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Automatic Grading of Images based on Retinal Vessel Tortuosity Analysis

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Abstract

Background: Blood vessel tortuosity analysis in fundus image is used to develop a Clinical Decision Support System (CDSS) to diagnose hypertensive retinopathy, retinopathy of prematurity, cardiovascular problem and stroke. **Methods:** A Novel approach using machine learning algorithms has been proposed in this paper to determine global tortuosity in a clinical perspective. After preprocessing and blood vessel extraction, eight dimensional feature vector is formed by evaluating tortuosity. By applying Correlation based feature selection procedure top four features are selected for classification purpose. We have collected images from database and hospital, and images are graded by senior ophthalmologist under two labels namely normal and tortuous image. **Findings:** Highest sensitivity is obtained in the case of SVM classifier. By keeping clinical classification as ground truth highest sensitivity of 96.6% is achieved in case of SVM with radial basis function as kernel. Feature selection process improves the overall sensitivity by 4% and also reduces the computational complexity. In the proposed method decision making is done based on the four features followed by classification, which outperform the other methods in the literature. By using the novel feature-classifier combination, highest sensitivity is obtained. **Improvement:** In the proposed method decision making is done based on the four features, which outperform the other method proposed in the literature. By using the novel feature-classifier combination, highest sensitivity is obtained.

Keywords: Bayesian Classifier, Correlation Feature Selection, *K*-Nearest Neighbor, Random Forest, Support Vector Machine, Tortuosity

1. Introduction

The first sign change in morphology of blood vessel is tortuosity[1]. Normal retinal blood vessels are straight or gently curved[2]. In case of the images of the patient affected with hypertension, retinal blood vessel become tortuous, takes the serpentine path. Clinical perception of tortuosity mainly depends on how many times a vessel twists and the amplitude of each twist[2.] With increase in harshness, tortuosity value increases in retinopathy of prematurity[3]. Five level grading was introduced for the measurement of tortuosity[4]. After extracting six dimensional feature vector, by applying Fisher linear discriminant analysis, 89% sensitivity is obtained[5]. By considering thickness of vessel also into account, an overall agreement of 92.4 with clinical judgment is obtained[6]. Blood vessel extraction using entropy thresholding algorithm is explored in[7]. Based on curvature estimation vessel tortuosity is calculated in[8]. Geometrical and topological features of blood vessels are explored for the diagnosis of hypertensive retinopathy[9]. With a set of five feature Ret Tort database tortuosity measurement is analyzed in[10]. An overview of methods and calculation used in retinal vessel tortuosity calculation is analyzed in[11]. Athersclerotic changes is analyzed by using image processing techniques in[12]. Chain Coding technique is used for the tortuosity analysis in[13]. To quantify Retinopathy of Prematurity blood vessel width change and tortusosity analysis is used in[14]. Quadratic polynomical decomposition method is used for the analysis of blood vessel tortuosity in[15].

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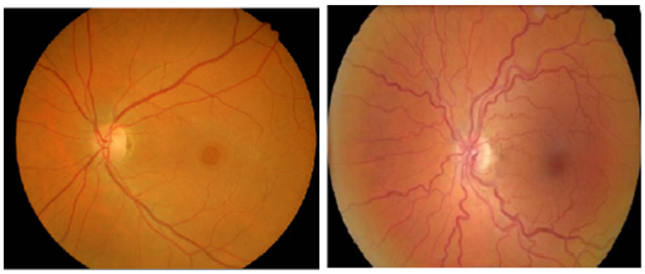
Using Machine learning technique, thickness dependent tortuosity and curvature based improved chain code is explored for tortuosity measurement in[16,17,19]. By using morphological transformation vessel partition is done and it is followed by tortuosity measurement is discussed in[21]. Figure 1(a) and 1(b) depicts normal and tortuous image.



(a) (b)

Figure 1. (**a**) Healthy fundus image. (**b**) Fundus image with severe vessel tortuosity.

