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A Methodical Approach for Segmentation of Diabetic Retinopathy Images

R. Ravindraiah[1]*, S Chandra Mohan Reddy[2] and P. Rajendra Prasad[1]

[1]ECE Department, MITS, Madanapalle - 517325, Chittor Dt, Andhra Pradesh, India; ravindra.ranga@gmail.com, rajendra.mcu@gmail.com
[2]ECE Department, JNTU College of Engineering, Pulivendula – 516390, Andhra Pradesh, India; cmr.ece@jntua.ac.in

Abstract

Background/Objective: Exudates are the significant portions for the detection of Diabetic Retinopathy (DR). This paper demonstrates a complete framework for the detection of hard exudates in retinopathy images. **Methods/Statistical Analysis**: This paper presents two variants of Multiple Kernel induced Gaussian Spatial Fuzzy-C Means (MKGSFCM) algorithm for the segmentation of retinal fundus images. The algorithm is applied on different DR images and the performance of the algorithm is evaluated qualitatively and quantitatively. **Findings:** FCM and KFCM algorithms are commonly used clustering methods but are very sensitive to noise and other imaging artefacts. This paper presents a hybrid version of KFCM with induced Gaussian spatial information. Sensitivity and specificity values of the proposed work are observed to be high and also the possibility of exudate misclassification is significantly reduced by the proposed method as compared to existing algorithms. **Improvement:** The frame work presented can be developed further by the inclusion of adaptive weights for the multiple kernels.

Keywords: Diabetic Retinopathy, Exudates, FCM Clustering Algorithm, Multiple Kernel Induced Gaussian Spatial FCM Algorithm.

1. Introduction

Diabetic Retinopathy is the disorder of retina caused by diabetes and the incidence of vision loss has been increased if it is left untreated. It is caused by persistent sugar glucose levels in blood which can deteriorate and damage tiny blood capillaries within the retina[1]. Persistent sugar glucose levels in blood can deteriorate and damage tiny blood capillaries within the retina. Persistent high sugar levels get the damaged vessels rupture and this allows the leakage and accumulation of blood and fluid into retina which can cause macular edema. Over time, the severity of blockage of retinal veins increases and the retina undergoes self-nourishment leads to the development of new fragile blood veins can cause retinal detachment which makes the situation chronic. The abnormalities that are considered for the Diabetic Retinopathy diagnosis are nicro-aneurysms, exudates and haemorrhages etc. Exudates are the significant portions and one of the major symptoms useful for the detection of DR. The patients enduring with DR needs early identification and diagnosis will help them a lot. Exudate detection has a significant share in automatic screening systems. Manual demarcation of exudates is time-consuming, highly user dependent and difficult to delineate in areas of indistinct borders. Hence it is important to ensure computer aided framework for the detection of exudates in Diabetic Retinopathy images.

1.1 Related Work

Many techniques have been employed previously for the extraction of exudates in DR fundoscope images. In the work of[2] the method uses the outputs of different exudate extraction algorithms and these results of exudate candidate regions were given ensemble weights using simulated annealing and classified the exudate regions using machine learning technique. Both morphological

**Author for correspondence*

method and FCM algorithm were used for the detection of exudates followed by optic disc removal using the combination of circular hough transform and propagation through radii method[3]. The outputs of two different methods i.e. morphological operation based segmentation and intensity based thresholding techniques were used for the accurate exudate detection by removing false positives[4]. The methodology for the segmentation of exudates in DR fundus images using the Laplacian Kernel induced spatial FCM algorithm was presented and evaluated the results using sensitivity and specificity values[5]. The combination of multi-scale background subtraction and histogram thresholding technique were used for the segmentation of hard exudates of different sizes and intensities and presented computer-aided classifying methodology to determine the severeness of the Diabetic macular edema based on the spatial distribution of exudates around macula[6]. The referral scheme for the detection of hard exudates using different techniques which were used are Scale Invariant Feature Transform (SIFT), fuzzy clustering technique using K-means Clustering, Visual Dictionaries and machine learning technique using Support Vector Machine (SVM) techniques followed by the classification of system using Back propagation neural network classifier[7]. A new exudate segmentation method based on mathematical morphology and a random forest algorithm was used to identify the exudates within the candidate regions[8]. An automated method for the extraction of texture based features using Gray Level Co-occurrence Matrix (GLCM) and the retrieved features were served as input response to the SVM classifier to classify exudate and non-exudate regions[9]. Histogram thresholding based segmentation for the segmentation of exudates was used and the exudate features extracted were used as input to the K-Nearest Neighbour classifier to classify the severity of the Diabetic Retinopathy[10]. Extracted exudates using Artificial Nueral Network having three-layer feed-forward structure with 5 hidden units and extracted exudates were visualised using radar chart and Color Auto Correlogram (CAC) technique[11]. Hierarchical fuzzy c-means clustering algorithm was used for the retrieval of exudates[12]. The exudates were detected using morphological operations applied on the green component of the DR fundus images[13].

