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# A Novel Method for Identifying Retinal Blood Vessels using Fractional Fuzzy Local Binary Patterns

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**Abstract:**
Detection of blood vessels in retinal is a primary step for diagnose hypertension and glaucoma. Numerous techniques have been developed for detection of retinal blood vessels but lack of robustness. In this paper, a new method is presented to improve the accuracy of finding retinal blood vessels and to remove the unwanted hair line by fractional fuzzy local binary pattern (FFLBP). In FFLBP several membership functions is applied for each pixels and the membership function having maximum entropy is opted as membership function for the corresponding pixel and new weightage matrix have been introduced for find local binary pattern(LPB) code. After applying FFLBP, it gives improved results along with the removal of hair lines. The results of the presented method are compared with existing edge detection methods. Quantitative measures show that the presented work gives finer performance.

**Keywords**: Edge detection, Fractional derivative, Fuzzy set theory, Local binary pattern, Membership function.

## 1. Introduction

Edges appear when there is a change in gray level, shades, and light in the image. Edges are an important factor in image processing and it is used to discover the object, size, extract texture, and depth region of an image. Edge detection is applied in many fields including traffic systems, defense, remote sensing, and medical image analysis. In the early 20th century deduction of blood vessels in the retina was introduced [2]. Retinal blood vessels can be brought into play by monitoring and discovering the disease such as diabetes or macular degeneration. Approximately 26% population is affected by this disease. Also, detection of blood vessels plays a crucial role in biometric systems. There are several edge detectors available in practice such as Canny, Sobel, Robert etc., these mask operators are giving better results for simple images. When one deals with an image having noise, these methods are not working properly and also it fails to find complex image edges. In recent times, plenty of methods are developed to address this shortcoming.

In the beginning of 10th century most of the mathematical problems have used binary pattern. But in end of the 19th century, binary pattern is insufficient to model the real world problem because real world problems contain uncertainty [3]. In 1965, Lotfi Zadeh introduces the concept of fuzzy set. Prewitt [4] is the first person to apply the concept of fuzzy set in image in 1970. In 1992, S. K. Pal [5] developed the fuzzy set theory for image processing and pattern recognition. Rather than binary concept in set theory fuzzy logic gives more reliability to interpret the uncertainty in real world phenomena. Fuzzy logic has made impact in many fields of mathematical science.

Local binary pattern (LBP) method has been described by T. Ojala in 1994 [6] and it is used far and widely by countless researchers in the field of face detection and texture recognition. Fuzzy logic combined with local binary pattern model is developed by Keramidas in 2011 [9]. It is relating the concept of generalized fuzzy with binary pattern. While using local binary pattern each pixel is compared with neighborhood pixel and gives a binary code either zero or one but in fuzzy local binary pattern it compare with the neighborhood pixel and gives the value in between 0 to 1 depending up on the degree of existence.

Kaya Burhan [7] found new method of edge detection based on reflectance transformation imaging photographing, that is several images captured at fixed position with different lighting. Canny edge detection operator is a classical operator for edge detection but it fails when noise appeared in image like salt and pepper noise. Yibo Li [8] introduced a new improve Canny edge detection operator to solve such type of noise appearance. Zeng [12] introduced a new method H-LBP (Hyperbolic- Local binary pattern) with the help of arctan function a new H function is introduced in LBP. Unlike normal LBP, H-LBP gives more bounce. In this H-LBP, LBP value gives larger value for the pixel having maximum intensity value and minimum value for the pixel having minimum intensity value. Nakharacruangsak [10] introduced a method in which binary matrix is multiplied with hyperbolic tanh. It gives smooth results when compared to H-LBP. Katsigiannis [13] introduced fuzzy local binary pattern descending membership function LBP and contribution LBP codes are calculated. It also provides a fine result compared to previous existing methods. All these methods failed to detect edges in low contrast images and broken edges.

Fractional derivative, in other words, a non-integer order derivative has played a crucial road in past two decades in various fields like physical science, chemical science, biology and image processing etc. In image processing, edge detection is a bottom level process and it is done probably by the use of integer order derivative operators. Compared to the integer order derivative mask operator a non-integer order derivative mask operator detects thin edges also.