1.1 Materials and Methods

Images collected from databases VICAVR, INSPIRE AVR, DRIVE and also from Deepam Eye hospital, Chennai, Tamilnadu, India. Total of 200 images used for the study. Matlab Software tool is used for the implementation. All the images grouped under two labels namely normal and tortuous, which is used as ground truth for the evaluation of the proposed method.

1.2 Methodology

1.2.1 Preprocessing

Green channel of the image is chosen, because of high contrast between vessel and background. Then enhancement is done by Contrast Limited Adaptive Histogram Equalization (CLAHE), which partition the image into contextual region and then histogram equalization is applied.

1.2.2 Blood Vessel Extraction

Piecewise linear segments of blood vessel is enhanced by Matched filtering. To enhance the blood vessel prototype matched filter kernel is convolved with the preprocessed

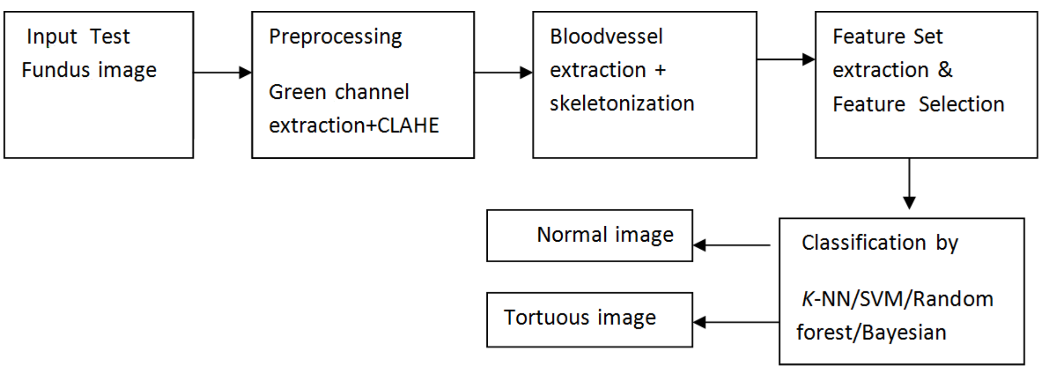
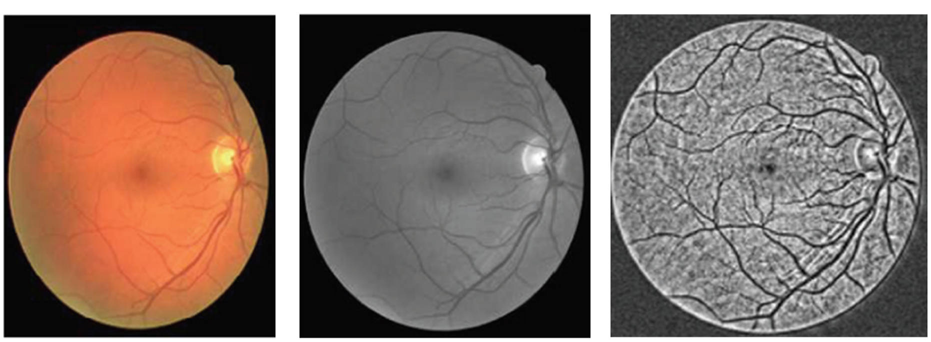


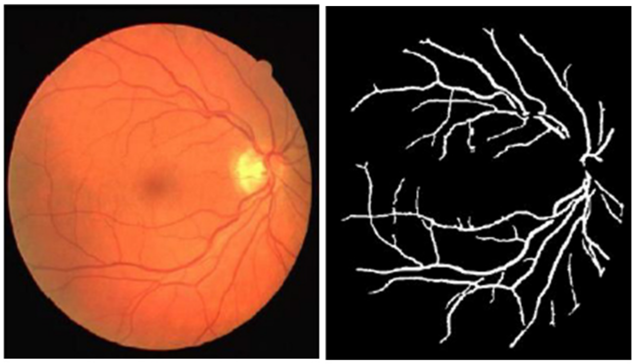
Figure 1. Block Diagram of proposed method.



