CLBP for Retinal Vascular Occlusion Detection

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Abstract

Retinal vein occlusion (RVO) and diabetic retinal disease is the most widespread type of retinal disorders. The precisely extracted Retinal blood vessel provides a vital factor in the early diagnosis of retinopathy. In this paper a programmed method is proposed to enhance the performance evaluation of feature extraction technique to obtain the affected ocular fundus images in the retinal blood vessel database. The ophthalmologists make use of these tools for patient screening, treatment evaluation, and clinical study. The study consists of two parts: an image acquisition and an adept algorithm for performance rate calculation to detect the retinal vein occlusion in human eye. The features are extracted using completed local binary pattern and the extracted data's are classified using artificial neural network. The precise results exhibit the feasibility of the proposed system in terms of performance evaluation.

Keywords: *Retinal Vein occlusion, Ocular, CLBP, ANN, Performance rate.*

1. Introduction

Many researches has been conducted for over 15 decades across the globe which has yielded an huge amount of data which is used in the treatment of diabetic retinopathy, hypertension, glaucoma, obesity, arteriosclerosis and retinal artery occlusion, etc. These data's include Retinal arteries and arterioles and their corresponding veins which provides an overview to diagnose the patients for such diseases in patients at the early stage. According to the studies conducted by IEDC (International Eye Disease Consortium) across the world about 16.4 million adults are affected by RVO. More specifically 2.5 million people are affected by CRVO (Central RVO) and 13.9 million people are affected by BRVO (Branch RVO).

Retinal vein occlusion is commonly known as "eye stroke". It occurs when one of the tiny retinal veins becomes clogged by a blood clot. The blood clot prevents the blood flow to drain away from the blood vessels of retina as quickly as possible. As a result there is a backlog of blood in the retina. This intensifies pressure in the blood vessels. So, the blood start to discharge from the blood vessels, which can damage and cause inflammation of the retina. Hence the eyesight is affected. The ill effects of RVO can be reduced if it is diagnosed at the early stage. So here in this paper a novel technique is proposed which uses more recent advances on the technique to identify such disease. After investigating the various techniques, it is found that the performance capabilities of the conventional system can be greatly improved. The textures of the blood vessel are extracted using CLBP which is a Completed LBP technique. Supervised learning classification technique like neural network is used to train and classify the extracted features. Hence the affected retinal images can be easily identified.

1.1 Related Work

Several researchers have focused on analysis and understanding of retinal vein occlusion. Features extracted from retinal vein being lines, texture, edges, bifurcations, and minutiae points.

An extraction method for retinal blood vessel called the MF-FDOG [2] which incorporates the matched filter (MF) and the first-order-derivative of the Gaussian (FDOG). A thresholding method is used to detect retinal blood vessels with respect to MF and the FDOG is to adjust the thresholding values of the image accordingly. In comparison with the MF, the MF-FDOG can better extricate the true vessel structures from non-vessel structures. The simulation results shows MF-FDOG can significantly decrease the false detection to that of MF miss. Another literature [4] proposed a trainable v4filters which is used to find vascular bifurcations in retinal fundus images. In the training process, an observer identifies a typical bifurcation by a point of interest in an image. The properties of all line segments in the concerned feature and their related geometrical arrangement are determined by the bifurcations detector from the identified feature. The filters are configured by the above training process which is then used to identify the features of similar patterns. The automatic configuration of v4 filters increases the degree of generalization so that exact selection of filter parameters can be tuned easily.

In a probing technique for thresholding [6], the probe examines the image in pieces. If there is a piece in vessel it segments and classifies according to the region-based properties. In comparison with the Classifier based Method, probing technique permits a pixel to be tested in multiple region configurations. Since, it is a region based probing method it certainly allows multiple branches. In case of neovascularnets, the commonly used matched filter methods frequently produce false positive detections because it detects non-line edges as well as lines. So a modified matched filter [1] for retinal vessel extraction in which the false response to non-line edges is reduced due to the application of double-sided thresholding. The modified matched filters results in higher accuracy and lesser false acceptance rate than the existing matched-filter-based schemes in vessel extraction.

