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Detection of Exudates in Diabetic Retinopathy Images using Laplacian Kernel Induced Spatial FCM Clustering Algorithm

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Abstract

Diabetic Retinopathy (DR) is the consequence of micro-vascular retinal changes triggered by diabetes which can cause vision loss if not treated in a timely manner. The major sign of Diabetic Retinopathy are the presence of Exudates. This paper demonstrates a complete framework for the detection of Hard Exudates in Retinopathy images. This paper presents laplacian kernel and it is induced into the kernel spatial FCM clustering algorithm for the segmentation of retinal fundus images. In general, FCM and KFCM algorithms very sensitive to noise and other imaging artefacts because it doesn't have spatial information. To overcome this problem, we presented Laplacian kernel spatial FCM which incorporates spatial information into its objective function and the fuzzy membership function. The performance of our proposed algorithm evaluated on different Diabetic Retinopathy images. The presented methodology is assessed using statistical measures like Sensitivity and Specificity.

Keywords: Diabetic Retinopathy (DR), Fuzzy C Means Clustering algorithm (FCM), Kernel induced Fuzzy C Means Clustering algorithm (KFCM), Kernel induced Fuzzy C Means Clustering algorithm with induces Spatial constraint (KSFCM)

1. Introduction

Diabetic retinopathy is one of the major complications of diabetes which causes vision loss. The diabetic retinopathy usually begins as small variations in the retinal blood vessels and severity mainly increase during the time. Micro aneurysms, hard exudates, soft exudates, haemorrhages etc., are the pathologies which characterize Diabetic Retinopathy. The major sign of Diabetic Retinopathy are the presence of exudates[1]. Retina has the light sensitive muscular layer which consists of network of tiny blood vessels. The vision gets distorted where ever the tiny blood vessels in the retina get damaged. Diabetic Retinopathy classified as non-proliferative and proliferative based on the changes in the vascular capillaries of eye fundus. Neovascularization i.e. the development of new delicate vessels in the retina considered as Proliferative Diabetic Retinopathy (PDR). Non-Proliferative Diabetic Retinopathy (NPDR) is that the stage with no neovascularization. The stage with neovascularization leads to the visual impairment and blindness when the pathos evolves into Proliferative Diabetic Retinopathy (PDR). Micro-aneurysms are the first detectable abnormalities due to the vascular changes in the retina. The retinal capillaries which are weak and fragile got distended and ballooned out [Micro-aneurysms] before they break. These fragile blood vessels ooze blood, and protein particles into the eye fundus and leads to the accumulation of exudates. Also these vessels suffer from nourishment due to the blockages. Hence new blood vessels are stimulated which abnormal, weak, transparent and probably burst and makes this situation continuing. For preventing severe

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vision loss there is a need of early detection and diagnosis of DR will greatly help the patients suffering with DR[3,4]. There is a significance to have a methodology for the detection of Exudates in Diabetic Retinopathy images[2]. This frame work includes an automated methods of DR screening help to save time, cost and vision of patients, compared to the manual methods of diagnosis[3,4].