The main motive of this paper is the segmentation of the hard exudates in Diabetic Retinopathy fundus images using two variants of Multiple Kernel induced Gaussian Spatial Fuzzy C- means (MKGSFCM) algorithm.

The rest of the paper is organised as follows: In Section 2 of this paper described the two variants of algorithm; methodology for the segmentation of exudates from the fundus image and its implementation using Raspberry pi 2 board. Experimental results reported in Section 3 the various experimental results and Section 4 finally offers conclusion to the paper and future work.

2. Proposed Method

Segmentation is a key tool in medical image processing in which it is useful to classify image pixels into pathological regions which is useful for diagnosis of the disease. There are many image segmentation techniques are available among them fuzzy clustering techniques are the widely used and most prominent techniques for the medical image segmentation. Performance of the existing methods i.e., FCM, KFCM, SFCM and LKSFCM on DR images are discussed in our earlier paper[14,15]. This paper presents two variants of KSFCM with the inclusion of two and four kernels. The schematic approach of this method is shown in Figure 1.

2.1 Multiple Kernel Induced Gaussian Spatial Fuzzy-C Means Algorithm

Usage of multiple kernel combinations into KSFCM embeds dissimilar information from multiple diverse or similar sources in the kernel space especially in image segmentation problems[16]. In addition the Gaussian spatial function is incorporated into the membership function of proposed algorithm. The approach of the proposed work is as follows:

Let the image of size M x N having L gray levels where each pixel can represented as a set of pattern samples indicated as a finite set denoted as $P = (p_1, p_2, p_3 ..... p_n)$ which are represented as the 'c' partition clusters with centers denoted as $c_i = (c_1, c_2, c_3 ..... c_c)$. The partition clusters are denoted as $\{u_1, u_2, ... u_c\}$ where ith partition class is denoted as u_i. Consider M_{ij} is the membership metric of the jth pixel in the ith partition class. The membership metric is based on the following conditions.

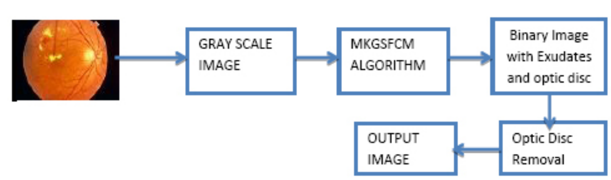


Figure 1. Flow chart of proposed method.

$$M_{ij} \in \{0,1\}\,;\ \sum_i M_{ij} > 0 \text{ and } \sum_i M_{ij} = 1$$

Where $j = 1, 2, \ldots\ldots, c$

The objective function of kernel induced FCM clustering algorithm defined as follows:

$$J_{KFCM} = \sum_{i=1}^{c}\sum_{j=1}^{n} M_{ij}^{m}\left(1 - K\left(p_j, c_i\right)\right) \qquad [1]$$

Where M_{ij} is the membership matrix of the pattern sample j which belongs to the partition class i, m is the fuzziness coefficient and $K(P_j, c_i)$ is the induced kernel distance metric in place of Euclidean distance metric in FCM algorithm.

The improved objective functions of multiple kernels metric induced FCM with Gaussian spatial information[16] is defined as follows:

$$J_{OBJ\_NEW} = \sum_{i=1}^{c}\sum_{j=1}^{n} M_{ij}^{m}\left(1 - K_M\left(p_j, c_i\right)\right) + \sum_{i=1}^{c}\sum_{j=1}^{n} h_{ij} \qquad [2]$$

Here $K_M(P_j, C_i)$ represents combination of multiple kernels. Equation for two kernels represented as:

$$K_M(P_j, C_i) = K_1(P_j, C_i) \times K_2(P_j, C_i) \qquad [3]$$

and h_{ij} is the added spatial information and is defined as:

$$h_{ij} = \sum_{k \in NB_{P_j}} \sum_{l \in NB_{P_j}} \frac{1}{2\pi\sigma^2} e^{\frac{k^2+l^2}{2\sigma^2}} M_{k,l} \qquad [4]$$

h_{ij} is the possibility that the pattern sample P_j belongs to the i^{th} partition class and NB_{P_j} is a square window of size 5 x 5 matrix having neighbouring pattern samples centered on the pixel P_j which represents Gaussian spatial information.