(a) (b) (c)

Figure 2. (**a**) Original image. (**b**) Green plane of the image. (**c**) CLAHE output.

image. To detect the vessel oriented in all direction, a set of twelve 15*16 pixel kernel is applied by convolving to a fundus image. The obtained matched filter response is processed by proper thresholding as proposed in[7].



(a) (b)

Figure 3. (**a**) Original image. (**b**) blood vessel extracted image.

1.2.3 Vessel Selection and Tortuosity Calculation

Morphological thinning operation is done to get skeleton of the blood vessel. The major arteries and vein of uniform length with minimum overlap is chosen for tortuosity calculation.

1.2.3.1 Feature Vector Extraction

Method 1: Arc length [2]of the skeletonized vessel with n pixel is calculated from

$A=\sum_{i=1}^{n-1}\sqrt{(x_i-x_{i+1})^2+(y_i-y_{i+1})^2}$ (1) 1 and the chord length

$$C = [(x_1 - x_{n-1})^2 + (y_1 - y_{n-1})^2]^{0.5} \quad (2)$$

$$\tau = \frac{A}{C} \quad (3)$$

Method 2: New tortuosity index is proposed in[1]. A vessel is decomposed in to a set of consecutive segments of constant curvature sign.

$$\tau(s)=\frac{n-1}{n}\frac{1}{Lc}\sum_{i=1}^{n}\left[\frac{Lcsi}{Lxsi}-1\right] \quad (4)$$

Where 'n' is the number of segments.

Method 3: Tortuosity calculation is done by simple method proposed in[8]. A circle with a center at the specified point and of radius b is drawn. Tortuosity is calculated by the ratio of the larger area to the smaller area. If no curvature is found the answer will be one.

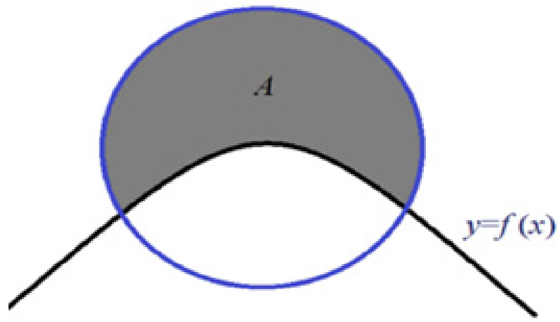


Figure 4. Curvature calculation using circular mask.

$$m=\frac{A}{A_{tot}-A} \quad (5)$$

and $\tau=\frac{1}{m}\sum_{i=1}^{m}m_i$ (6)

In this equation 'm' is calculated at m number of points in the vasculature structure.

Method 4: Mean Angle Change[1] measures local direction variation of the vessel. It computes the average of the angle between the sample center points describing the vessel. d_{i+n} is the coordinates.

$$v_{i+n}=d_{i+n}-d_i$$
$$v_{i-n}=d_{i-n}-d_i$$
$$\theta(i)=\arccos(v_{i+n}.v_{i-n})$$

$$MAC=\frac{1}{N-2.n}\sum_{i=1}^{n}\theta(i) \quad (7)$$

Where N is the number of Vessel sample and n is the fixed user defined parameter.

Method 5: In Slope Chain Coding(SCC)[11] method , a vessel centreline is approximated by a linear piecewise curve formed by line segments of fixed length and change in slope between line segment is computed.

$$SCC=\sum_{i=1}^{n}|a_i| \quad (8)$$

'n' is the number of slope changes and a_i is the change of slope after i^{th} segment.

Method 6: Quadratic polynomial decomposition[15] (QPD) helps to model the tortuosity of vessel, as sum of the contribution of polynomial(P_i).

$$\tau(v)=\sum_{i=1}^{n}\psi(p_i) \text{ where } \psi(p)=\frac{Area(p)}{l^2 * L} \quad (9)$$

'L' indicates the chord length of the entire vessel segment and 'l' helps to normalize the measure by its chord length to give importance to local bend.