1.1 Related Work

Medical Image Segmentation aims at automatic delineation of constituent regions in images to analyse the pathological regions. Image Segmentation is a process of segregating an image into significant regions with similar features. In literature the techniques for the exudate detection have been explained. D. Keating et al.[5] used back propagation neural network as an automatic method for detection of diabetic retinopathy pathology and achieved higher sensitivity and specificity values as compared to the results of the ophthalmologist. C Sinthanyothin and JF Boyce[6] detected the exudates by using region growing segmentation method and the optic disk center found using maximum variance method. Multilayer perceptron neural network with PCA used for detection of blood vessels and used match correlation for the detection of fovea[7]. HuanWang et al.[8] used Minimum distance discriminant classifier along with brightness correction technique for the detection of Exudates. A. Singh et al.[9] presented combination of morphological processing and intensity thresholding techniques for the detection of any small Exudates present by avoiding all false positives. Huiqi Li and Opas Chutatape[10] used region extraction and edge detection techniques for the detection of bright lesions and identified optic disc using combination of PCA and ASM techniques. Sanchez C.I et al.[11] presented detection of bright lesions mainly based on statistical classification and edge detection using kernel. Mahendran et al.[12] used the JSEG algorithm for the segmentation of lesions in macular region. R. Ravindraiah et al.[13] presented image segmentation based on expectation maximisation. Niemeijer et al.[14] presented supervised machine learning technique for the classification of true exudates as compared to other pathologies of Diabetic Retinopathy. Franklin et al.[15] used artificial neural network by considering the the colour, size, shape and texture as the features for the detection of Exudates. Aqeel, A. F et al. used adaptive threshold, and morphological operators for the segmentation and classification Exudates and Drusens[16]. Functional Link Artificial Neural Network (FLANN) classifier was implanted for the extraction of Hard Exudates[17]. Datta et al.[18] introduced new contrast enhancement techniques GHE and CLAHE method for Diabetic Screening System. Dunn et al.[19] developed the Fuzzy C-Means (FCM) clustering algorithm and Bezdek[20] extended the Fuzzy C-Means clustering algorithm. For retinal image segmentation FCM clustering algorithm has been used[21,22-24]. Combination of FCM clustering algorithm and neural network classifier has used for segmentation and classification of bright lesions. Mazher Iqbal et al.[25] have presented Gradient Controlled fuzzy C Means Clustering Algorithm for the detection of hard exudates. Chen and Zhang[26] have presented the kernel versions of FCM with spatial constraints, called KFCM_S1 and KFCM_S2.R. Ravindraiah et al.[27] presented subjective approach for the segmentation of exudates. Asha et al.[28] presented FCM for the segmentation of exudates and used Single-hidden Layer Feed forward neural Networks (SLFNs) for the classification of exudates. Rajput et al.[29] presented k-means clustering algorithm applied on LAB color space image. Ramasubramanian et al.[30] used fuzzy kernel c-means algorithm for the segmentation of exudates and classified exudates using active SVM classifier. Pavle Prentasic et al.[31] presented the combination of different candidate extraction algorithm into an ensemble weights for the detection of Exudates. Yang and Tsai[32] have proposed Gaussian kernel induced FCM clustering algorithm for pattern recognition. Karman et al.[33] used hyperbolic tangential kernel induced FCM algorithm for the segmentation of breast images.

The paper is structured as follows: Section II furnishes about the framework used for the segmentation of exudates. The proposed work and experimental results are furnished in section III and section IV respectively.

2. Existing Methods

2.1 FCM Algorithm

Fuzzy C-Means (FCM) proposed by Dunn (1974) and extended by Bezdek[34] (1981) is one of the most well-known methodologies in clustering analysis. It is an approach, where the data points have their membership values with the cluster centers, which will be updated iteratively. Let the image pixels are treated as $p_j = (p_1, p_2, p_3, \ldots p_n)$ be the set of data points and $c_i = (c_1, c_2, c_3, \ldots c_c)$ be

the set of cluster centers. The objective function of FCM algorithm is,

$$J_{fcm} = \sum_{i=1}^{c} \sum_{j=1}^{n} M_{ij}^{m} D_{ij}^{2} \quad (1)$$

Where D_{ij} is the Euclidean distance from pixel p_j to center c_i and is defined as,

$$D_{ij} = \sqrt{\sum_{k=1}^{c} (c_{ik} - p_{jk})^2} \quad (2)$$

The cluster centers and membership functions which minimises the objective function are defined as follows,

$$C_i = \frac{\sum_{j=1}^{n} M_{ij}^{m} p_j}{\sum_{j=1}^{n} M_{ij}^{m}} \quad (3)$$

$$M_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{D_{ij}}{D_{kj}} \right)^{2/m-1}} \; for (m \neq 1) \quad (4)$$

2.2 KFCM Algorithm

The KFCM algorithm[35] uses kernel metric instead of distance metric as compared to the standard fuzzy c-means (FCM) algorithm and KFCM algorithm can also work well if there exists small dissimilarities between clusters and it is not the case with classical FCM algorithm. The objective function of KFCM algorithm is,

$$J_{KFCM} = \sum_{i=1}^{c} \sum_{j=1}^{n} M_{ij}^{m} \left(1 - K\left(p_j, c_i\right)\right) \quad (5)$$

Where M_{ij} is the membership matrix of the j^{th} pixel in the i^{th} cluster, m is the fuzziness coefficient $K(P_j, c_i)$ and is the induced kernel instead of distance metric.