The prototype of each partition class and membership functions which optimizes the objective function using the iteration process are defined as follows:

$$C_i = \frac{\sum_{j=1}^{n} {M_{ij}}^m K_M(P_j, C_i) p_j}{\sum_{j=1}^{n} {M_{ij}}^m K_M(P_j, C_i)} \qquad [5]$$

Where i = 1, 2, 3. . . . . , C.

$$M_{ij} = \frac{\left(1 - K_M(P_j, C_i)\right)^{\frac{-1}{m-1}}}{\sum_{k=1}^{c}\left(1 - K_M(P_j, C_i)\right)^{\frac{-1}{m-1}}} \qquad [6]$$

The improved membership function with included spatial function h_{ij} is given as:

$$M'_{j} = \frac{M_j^m h_j}{\sum_{k=1}^{c} M_j^m h_j} \qquad [7]$$

The two variants of MKGSFCM algorithm which are presented in this paper are MKGSFCM_T and MKGSFCM_H. The algorithm MKGSFCM_T consists of combination of two kernels defined as, $K_M(P_j, C_i) = K_1(P_j, C_i).K_2(P_j, C_i)$. Where $K_1(P_j, C_i)$ is laplacian kernel, $K_1(P_j, C_i) = exp\left(\frac{\|p_j - c_i\|}{\sigma}\right)$ and $K_2(P_j, C_i)$ is tangential kernel and is defined as $K_2(P_j, C_i) = 1 - tanh\left(\|p_j - c_i\|^2 / \sigma^2\right)$. The algorithm MKGSFCM_H has hybrid combination of kernels consists of two tangential kernels and two laplacian kernels defined as $K_M(P_j, C_i) = K_H(P_j, C_i).K_L(P_j, C_i)$ Where $K_H(P_j, C_i)$ is combination of two tangential kernels $K_H(P_j, C_i) = \left(1 - tanh\left(\|p_j - c_i\|^2 / \sigma_1^2\right)\right).\left(1 - tanh\left(\|p_j - c_i\|^2 / \sigma_1^2\right)\right)$, and $K_L(P_j, C_i)$ is combination of two laplacian kernels defined as:

$$K_L(P_j, C_i) = exp\left(\frac{\|p_j - c_i\|}{\sigma_1}\right).exp\left(\frac{\|p_j - c_i\|}{\sigma_2}\right).$$

2.2 Implementation of Proposed Method in Raspberry pi

The Raspberry pi is a single board computer with a size equal to the size of debit card which has given convention to connect to the monitor through HDMI port, keyboard and mouse through USB port. The proposed method implemented in Raspberry pi 2 B board which has 900 MHz quad-core ARM Cortex-A7 CPU and 1 GB RAM. The requirements are Raspbian Jessie as OS and it is installed with Octave version 3.8 with image as package. The Raspberry pi based implementation of the proposed method is shown in Figure 2.

3. Experimental Results

The results of MKGSFCM_T and MKGSFCM_H algorithms on different color digital fundus images are shown in Table 1. The performance of the proposed method is statistically evaluated using Sensitivity and Specificity which are defined as:

$$Sensitivity = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

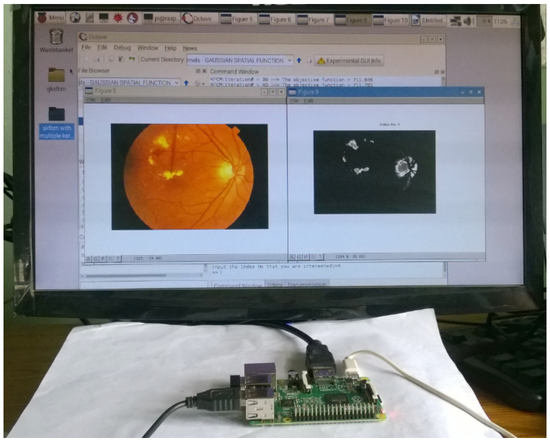
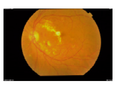
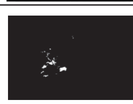
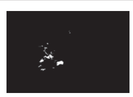


Figure 2. Raspberry pi based implementation.