2. Proposed Work

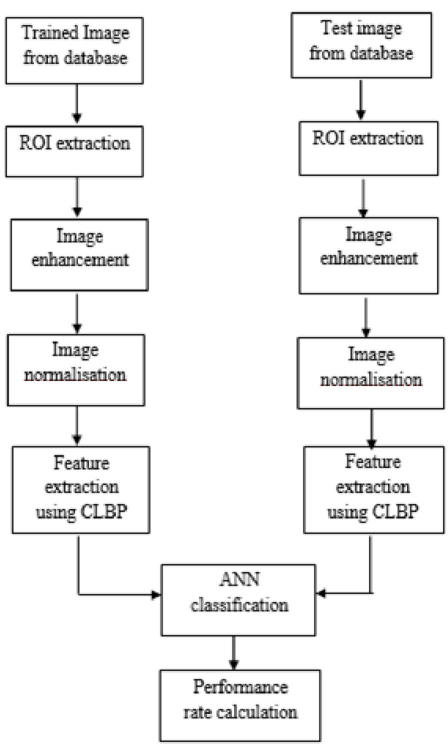

Fig.1 Proposed Block

The existing methods of retinal vein occlusion detection involve the detection of retinal veins through filters. We introduce a novel technique which involves the detection of texture of the retinal veins. The samples of retinal vein are analogous to samples of palm veins to some extent. Thus texture based feature extraction techniques are helpful in determining the performance. The remaining paper is divided into two sections one explaining the preprocessing process and another elucidating the texture extraction and classification techniques. In order to attest the feasibility of the process experimentation results are shown at the result section.

2.1 Image Acquisition

In the proposed experiment, 400 images from stare database are taken. The database consists of thirty people who has provided with retinal data. These data's are recorded at the University of California by the shiley eye center and the Veterans Administration Medical Center in Scan Diego provided the necessary images and clinical data.

2.2 Preprocessing

Our preprocessing consists of three steps namely

1. RGB to gray scale image conversion
2. Image enhancement
3. Image normalization

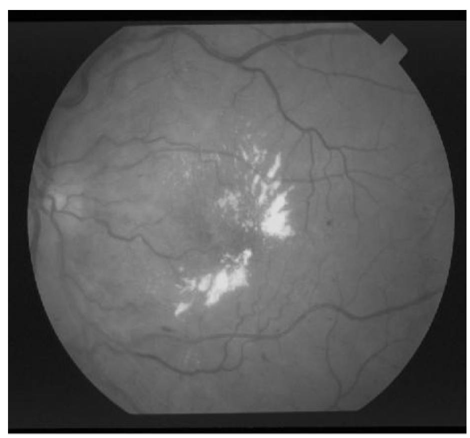

Fig.2 Retinal Vascular Image

The vascular patterns are captured using an optical camera. Image enhancement removes the noise and thereby increases the contrast of the image. There are various image enhancement techniques like histogram processing and spatial filtering. In this paper to suit our needs we utilized the technique of edge detection and smoothing technique. These techniques are quite helpful in discerning the sharpness of the image. In order to remove the global values, image normalization is applied.

3. Feature Classification

The features exhibited in the retinal veins are lines, minutiae, bifurcation, texture, and edges. Texture classification technique is prevailing in the field of computer research and pattern recognition. The texture of an image remains the same even under low-resolution conditions. The feature extraction technique extracts the desired features. There are various techniques available like radon transform, Gabor filters, v4 filters, matched filters, and MF-FDOG filters. According to the needs of the biometric feature the respective algorithms are applied to extract it.

