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Application of Spatially WeightedSoftClustering Methods for the Detection of DiabeticRetinal Abnormalities in Multiple Kernel domain

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Abstract: Microvascular discrepancies linked with persistent hyperglycaemia triggers vision threatening Diabetic Retinopathy (DR). It is a metabolic inability to control the blood glucose levels. It is originated with less production of pancreatic secretion or the body resistance to make use of it. The progression of the condition can be slowed with proper diet supervision and periodic medical administer. DR will lead to complete vision loss in the victim's having prolonged history of diabetes, who do not taken mere steps to manage it. The condition is characterized with blocked or ruptured blood vessels (BVs) leaking blood, protein and fat based particles into the retinal fundus. These particles are get clotted and are called as Exudates, which obstruct the light flow onto the retina and hence affects the vision. Due to the lack of blood supply, new BVs are triggered to nurture the retina. These new BVs are more sensitive and can get easily ruptured, which makes the complication more severe. Instinctive methods aids the clinicians in easy identification and conclusions regarding the state of the pathology. This paper presents a spatial weight induced soft clustering methods for the detection of lesions in DR fundus images using a novel kernel domain. The performance of these methods are compared with the existing state of art methods and is observed statistically optimum.

Keywords: Diabetic Retinopathy (DR), Clustering methods, spatial weight metrics, kernel operators

I. INTRODUCTION

Diabetes mellitus is a metabolic disorder arises with condition called chronic hyperglycemia. Inadequate insulin or the body's resistance to make use of it will leads to this situation. This causes a disturbance of controlling the levels of blood glucose produced from protein, carbohydrate and fat particles in the diet [1]. This tends to affect vital organ of the body like eyes, kidneys, heart, neurons etc. Eyes are sensitive organs that can easily get affected with is metabolic disorder which tends to many vision threatening disease to the eye. Therefore the diabetic eye disease is treated as Diabetic Retinopathy (DR). It is an ocular complication and is usually found in working age adults (20 to 64 years) [2]. Neo vasculature, intraocular hemorrhages (HAs), microaneurysms (MAs) are observed in the initial stages and tends to macular/ fovea damage with possible retinal detachment in the extreme characteristics of this pathology. Also the remnants of blood, protein and fat particles get hardened and accumulated as exudate particles. These exudates are easily identified as yellow and white patches and can be washed away with the usage of laser treatment.

The exudates are considered as soft or hard exudates based upon their size, shape and density. They acts as an uncertain barriers present in the eye fundus and obstruct the light flow towards the retina. Thus it creates blurred, hazy and shadowed vision. DR is predominantly classified into Non Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) [3]. NPDR is an acute state in which the DR initial symptoms of HAs and MAs are observed at the walls of the affected BVs. The HAs and Mas are identified at ballooned out walls of BVs. If proper care is not taken in this initial stage, the BVs are further effected and these ballooned spots will get ruptured and the leads to the accumulation of exudates. Due to this the retinal muscles suffers with the lack of proper nourishment and triggers the origin of new BVs. These new BVs are very sensitive and can be easily ruptured. Thus it complicates the condition much further and the victims are at the chance of temporary or complete vision morbidity. This is a case of PDR

and the victims need immediate and effective clinical administration to reduce the risk of complete vision loss [4-8].

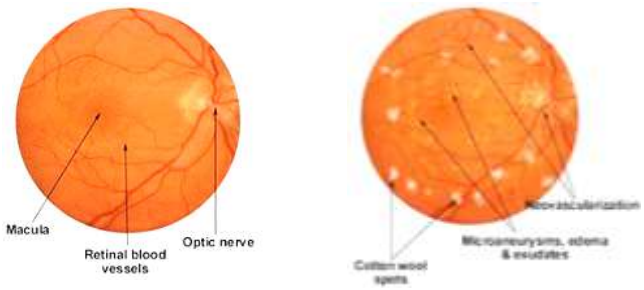


Figure 1: (a) Normal retinal fundus image; (b) Typical DR image

Figure 2: (a) Normal vision; (b) Vision with DR

The figure 1 (a) shows the typical normal eye fundus image which represents the typical parts of the eye like Optic disc (OD), BVs and macula. In figure 1 (b), all probable lesions that appear in a DR victim can be observed. Figure 2 (a) represents the normal vision and figure 2(b) represent the blurred and shadowed vision of a DR patient.

Medical image processing can aid the clinical experts by making the easy diagnosis with less effort and patients can be made to avoid the pre diagnosis stage. This paper presents a soft clustering technique calledPossibilistic C Means clustering methods in multi kernel domain and appended spatial weight variants for the automatic detection of lesions in DR images. The rest of paper is organized as follows: section 2 brief the literature review of existing methods, section 3 describes the design and development of the proposed methods followed with results in discussions in section 4 and 5 respectively.