In this paper, four different fuzzy membership functions used to finding edge image by fuzzy local binary pattern. Four membership functions are tested with every pixel and entropies are calculated. Membership function having maximum entropy is the best membership function for the concern pixel. Then, instead of using normal weightage matrix fractional gradient of the concern pixel is used as weightage matrix. The same procedure is done for all the pixel and the membership function having maximum entropy selected for all pixels. Consolidate all the pixel values and get better edge image of the input image.

Section 2 describes the basic theory of fuzzy set and LBP. In section 3, steps involved in this proposed study have been presented. The experimental output is discussed in section 4 by both qualitative and

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quantitative assessment with the existing methods used in practice. Finally in section 5 conclusion have been drawn.

## 2. Preliminary

In this section some basic concepts which are used in this paper has been described below. It helps to understand the concepts.

### 2.1 Fuzzy set

A fuzzy set is mathematically defined by

$$P = \{< x_{ij}\ \mu_P(x_{ij}) > |\forall x_{ij} \in P, \qquad 1 \leq i \leq m, 1 \leq j \leq n,\}$$

where $P$ is an input image of size $m \times n$ and $\mu_P(x_{ij})$ is a fuzzy membership function from the image $P$ to [0,1] and it gives the degree of belongingness of the element $x_{ij}$ in P and $1 - \mu_P(x_{ij})$ is represent non-membership and it is denoted by $\tau_P(x_{ij})$ with $0 \leq \mu_P(x_{ij}) + \tau_P(x_{ij}) \leq 1$.

### 2.2 Local binary pattern

Local binary pattern produces a binary matrix by examining the neighbourhood pixel values to the center pixel value. If the neighbourhood pixel value is larger than the center pixel value then the neighbourhood pixel value is replaced by 1 otherwise it is replaced by 0. Then, the LBP code is generated by multiplying the binary matrix with predefined weightage matrix. The process is illustrated in Figure 1.

$$LBP = \sum_{i=1}^{8} f(p_i - p_c) * 2^{i-1}$$

where $p_c$ denotes the center pixel and $p_i$ denotes the surrounding pixel of $p_c$. In this present work a new weightage matrix for LPB have been presented.

$$\underset{(a)}{\begin{array}{|c|c|c|}\hline 2 & 20 & 25 \\ \hline 15 & 10 & 5 \\ \hline 4 & 11 & 16 \\ \hline \end{array}} \longrightarrow \underset{(b)}{\begin{array}{|c|c|c|}\hline 0 & 1 & 1 \\ \hline 1 & & 0 \\ \hline 0 & 1 & 1 \\ \hline \end{array}} * \underset{(c)}{\begin{array}{|c|c|c|}\hline 2^0 & 2^1 & 2^2 \\ \hline 2^7 & & 2^3 \\ \hline 2^6 & 2^5 & 2^4 \\ \hline \end{array}}$$

LBP code = 182

**Figure 1**: (a) 3×3 image matrix (b) binary matrix produced by LBP and (c) Weightage matrix

## 3. Algorithm design

The steps involved in the proposed work are given as follows and the schematic diagram of this method is shown in Figure 2.

**Step 1:** Consider an image $P$ of size $m \times n$.

**Step 2:** For each pixel with its neighbourhood of window size 3×3, membership window of the concern pixel are

computed using the following four different membership functions.

