Niemeijer, Max A Viergever and Bram van Ginneken, "Ridge Based Vessel Segmentation in Color Images of the Retina" , IEEE Transactions On Medical Imaging, vol. 23, no. 4, April 2004.

[2] Chanjira Sinthanayothin, James F Boyce, Helen L Cook, and Thomas H Williamson, "Automated localization of the optic disc,fovea and retinal blood vessels from digital color fundus images" , Br J Ophthalmol, vol. 83, pp. 902-910, December 2012.

[3] Elisa Ricci and Renzo Perfetti, "Retinal Blood Vessel Segmentation Using Line Operators and Support Vector Classification", IEEE Transactions on Medical Imaging, vol.26, no.10, October 2007.

[4] C.Lupascu, D.Tegolo and E.Trucco, "FABC: Retinal Vessel Segmentation using AdaBoost", IEEE Transactions on Information Technology in Biomedicine, vol. 14, no.5, September 2010.

[5] J.Orlando and M.Blaschko, "Learning fully connected CRFs for blood vessel segmentation in retinal images", Med. Image Comput.Comput.Assist.Interv., 2014, pp. 634-641.