The cluster centers and membership functions which minimises the objective function are defined as follows,

$$C_i = \frac{\sum_{j=1}^{n} M_{ij}^{m} K\left(p_j, c_i\right) p_j}{\sum_{j=1}^{n} M_{ij}^{m} K\left(p_j, c_i\right)} \quad (6)$$

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

$$M_{ij} = \frac{\left(1 - K\left(p_j, c_i\right)\right)^{\frac{-1}{m-1}}}{\sum_{k=1}^{c} \left(1 - K\left(p_j, c_i\right)\right)^{\frac{-1}{m-1}}} \quad (7)$$

3. Proposed Algorithm

Fuzzy c-means algorithm is the widely used technique for image segmentation. Since FCM algorithm not work well for noisy images. The KFCM algorithm uses kernel metric rather than distance metric as compared to the classical fuzzy c-means algorithm and KFCM algorithm can also handle the small differences between clusters and it is not case with classical FCM algorithm. KFCM is sensitive to noise and other imaging artifacts because it doesn't have spatial information. To overcome this problem, we presented Laplacian kernel spatial FCM which incorporates spatial information into its objective function. Here we have considered Laplace kernel instead of Gaussian kernel since Laplace kernel follows Cauchy distribution which drops much slower than the Gaussian distribution that is function with Cauchy distribution will have more frequency components.

3.1 Laplacian Kernel Spatial FCM

Let the image pixels are treated as $p_j = (p_1, p_2, p_3, \ldots p_n)$ be the set of data points and $c_i = (c_1, c_2, c_3, \ldots c_c)$ be the set of cluster centers. The objective function of kernel induced FCM clustering algorithm defined as follows,

$$J_{KFCM} = \sum_{i=1}^{c} \sum_{j=1}^{n} M_{ij}^{m} \left(1 - K(p_j, c_i)\right) \quad [8]$$

Where M_{ij} is the membership matrix of the j^{th} pixel in the i^{th} cluster, m is the fuzziness coefficient and L is the induced kernel instead of distance metric.

Here the kernel used is laplacian kernel and is defined as follows,

$$K(p_j, c_i) = exp(||p_j - c_i||/\sigma).$$

Where σ is the user defined function.

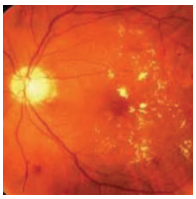
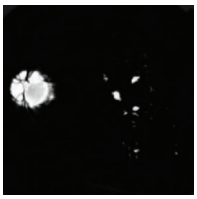
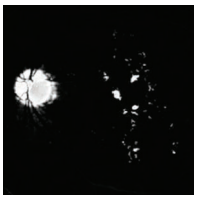
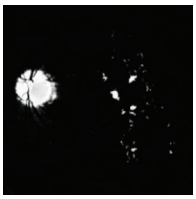
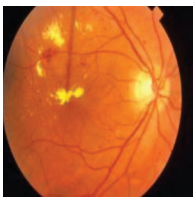
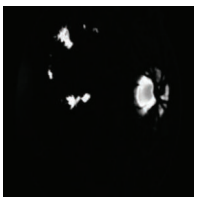
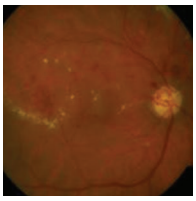
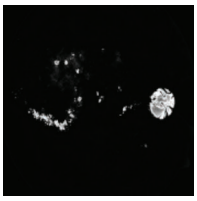
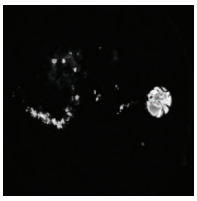
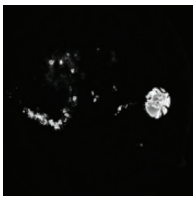
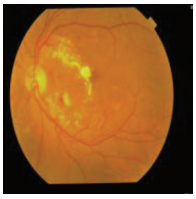
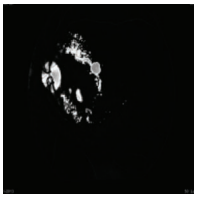
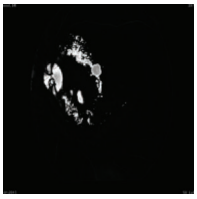
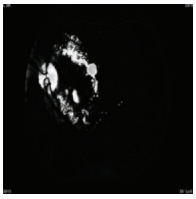
The modified objective function of laplacian kernel metric induced FCM with spatial information is defined as follows,