LBP is a special case of CLBP using CLBP_S. Suppose the texture image is of size i×j. The texture image is represented by constructing the histogram as followed in Eqn (1):

$$k(s) = \sum_{n=1}^{i}\sum_{m=1}^{j} f'(LBP_{x,y}(n,m), s), s \in [0, s] \quad (1)$$

$$f'(u,v) = \begin{cases} 1, u = v \\ 0, otherwise \end{cases} \quad (2)$$

where s - Maximal LBP pattern value
x - Number of neighbors
y - Radius of the neighborhood
n, m - The pixel

3.1 CLBP

10	24	16
34	50	61
75	88	92

(a)

-40	-26	-34
-16		11
25	38	42

(c)

40	26	34
16		11
25	38	42

(b)

-1	-1	-1
-1		1
1	1	1

(d)

Fig.3 Illustration of CLBP (a) 3*3 sample block (b) The local differences (c) The magnitude component (d) The sign component

The generalized and completed LBP pattern is CLBP. CLBP is a fused output of CLBP_C, CLBP_S, and CLBP_M. The regions present in CLBP are analogous to LBP. They are represented by its center pixel and a local difference sign-magnitude transforms (LDSMT). Global thresholding is used to reveal the two peaks in the histogram. Binary codes are used to code the center pixel which is termed as CLBP_CENTER (CLBP_C). The image is decomposed into two components namely sign and magnitude by LDMST and are termed as CLBP-Sign and CLBP-Magnitude. Since the data is in binary format they are combined to produce the histogram image. The CLBP reveal better rotation textures invariant compared to LBP.

A central pixel p_c and its circularly and evenly spaced neighbours p_i, i=0, 1,…, i-1, we can simply calculate the difference between p_c and p_i as,

$$d_i = p_i - p_c \quad (3)$$

It is further decomposed into sign and magnitude component and d_i can be represented as

$$d_i = s_i * m_i \quad (4)$$

where s_i - sign component d_i
m_i -magnitude component of d_i

The equation (4) is called Local Difference Sign Magnitude Transform (LDSMT).
The CLBP_S operator being the same as that of feature, it is calculated from equation (1).
The CLBP_M operator can be calculated using the equation

$$CLBP\_M_{i,} = \sum_{i=0}^{i-1} t(m_i, 0)2^i, t(x,0) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \quad (5)$$

where 'o' is the adaptively determined threshold which is equal to the mean value of m_i from the whole image. In order to make the CLBP_C operator to be consistent with other two operators it is coded as

$$CLBP\_C_{i,j} = t(p_i, o_i) \quad (6)$$

where 'o_i' is the average gray level of the whole image. The histograms of the three operators denoted by equations (1),(5) and (6) are combined together to produce the CLBP histogram

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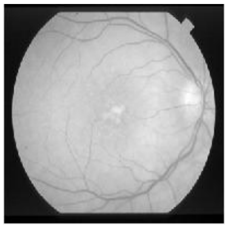
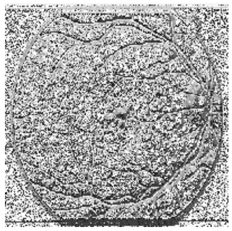
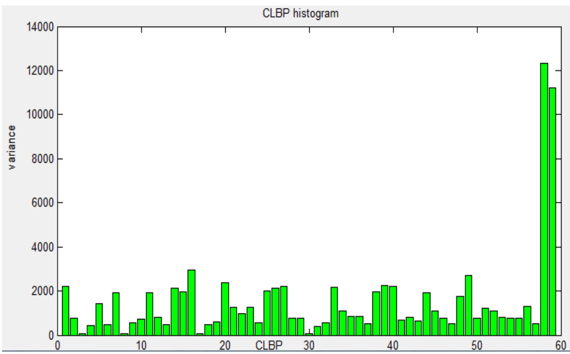


(a)



(b)



(c)

Fig.4 (a) Normalized image (b) CLBP
(c) CLBP histogram

4. Classification Schemes

Classification techniques are widely used in the field of biometrics. It is more evidently seen in applications such as bankruptcy prediction, credit scoring, medical diagnosis, quality control, handwritten character recognition, and speech recognition. It is one of the recurring tasks of human activity. The need for classification arises from the fact that data's needs to be assigned in structured groups or class based on the objects attributes so that it can be processed more efficiently.

