

Research Article

Support Vector Machine Based Pades Approximant for Diabetic Retinal Eye Detection

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Abstract: Diabetic Retina (DR), a problem of formation of blood clot must be diagnosed at an early stage for laser therapy. A number of automated diagnosis methods based on image segmentation of fundus image is present which can diagnose DR at late mild proliferative stage. Proposed work is aimed to detect DR at early mild proliferative stage. Method uses feature extraction of fundus image using 2D Gabor filtering and pre-classification for feature vector extraction using Pades approximation. The Padesvector are then again classified using SVM by forming a dual of convex quadratic type minimization problem for linearly separable hyper plane. The performance of the proposed work is tested with set of images taken from fundus camera.

Keywords: Diabetic Retina (DR), lagrangians multiplier, pades approximation, Support Vector Machines (SVM)

INTRODUCTION

Diabetic eye disease refers to a group of eye problems that people with diabetes may face as a complication of diabetes. All can cause severe vision loss or even blindness. Diabetic eye disease may include:

- **Diabetic retinopathy:** Damage to the blood vessels in the retina.
- **Cataract:** Clouding of the eye's lens. Cataracts develop at an earlier age in people with diabetes.
- **Glaucoma:** Increase in fluid pressure inside the eye that leads to optic nerve damage and loss of vision. A person with diabetes is nearly twice as likely to get glaucoma as other adults. A diabetic retinal eye in chronic case is shown in Fig. 1.

The retinal images can be obtained from a fundus camera or a 3-D microscopic camera. Jian *et al.* (2009) performed segmentation followed by density based clustering to obtain the image artifacts of the images. Method of Union of Balls or (alpha shape) algorithm was performed to reconstruct the boundary of clots in 2D to estimate and project the size of the clot. The stacks of 2-D images were processed to form a 3D map of the clot. Mona *et al.* (2008) used the macular Optical Coherence Tomography (OCT) technique and enhanced it by providing an automated approach for segmenting (3-D) macular OCT scans into five layers which were identified on the 3D composite image by transforming the segmentation task into that of finding a minimum cost closed set in a geometric graph constructed from edge/regional information and a priori determined



Fig. 1: Fundus camera image of diabetic retinal eyes in chronic stages

surface smoothness and interaction constraints. Gabor wavelet based retinal segmentation was performed (Selvathi and Lalitha, 2011), where the process had preprocessing of the retinal fundus images, followed by green channel or RGB extraction and inversion and thereafter applying Gabor transform which gave the significant information about the image. Pixel based segmentation based on vessel classification was performed using Kernel classifiers to conclude the extent of the damage or the clot in the retinal blood vessels.

Texture based segmentation (Alauddin *et al.*, 2007) was performed to overcome the problem of variation in local contrast especially in case of minor vessels. Gaussians and L*a*b perceptually uniform color spaces with original RGB for texture extraction was used. A bank of Gabor Energy filters were used to analyze the texture feature. Fuzzy C means clustering was used for the classification of feature vector into vessel or non-vessel components. Sensitivities of 84.37% and specificity of 99.61% was obtained. An ensemble classification based approach (Muhammad *et al.*, 2012) was performed on the retinal blood vessels. The ensemble system of bagged and boosted decision trees