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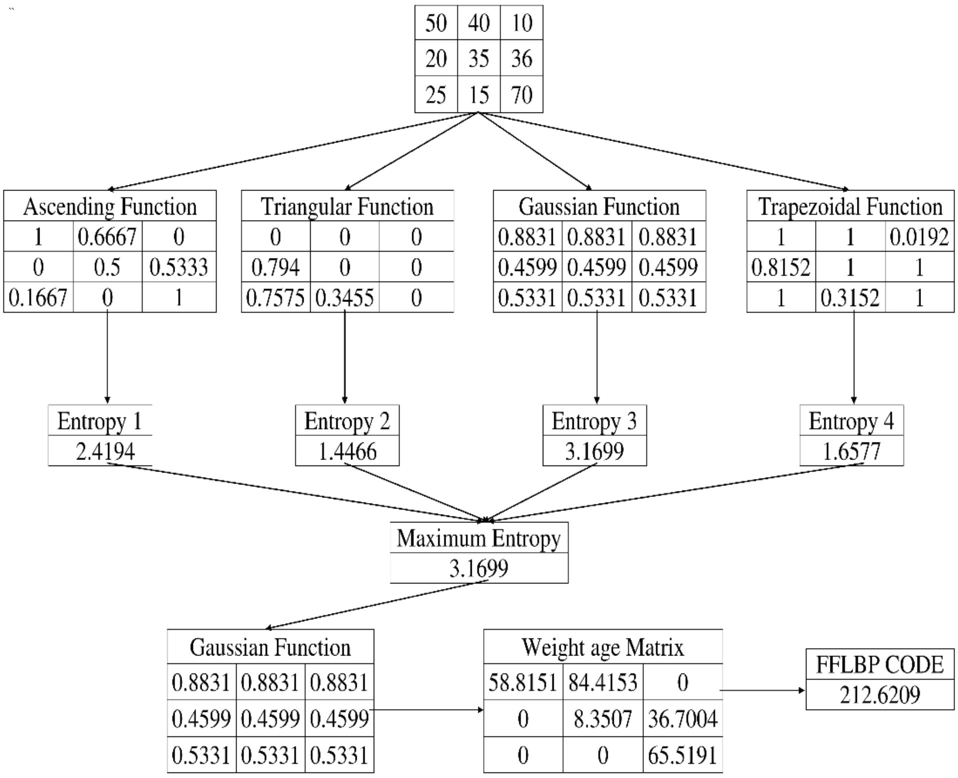


**Figure 2: The schematic diagram of the proposed method**

Trapezoidal membership function is defined as

$$\mu_P(x) = \begin{cases} 0 & if\ x \le a, \\ \frac{x-a}{b-a} & if\ a < x \le b, \\ 1 & if\ b < x \le c, \\ \frac{d-x}{d-c} & if\ c < x < d, \\ 0 & if\ x \ge d, \end{cases} \quad (1)$$

where a, b, c and d are four threshold values of an image.

Ascending membership function is mathematically represented as follows

$$\mu_P(x) = \begin{cases} 1 \quad if\ x_{nbhd} - x_c \ge T, \\ \dfrac{T + x_{nbhd} - x_c}{2T}\ if\ |x_{nbhd} - x_c| < T, \\ 0\ if\ x_{nbhd} - x_c > -T \ \ T \ne 0, \\ 0\ if\ x_{nbhd} - x_c < -T \ \ T = 0, \end{cases} \quad (2)$$

where $x_c$ is center value of the pixel, $x_{nbhd}$ is surrounding pixel and T=15 [13].

Gaussian membership function is defined as

$$\mu_P(x, x_1, x_2, x_3) = exp\left(-\frac{1}{2}\left(\frac{x - x_1}{x_2}\right)^{x_3}\right) \quad (3)$$

where $x_1$ maximum gray value, $x_2 = \max\,(T - \bar{x}, x_1 - T)$ where T is threshold value, $\bar{x}$ is average gray value and $x_3$=2 [14].

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Triangular membership function is represented as

$$\mu_P(x) = \begin{cases} 0 & if\ x \le a, \\ \dfrac{x-a}{b-a} & if\ a < x \le b, \\ \dfrac{c-x}{c-b} & if\ b < x < c, \\ 0 & if\ x \ge c, \end{cases} \tag{4}$$

**Step 3:** Entropy for the four membership windows of the concerned pixel is calculated using the following function

$$Entropy = -\sum_i p_i log_2 p_i, \tag{5}$$

where $p_i$ is the probability of existence of that pixel.

**Step 4:** The best membership function for the corresponding pixel is identified by finding maximum entropy among the four entropy values obtained from step 3.

**Step 5:** Same process is repeated for all the pixels by finding suitable membership function.

**Step 6:** In FFLBP, the weighted matrix of each pixel is calculate by gradient of that pixel using two dimensional fractional mask operator [16]. The horizontal and vertical derivatives as defined in Figure 3 $N(\alpha)$ is a normalization function defined as follows

$$N(\alpha) = 1 - \alpha + \frac{\alpha}{\Gamma(\alpha)}$$

where $\alpha$ is the order of the fractional derivative and $\Gamma(\alpha)$ is a gamma function.