One of the significant tools for classification is neural networks. Researches based on neural network prove its competence to various traditional classification schemes. Neural networks have the capacity to fine-tune themselves to the data exclusive of any functional specification. They have tremendous capacity to act as universal function approximations with high fidelity. The nonlinear models are capable of being more flexible that they can provide even with subsequent probabilities which are vital for statistical taxonomy.

Artificial neural networks observe the nodes as 'artificial neurons'. The artificial neurons are akin to that of natural neurons. The inputs along with the weights determine the activation of neurons are fed into a function which performs the necessary operation. As the weight of the neuron increases, stronger is the capacity for it to mix with the input signal. In some cases varying the weights of the neurons will help in achieving the desired output. This process is known as training.

The training algorithm used in this literature is the Levenberg-Marquardt method. It is a non-linear algorithm which adaptively switches between gradient-descent method and Gauss-Newton method depending on the position of parameter values with respect to their parameters optimal values.

The Levenberg-Marquardt algorithm is given by the equation

$$K^T LK + \gamma diag[K^T LK]h_{im} = K^T L(x - \hat{x}) \qquad (7)$$

where $K^T LK$ is the Hessian of the chi-squared fit criterion

γ is a small values of result in Gauss Newton update and large values result in a radiant descent update.

The mean square for performance calculation is done using the equation

$$\begin{aligned} MSE &= E[(j - f(i;P_N))^2] \\ &= E[(j - F(i))^2] + (f(i;P_N) - F(i))^2 \end{aligned} \qquad (8)$$

where $j = F(i) + \varepsilon$

P_N -dataset

F (i)-target of underlying function

ε -zero mean random variable

Performance plots and regression plots are shown below

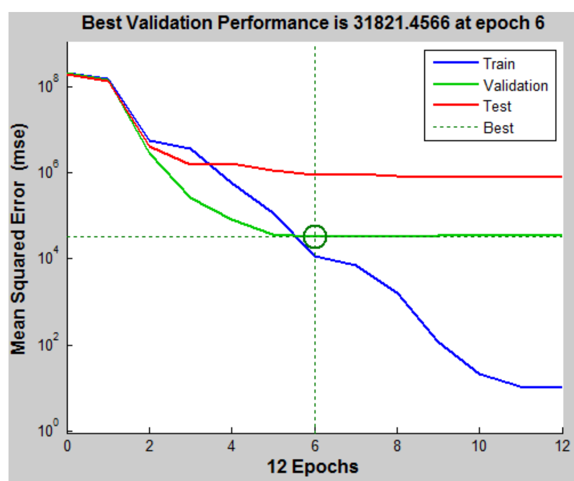
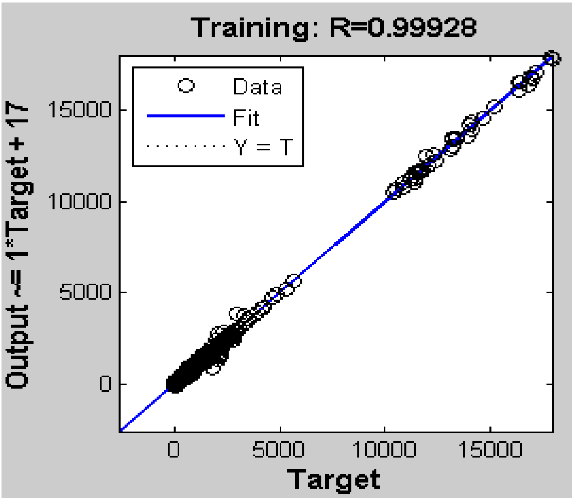
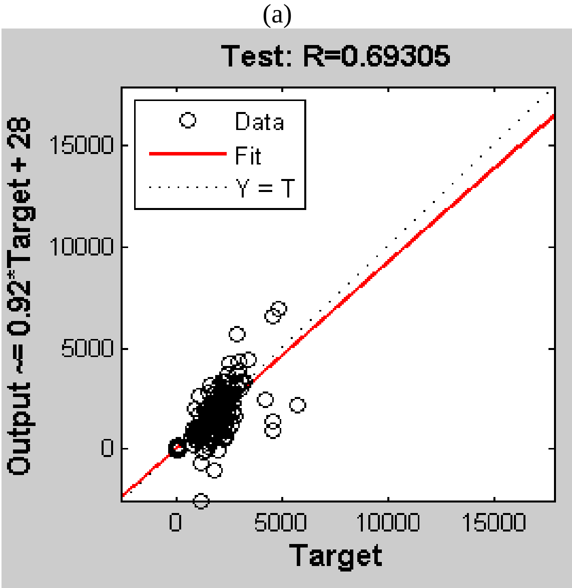