Table 1. Segmentation results using MKGSFCM_T algorithm

S.NO	INPUT IMAGE	Method	
		MKGSFCM_H	MKGSFCM_T
1.			
2.			
3.			
4.			

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives}$$

- True Positive: Exudate regions pels accurately identified as exudates.
- True Negative: Non-exudate regions pels accurately identified as non-exudates.
- False Positive: Non-exudate regions Pels erroneously identified as exudates.
- False Negative: Exudate regions Pels erroneously identified as non-exudates.

Statistical evaluation of the proposed algorithms MKGSFCM_T and MKGSFCM_H are presented in Table 2. The specificity and sensitivity values for the proposed method were illustrated using bar graphs presented in Figures 3 and 4.

Table 2. Performance of the proposed exudate detection algorithm

METHOD	Parameter	Image-1	Image -2	Image -3	Image -4
MKGSFCM_T	Sensitivity	0.99904	0.99825	0.99424	0.99922
	Specificity	0.99939	0.99610	0.99464	0.99821
MKGSFCM_H	Sensitivity	0.99919	0.99855	0.99741	0.99932
	Specificity	0.99935	0.99995	0.99990	0.99907

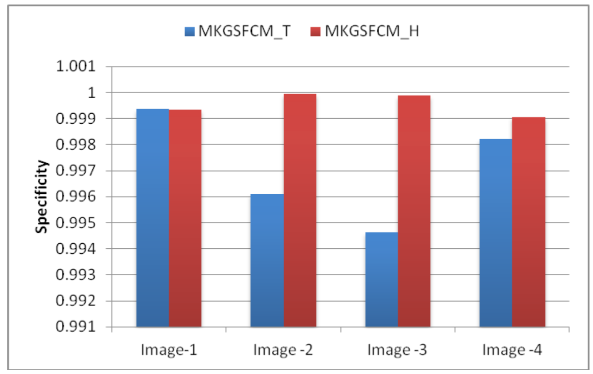


Figure 3. Specificity values.

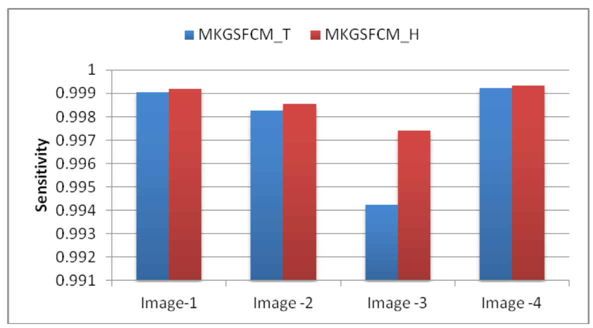


Figure 4. Sensitivity values.

Table 3. Elapsed time in seconds for different processors

METHOD			Image -1	Image -2	Image -3	Image -4
MKGSFCM_T	I-3	MATLAB	54.27	9.44	6.57	20.04
		OCTAVE	165.88	29.77	22.19	64.74
	ARMv7- OCTAVE		897.36	164.09	123.1	341.16
MKGSFCM_H	I-3	MATLAB	61.8	11.96	7.53	23.62
		OCTAVE	269.66	61.49	31.8	123.99
	ARMv7- OCTAVE		1296.76	221.77	160.69	480.06

The elapsed time for the execution of proposed algorithms in I-3 and ARM v7 processors are tabulated in the Table 3. Though Raspberry pi is a simple and smaller hardware and it takes more time for the execution of proposed algorithms as compared to the I-3 processor.

4. Conclusion

From the above experimental results it can be observed that the fine details of the lesions are more evitable and the statistical analysis reveals that the proposed MKGSFCM_T and MKGSFCM_H methods has greatest Sensitivity and Specificity as compared to the existing methods. MKGSFCM_H algorithm has better segmentation results as compared to the MKGSFCM_T in terms of statistical measures Sensitivity and Specificity values. The possibility of exudate misclassification is significantly reduced by the proposed method as compared to existing algorithms. The frame work presented can be developed further by the inclusion of adaptive weights for the multiple kernels.

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