utilized the feature vector based on the orientation analysis of gradient vector field, morphological transformation, line strength measures and the Gabor filter responses followed by Quantifiable measurement for each pixel was done in such a way that the 9D feature vector differentiates the blood vessels and the bright and dark lesions. Diego *et al.* (2011) used the method of NN scheme (Neural Network) for pixel classification and computed the 7-D vector composed of gray level and moment invariants based features for pixel representation. Ding *et al.* (2011) applied the retinal image segmentation using Fuzzy clustering in combination with morphological filters. Giri *et al.* (2008) performed the retinal blood vessel segmentation using spatially weighted Fuzzy C Means (FCM) clustering and Histogram Matching which enhanced blood vessel contrast and differentiation. Semi-automated framework (Carmen and Domenico, 2012) was used for minimal path tracking in the skeletal of the available segmented vessels and using an undirected graph for significant edge detection. Dijkstras and Floyd-Warshall algorithms were applied for the detection of the minimal paths within graph giving accurate vertex connectivity of segmented blood vessels. Fast multi scale algorithm using a recursive coarsening in segmentation was proposed by Sharon *et al.* (2000). Method of global impression extraction for dissimilar blood vessel extraction was proposed by Shi and Malik (2000). A dynamic region merging based segmentation for DR was suggested by Peng *et al.* (2011).

The existing methodologies focus on detection of DR at late mild proliferative stage. The proposed work focus on detection of DR at early mild proliferative stage. The fundus images are preprocessed and 2D Gabor filtering is done to form a feature vector. The feature vector is applied to a pre classifier based on Pades approximant. A final classification is done using a Support Vector Machine classification for discrimination of retinal blood vessels with larger diameter than normal for early mild proliferative stage.

MATERIALS AND METHODS

The diabetic retinal eye detection proposed here has the following steps as shown in the Fig. 2.

Feature extraction is a method of capturing visual content of images for indexing and retrieval. Visual features could be primitive or low level based on the extent of feature to be retrieved. Domain specific feature extraction like color, texture and shape are used for the extraction of features for the retinal image feature extraction. Ophthalmologists use features such as size edge strength shape and texture for the exudate detection. The feature extraction should be in such a way that the distances between the proximity classes should be maximum and the farther classes with higher distance between the features should be minimum. The

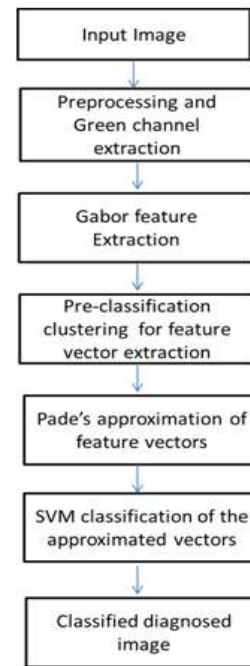


Fig. 2: Method of early diagnosis of diabetic retina using SVM

retinal image feature extraction should carry enough information about the retinal vessels and skeletons to distinguish between the retinal vessel features and the surrounding areas of the eyes. Because of perception subjectivity, there exists a single best representation for a feature. The retinal image feature extraction takes into account the global features like moment invariant, Aspect ratio and circularity as well as the local features like boundary segments.

A Gabor filter is a linear filter and is broadly used for multi-scale and multi directional edge therefore acts as a low level feature extraction and background noise suppressor. The decomposition of an image can be performed by using a Gaussian windowed Fourier transform. Gabor function in its generalized form can be given as:

$$G(x, y) = \frac{1}{2\pi\sigma\beta} e^{-\pi \left[\frac{(x-x_0)^2}{\sigma^2} + \frac{(y-y_0)^2}{\beta^2} \right]} e^{i[\xi_0 x + v_0 y]} \quad (1)$$

where, (x_0, y_0) is the center of the respective field in the spatial domain and (ξ_0, v_0) is the optimal spatial frequency of the filter in the frequency domain. σ and β are the standard deviations of the elliptical Gaussian along x and y.

In other form Gabor filter can be represented as complex sinusoidal signal modulated by a Gaussian function (window). A 2D Gabor filter can also be formulated as:

$$G(x, y; \sigma, \lambda, \theta_k) = G(x, y; \sigma) \exp\left(\frac{2\pi x \theta_k i}{\lambda}\right) \quad (2)$$

or can be represented as:

$$G(x, y; \sigma) = \exp\left(\frac{-x_{\theta_k}^2 + \gamma^2 y_{\theta_k}^2}{2\sigma^2}\right) \quad (3)$$

where,

$$x_{\theta_k} = x \cos(\theta_k) + y \sin(\theta_k)$$

and

$$y_{\theta_k} = -x \sin(\theta_k) + y \cos(\theta_k)$$

θ_k is the orientation angle of the filter and the γ is spatial aspect ratio. A feature vector is formed from the 2D Gabor filter.