The gradient of the pixel is calculated from horizontal and vertical derivatives by

$$Grad = \sqrt{h_x^2 + h_y^2}\,.$$

| | | |
|---|---|---|
| $\frac{1}{N(\alpha)}$ | $\frac{\alpha^2}{N(\alpha)}$ | $\frac{\alpha^3-\alpha^2}{2N(\alpha)}$ |
| $-\frac{\alpha^2-\alpha^4}{6N(\alpha)}$ | 0 | $\frac{\alpha^2-\alpha^4}{6N(\alpha)}$ |
| $-\frac{\alpha^3-\alpha^2}{2N(\alpha)}$ | $-\frac{\alpha^2}{N(\alpha)}$ | $-\frac{1}{N(\alpha)}$ |

(a)

| | | |
|---|---|---|
| $-\frac{\alpha^3-\alpha^2}{2N(\alpha)}$ | $-\frac{\alpha^2-\alpha^4}{6N(\alpha)}$ | $\frac{1}{N(\alpha)}$ |
| $-\frac{\alpha^2}{N(\alpha)}$ | 0 | $\frac{\alpha^2}{N(\alpha)}$ |
| $-\frac{1}{N(\alpha)}$ | $\frac{\alpha^2-\alpha^4}{6N(\alpha)}$ | $\frac{\alpha^3-\alpha^2}{2N(\alpha)}$ |

(b)

**Figure 3**: (a) $h_x$ is horizontal derivative and (b) $h_y$ is vertical derivative

**Step 7:** Consolidate all the pixels and get the crisp blood vessel image by defuzzifying it.

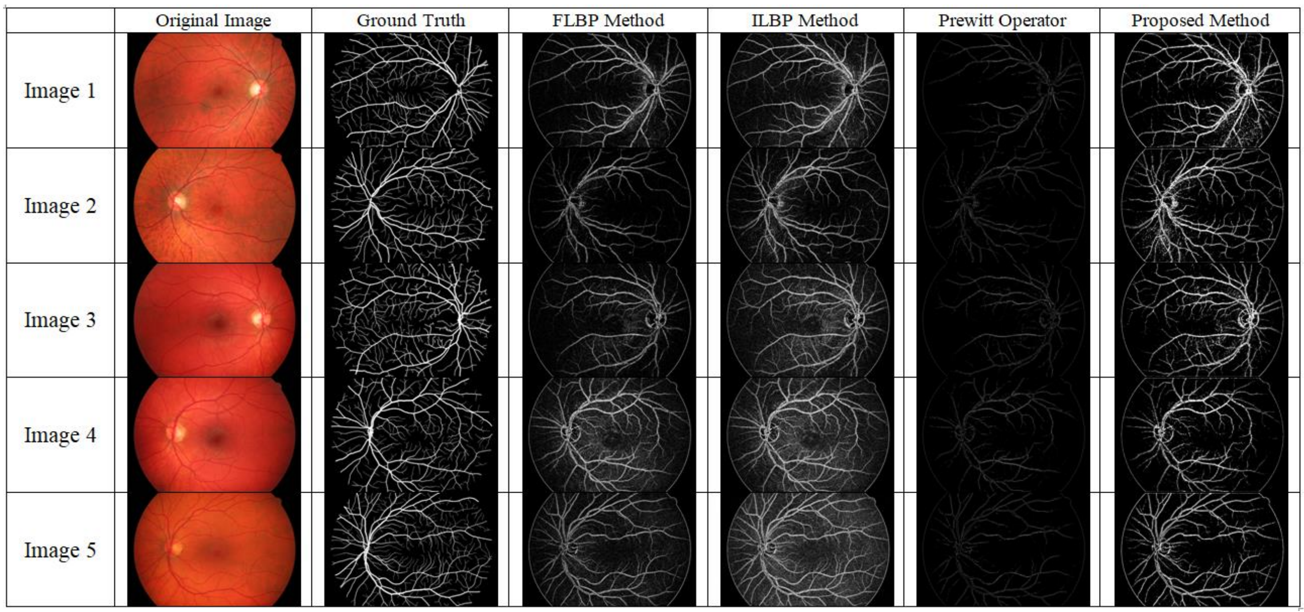


**Figure 4: Comparison result of proposed method with existing edge detection methods**

## 4. Experimental study

The source code is written in Matlab R2014a and the simulation have been run on a 6$^{th}$ Generation Intel ®Core$^{TM}$ i3 processor. For quantitative assessment, PSNR and Jaccard index have been used.