The numerator of Ψ (p) is computed as follows

$$Area(p_i(a_i,b_i,c_i,s_i,l_i)) = \int_1 (a_i x^2 + b_i x + c_i)dx$$
$$= \frac{a_i}{3} * (l^3 - 1) + \frac{b_i}{2} * (l^2 - 1) + c_i * (l - 1) \tag{10}$$

Method 7: Tortuosity measure based on number of inflection point is proposed[16]. Inflection Count Metric(ICM) is defined as the ratio between straight line distance between two end point of the vessel 'C ' to the meandering vessel length L.

$$\text{Inflection Count Metric (ICM)} = \frac{(n_{ic}+1)C}{L} \tag{11}$$

Where n_{ic} is the number of twists.

Method 8: An efficient method based on improved chain coding is proposed in[17].

$$\tau = \left(\frac{n_{ic}-1}{n_{ic}}\right)\frac{1}{L}\sum_{i=1}^{n} k(p_i,k) \tag{12}$$

Where n_{ic} and L is the number of inflection and arc length.

Table 1. Number of images used for training and testing

Category	No. of training Set	No. of testing Set
Normal	40	50
Tortuous image	50	60

1.2.3.2 Feature Selection

Feature Selection Algorithms (FSA) consist of four steps namely, subset generation, subset evaluation, stopping criterion and result validation. FSA can be categorized under three groups namely, embedded, filter and wrapper approach. Correlation Feature Selection (CFS) method is used in the present work. CFS method selects subset of features based on the hypothesis, good feature subset consist of features, which are highly correlated with classification, yet uncorrelated with each other. Irrelevant features have low correlation with class and redundant features having high correlation with one or more of the remaining feature. The implementation of CFS[20] is based on three search mechanism forward selection, backward elimination and best fit. Best fit method is used in the present work. The chosen features are tortuosity index proposed by Grisan, slope chain coding, quadratic polynomical decomposition method and mean angle change method. Further addition of features shows no improvement, hence the feature subset with four features are used for classification.

1.2.4 Classification

Classifying data is a more common task in Machine learning. With a selected feature subset, four different classifiers are used for the classification of the test input. *K*-nearest neighbor method is the non parametric method used for classification. Test image is classified based on the majority vote in the k closest training example in feature space. By using kernel trick support vector machine is used for non linear classification. In the present work radial basis function is used as kernel. Bayesian classifier principle is based on Bayes theorem. Classification is done based on the posterior probability value. Random forest grows many trees. To classify the test image, put the test image feature vector down each of the trees in the forest. Each tree assigns the label or vote and forest choose the label for which the maximum number of trees voted. Evaluation of the performance of the classifier is done based on the three attributes namely Sensitivity, specificity and positive predictive accuracy. TP – True positive corresponds to the number of images correctly classified as tortuous, TN-True negative corresponds to the number of images correctly classified as normal, FP – False positive corresponds to the number of images misclassified as tortuous and FN – False negative corresponds to the number of images misclassified as normal.

$$\text{Specificity} = \left(\frac{TN}{TN+FP}\right) * 100 \tag{13}$$

Table 2. Analysis of the performance of classifier

Classifier	TN	TP	FP	FN	Sensitivity (%)	Specificity (%)	Positive Predictive Accuracy (%)
K-Nearest Neighbour	45	55	5	5	91.6	90	91.66
SVM	48	58	2	2	96.66	96	96.666
Naïve Bayes	46	56	4	4	93.33	92	93.333
Random Forest	48	58	2	2	95	96	96.6

$$\text{Positive predictive accuracy} = \left(\frac{TP}{TP+FP}\right)*100 \quad (14)$$

2. Conclusion

In this paper novel approach has been proposed to classify the image as tortuous or normal using a classifier. After preprocessing the original image, blood vessels extracted followed by skeletonization. Skeletonized blood vessel image is used for tortuosity calculation. Eight dimensional feature has been extracted and after feature selection by correlation method four, discriminative features are chosen for classification. Highest sensitivity is obtained in the case of SVM classifier. In the proposed method decision making is done based on the four features and classification, which outperform the other method proposed in the literature. By using the novel feature-classifier combination, highest sensitivity is obtained.

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