The observation of a feature extraction could be taken in the form of a linear vector with $1 \times l$ size. Let y_i be a set of associated truths given by a trusted source while the process of learning takes place. Let x_i be a vector of pixel values and y_i would be 1 if the image contains a retinal blood vessel or associated skeleton or the clot formation and otherwise let the value be -1 if other components are encountered (Alireza *et al.*, 2002). Let us assume that there exist a Probability Density Function (PDF) $P(x, y)$ from which the data's are driven. The probability density function allows the distribution of y for a given x . In this the trusted source would assign label y_i according to the fixed distribution conditional on x_i . Considering a machine whose task is to learn the retinal blood vessels such that $x_i \rightarrow y_i$. The machine is defined and trained for a set of retinal images defined by $x \rightarrow f(x, \alpha)$ where the function $f(x, \alpha)$ are labeled as the adjustable parameters α . The machine is assumed to be deterministic for a given value of x and choice α it will always give the same output $f(x, \alpha)$. The function $f(x, \alpha)$ could be approximated into a rational function using a Pades approximation for a concise detection of the blood vessels. The approximants power series is made to agree with the power series of the function it is approximating.

Assuming the function to be approximated for m^{th} order in the numerator and n^{th} order in the denominator. The Pade approximant of order (m/n) in the rational form is given as:

$$R(x) = \frac{\sum_{j=0}^m a_j x^j}{1 + \sum_{k=1}^n b_k x^k} \quad (4)$$

Which agrees with $f(x, \alpha)$ to the highest possible order which results in:

$$f\{x(0), \alpha(0)\} = R(0) \quad (5)$$

$$f'\{x(0), \alpha(0)\} = R'(0) \quad (6)$$

$$f''\{x(0), \alpha(0)\} = R''(0) \quad (7)$$

$$f^{(m+n)}\{x(0), \alpha(0)\} = R^{(m+n)}(0) \quad (8)$$

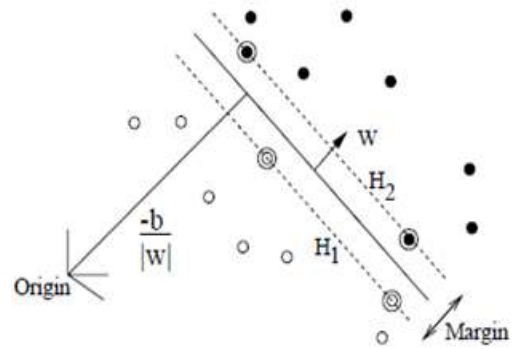


Fig. 3: Linear separable hyper-planes for the separable cases with margin and the distance from the origin

The particular value of α generates a trained machine. The expectation of the error (Simon *et al.*, 2010) for the trained machine is defined as:

$$R(\alpha) = \int \frac{1}{2} |y - f^{(m+n)}(x, \alpha)| dP(x, y) \quad (9)$$

The quantity $R(\alpha)$ is called the expected risk. Another parameter which can be is the empirical risk which gives the mean error for a set of observations:

$$R_{emp}(\alpha) = \frac{1}{2l} \sum_{i=1}^l |y_i - f^{(m+n)}(x_i, \alpha)| \quad (10)$$

The quantity $\frac{1}{2} |y_i - f^{(m+n)}(x, \alpha)|$ is defined as loss.