### 4.1 Peak Signal to Noise Ratio

It is a ratio between maximum possible power values of pixel and the power of the pixels that affect the standard of the images. PSNR value between two image of size $m \times n$ is

$$PSNR = 10\left(\frac{255^2 \times m \times n}{|P_1 - P_2|^2}\right)$$

| | **FLBP Method** | **ILBP Method** | **Perwitt Operator** | **Proposed Method** |
|---|---|---|---|---|
| **Image1** | 10.1207 | 9.2098 | 10.4471 | **10.4950** |
| **Image2** | 10.8608 | 10.1845 | 10.4897 | **11.0961** |
| **Image3** | 9.7469 | 8.5036 | 10.1719 | **10.7378** |
| **Image4** | 8.8055 | 8.1152 | 10.7247 | **11.5575** |
| **Image5** | 9.3460 | 7.4248 | 10.3542 | **11.2122** |

**Table 1: PSNR Metric**

### 4.2 Jaccard Index

Jaccard index is the proportion between intersection and union of two images and which ranges from 0 to 1 depending on the similarity of two images. If two images are identical then the index value is 1. Jaccard index is defined by

$$Jaccard\ Index(P_1, P_2) = \frac{|P_1 \cap P_2|}{|P_1 \cup P_2|}.$$

Comparison results of the proposed method have been shown along with the existing blood vessel detection methods in Figure 4. In Figure 4, the second column shows retinal images considered for presenting qualitative results. Their ground truth have been presented in the third column of Figure 4. The results of the existing techniques namely FLBP [13], ILBP [11] and Mekideche method [15] and the proposed method have been presented in the, fourth, fifth and sixth, seventh columns of Figure 4. One can clearly see that FLBP, ILBP and Mekideche's method results are under segmented while comparing to ground truth.

In the first retinal image, it is evident that the other three existing methods detect fewer edges in the corner and also more discontinuity in edges appears. The proposed method detects almost all edges in the corners. In second third and other images the existing methods having some in efficiency for finding corners edges also existing methods had produced some non edge regions when compared to the ground truth image. But, the proposed method produced less unwanted edges. In all images, many noises were seen around the retina in the edge images identified by the other three existing methods. But, the proposed method gives acceptable results when compared to the ground truth.

For quantitative assessment, PSNR and Jaccard index are tabulated in Table 1 and Table 2. Since PSNR values are larger for all the edge images providing by proposed method. Jaccard index values are given Table 2 for all five images obtained from the three existing methods along with the proposed method. Table 2 demonstrates that the proposed method produces better value when compared to the existing methods. So, quantitatively proposed method is superior to FLBP, ILBP and Mekideche's method.

| | **FLBP Method** | **ILBP Method** | **Perwitt Operator** | **Proposed Method** |
|---|---|---|---|---|
| **Image1** | 0.8610 | 0.8381 | 0.8706 | **0.8969** |
| **Image2** | 0.8805 | 0.8657 | 0.8752 | **0.9089** |
| **Image3** | 0.8566 | 0.8210 | 0.8686 | **0.8985** |
| **Image4** | 0.8316 | 0.8089 | 0.8810 | **0.9125** |
| **Image5** | 0.8402 | 0.7758 | 0.8678 | **0.9109** |

**Table 2: Jaccard Index**

## 5. CONCLUSION

Based on LBP, a novel technique for identifying blood vessels in retinal pictures has been developed. By selecting a membership function that is appropriate for the image under consideration, the fuzzy technique used in this paper decreases redundancy in identifying the relevant blood vessel pixel. A fractional derivative is used in the creation of the new weightage matrix in FFLBP, which also enhances the detection of thin blood vessels. According to the results, the suggested approach outperforms the three current approaches in both qualitative and quantitative aspects. As a future work, a new method is to be introduced by improving the present LBP that gives more performance.

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