Fig.5 Performance graph



(a)



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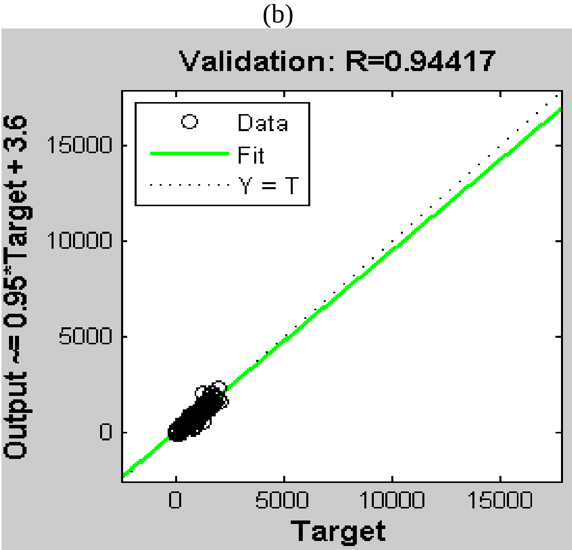
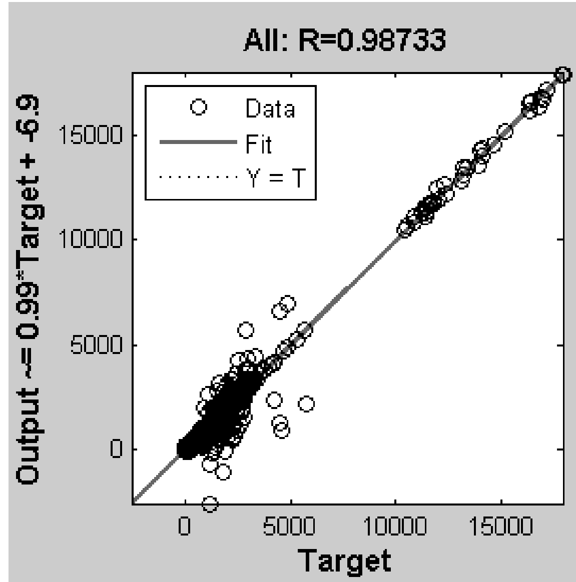


(c)



(d)

Fig.6 Regression graph
(a) Training (b) Test (c) Validation (d) all

5. Experiment Results

The performance and regression plots are shown. In Fig.5 the test and the validation curves remains close to each other indicating that no over fitting is done in the classification process.Fig.6 represents the regression plot and the dotted line indicates the faultless output. The solid line indicates the best fit between outputs and targets. The R-value is an indication of the relationship between the outputs and targets. The regression plot with r value of 0. 99717 indicate the perfect matching condition of test and trained databases. These values which achieve closer performance indicate the feasibility of this system.

6. Result and Future Work

This experiment has conducted a study on texture classification, by using Completed Local Binary pattern as the feature extraction and ANN classification method. The final experimental results using the above have proved that such texture classification approach is worth to be implemented in real life applications. Further the extraction of texture from retinal veins paves way for a new and diverse technique for others to follow.

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