For linearly separable cases the support vector algorithm looks for the hyper-plane separating the two regions with maximum margins. The formulation could be done as given below. Assuming the training data to satisfy the following constraints:

$$x_i \cdot w + b \geq +1 \text{ for } y_i = +1 \quad (11)$$


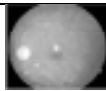

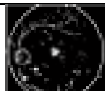

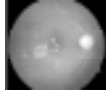






$$x_i \cdot w + b \leq -1 \text{ for } y_i = -1 \quad (12)$$

The equations could be written in the form of inequalities as given below:

$$y_i(x_i \cdot w + b) - 1 \geq 0 \forall i \quad (13)$$

Figure 3 shows the two planes denoted by the H1 and H2 and separating the points of x and other support vectors. The Lagrangian formulation (Berrichi and Benyettou, 2009) is taken as the solution where the constraints are taken and replaced with the Lagrangian multipliers itself which is easier to handle. Secondly the reformulation of the problem, the training data only appears in the form of dot products between the vectors. Hence a positive Lagrangian multiplier with $\alpha_i, i = 1, 2, \dots, l$ one for each of the inequality constraints is taken. The Lagrangian can hence be given as:

Table 1: Process of clot detection and results

Sl. No.	Input image	Green channel extraction	Gabor feature extraction	Clot detection
1.	 (a)	 (b)	 (c)	 (d)
2.	 (a)	 (b)	 (c)	 (d)
3.	 (a)	 (b)	 (c)	 (d)

$$L_p = \frac{1}{2} \|w\|^2 - \sum_{i=1}^l \alpha_i y_i (x_i \cdot w + b) + \sum_{i=1}^l \alpha_i \quad (14)$$

Hence the objective function becomes maximizing the dual of convex quadratic type problem.

RESULTS AND DISCUSSION

Table 1 shows the tested images of retina in early and proliferative stages. Image 1 which is in late proliferative stage shows clots at 4 places in both RGB colour space 1(a) and in Green channel 1(b) on the classifier developed. The classified image in 1(d) shows retinal blood clots at more than 9 places within the smaller blood vessels. Image 2 also belongs to the late proliferative case with cluster of clot at 3 places in 2(b). Post clot detection by a classifier showed more number of clotted vessels (17 min clots visible) in the 1(d). Image 3 belongs to an early proliferative stage where only 1 cluster is visible in 3(a) and 3(b). However 3(d) image showed presence of many growing clusters at 3 places. Such clots visible in the image could be treated in time by a laser therapy to contain the proliferation and vision loss.

Overall the black-and-white vessel maps often jagged edges that are not suitable for width estimations, the algorithm provides an improved version of the input image, in which vessel contours are smoothed and rendered. However, this procedure performed well for vessel extraction; and it renders the boundaries of retinal vessels. The algorithm is general enough to be applied to any kind of retinal image. As it can be inferred from the output, one important drawback of this approach is that its area evaluation performance strictly relies on the accuracy of the input image. The accuracy of this method is found to be 92.50%, the sensitivity is 94.73 and specificity is 90.47.

The method of Pade approximant for extracted feature vector followed by SVM classification. Use of classification both pre and post feature vector extraction extracts the clots effectively. The rate of false detections decreases by 22% and accuracy of the detection is 91% when Lagrangian multiplier was selected for the weights $b = 0.7$. The process can be

further enhanced by use of non linear hyper-planes in the classification of the extracted features.

CONCLUSION

The proposed method of early diabetic retina detection is free from any background noise and variable grey levels which are common in other types of image segmentation techniques involving wavelet transform. The proposed method also differentiates between the optic disc (which appears thick in diameter after segmentation and often classified as a blood clot by algorithms) and the neighboring optic nerves. The method of training the system on a healthy retinal image and then testing it on the diabetic retinal image (in early proliferative stage), detected the minor enlarged spots of retina in smaller blood vessels also. The results obtained so far suggested that the method had reduced level of interaction required in the segmentation. The method proved to be effective in detecting smaller retinal blood clots and hence effective in detection of early proliferative diabetic retina.

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