$$J_{OBJ\_NEW} = \sum_{i=1}^{c} \sum_{j=1}^{n} M_{ij}^{m} (1 - K(P_j, C_i)) + \sum_{i=1}^{c} \sum_{j=1}^{n} h_{ij} \quad (9)$$

The extra term added in the equation [9] is the spatial information and is defined as

$$h_{ij} = \sum_{k \in NBp_j} M_{ik} \quad (10)$$

Table 1. Results

S.NO	Input Image	FCM	KFCM	LKSFCM
1.				
2				
3				
4				

Where h_{ij} is the probability that the pixel P_j belongs to the i^{th} cluster and NB_{P_j} is a square window with neighbouring pixels centered on the pixel P_j.The square window which we considered is of the size. 3×3

The cluster centers and membership functions which minimises the objective function are defined as follows,

$$C_i = \frac{\sum_{j=1}^{n} M_{ij}^{m} K\left(p_j, c_i\right) p_j}{\sum_{j=1}^{n} M_{ij}^{m} K\left(p_j, c_i\right)} \tag{11}$$

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

$$M_{ij} = \frac{\left(1 - K\left(p_j, c_i\right)\right)^{\frac{-1}{m-1}}}{\sum_{k=1}^{c} \left(1 - K\left(p_j, c_i\right)\right)^{\frac{-1}{m-1}}} \tag{12}$$

The membership function can be modified by using the spatial function h_{ij} as

Table 2. Statistical Analysis

METHOD	Parameter	Figure-1	Figure -2	Figure -3	Figure -4
FCM	Sensitivity	0.97894	0.98422	0.98931	0.99235
	Specificity	0.07436	0.06145	0.03955	0.07727
KFCM	Sensitivity	0.98520	0.98796	0.99831	0.99632
	Specificity	0.76654	0.81406	0.7955	0.87607
LKSFCM	Sensitivity	0.99260	0.99072	0.99770	0.99633
	Specificity	0.84398	0.84398	0.89333	0.88285

$$M_{ij}^{\wedge} = \frac{M_{ij}^{m} h_{ij}}{\sum_{k=1}^{c} M_{ij}^{m} h_{ij}} \tag{13}$$

4. Experimental Results

The experimental results were evaluated by using sensitivity and specificity per image.

Abnormal retinal fundus classified as abnormal based on the Sensitivity value while normal retinal fundus classified as normal based on the specificity value. Sensitivity and specificity were defined as follows,

$$sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$specificity = \frac{True\ Negative}{True\ Negative + False\ Positive}$$

True positive = Correctly Classified Number of exudates pixels.
True negative = Correctly Classified Number of non – exudates pixels.
False positive = Misclassified Number of non – exudates pixels as exudates.
False negative = Misclassified Number of exudates pixels as non – exudates.

5. Conclusion

From the above experimental results it can be observed that the output images after each segmentation methods seems to be almost identical, but the statistical analysis reveals that the proposed LKSFCM method has greatest Sensitivity and Specificity. Thus the results are improved further so that it is able to avoid misclassification of lesions in the DR images. The proposed method can be improved further by the inclusion of multiple kernels and can be made adaptive if Weighted distance metrics are utilised.

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