II. BACKGROUND

This section presents a detailed description of few methods that employed soft clustering method called fuzzy c means clustering (FCM) and its derivatives in detection of retinal abnormalities

Osareh A. et. al. [9] extracted the features from FCM segmented DR images and classified them using five classifiers on a small dataset of 16 images, the exudates are detected optimally by NN classifier and attained 90.1% of maximum accuracy in lesion detection. They attained a sensitivity and specificity pair of 93% and 90.10% using FCM output features and feeding them to NN classifier in [10]. Morphological and FCM methods are used for DR feature extraction and applied to Support Vector Machines (SVM) classifier by Zhang X et. al. [11]. Sopharak.Aet. al., [12] preprocessed HIS DR images using median filter and stretched the contrast. An average sensitivity and specificity pair of 93.38%/ 98.14% and an accuracy of 98.05% is reported.In [13] they employed FCM for the detection of bright lesions and BVs are extricates using decorrelation stretch and thresholding methods.Dark and bright lesions discrimination is addressed by Silkar. S et. al., [14] using Differential Evolution and morphological methods. The BVs and ODare extricated using morphological operators and kernelized FCM methods. Then the retinal lesion features extracted using Laplacian of Gaussian filtering (LoG) method. 50% of images from DRIVE, STARE, DIARETDB1 and ROCh datasets and obtained 97.71% of accuracy. They addressed LoG and fuzzy entropy maximization methods for DR sorting in [15]. Using 95% of images from the earlier mentioned datasets a mean sensitivity of 93.14% and specificity of 93.19% is achieved.

All these methods didn't given any significance to the inclusion of spatial information associated by a pixel surrounded by its neighborhood. This feature makes the system more immune to noises. Also the existing methods are employed using spatial metrics, which generates the resultant segmented results based on specific mathematical constraint. These constraints will allow the extraction of only specific shaped clusters defined by the deterministic preference. By considering all these flaws a spatially weighted Possibilistic C Means clustering method with induced multiple kernels are used for the reliable detection of lesions in non-dilated DR fundus images.

III. METHODOLOGY

A total of 40 non dilated DR images are taken from five public datasets [16- 20] and from a privates dataset are used in this work. Green component is extracted from these methods are extracted and are allowed to median filtration for noise suppression.

A. *Proposed Possibilistic C means Clustering (MKPCM) method with induced multiple kernels:*

Then the proposed MKPCM is applied to attain the segmentation results. This algorithm aims to minimize the objective function which is used for implementing clustering process is given by

$$J_{MKPCM} = 2\sum_{j=1}^{n}\sum_{i=1}^{c} M_{ij}^{m}\,[1 - K(x_j, c_i)] + \sum_{i=1}^{c}\eta_i \sum_{j=1}^{n}(1 - M_{ij})$$

Where $M_{ij}$is the membership function which represents the degree of membership of the j[th] pixel in ith cluster. $K(x_j, c_i)$ is the induced kernel function that performs a non-liner operation between j[th] pixel with i[th] cluster centroid. η_i is the Possibilistic constraint which relaxes the M_{ij} function. The eq (1) is needed to be minimized to attain the maximum similarity of a particular pixel towards a cluster centroid and hence clustering is done. It can be done by differentiating eq (1) w.r.t to $\boldsymbol{M_{ij}}$ and $\boldsymbol{\phi(c_i)}$ and equate the resultant equation to zero. The resulting expressions for these function is given by

$$M_{ij} = \left[1 + 2\left(\frac{1-K(x_j,c_i)}{\eta_i}\right)^{\frac{1}{m-1}}\right]^{-1}; \forall i, j \quad (2)$$

$$\phi(c_i) = \frac{\sum_{j=i}^{n} M_{ij}^{m}\phi(x_j)}{\sum_{j=1}^{n} M_{ij}^{m}}; \forall i \quad (3)$$

Here $\boldsymbol{\phi(c_i)}$ is the non-linear operator which maps the data present in the spatial domain onto $\boldsymbol{N}$ dimensional kernel domain. The direct computation of this equation is difficult. It can be simplified by multiplying it with $\phi(x_j)^T$ and generates a revised expression given by

$$K(x_j, c_i) = \frac{\sum_{j=1}^{n} M_{ik}^{m} K(x_j, c_i)}{\sum_{j=1}^{n} M_{ij}^{m}};\ \forall i, j \quad (4)$$

And $\eta_i$is given by

$$\eta_i = \beta\frac{2\sum_{j=1}^{n} M_{ij}^{m}(1-K(x_j,c_i))}{\sum_{j=1}^{n} M_{ij}^{m}}; \beta > 0 \quad (5)$$

***Algorithm of the MKPCM**:*

1. Fix the initial cluster count ***'C'*** (with m>0) and arbitrarily set the cluster centers $\boldsymbol{C_i}$
2. Using eq(2) calculate the membership function, $\boldsymbol{M_{ij}}$
3. Using eq(4) compute the kernel metric, $\boldsymbol{K(x_j, c_i)}$
4. Using eq(5) update the possibilistic constraint $\boldsymbol{\eta_i}$
5. Update Objective function $\boldsymbol{J_{MKPCM}}$by using equation 1

Repeat the steps 2 to 5 iteratively until $|J^t - J^{t-1}| < \varepsilon$. Here ε is minimum value (say 0.0001)

B. *Proposed spatial weighted Possibilistic C means Clustering (MKSPCM) method in multi kernel domain:*

A Gaussian spatial which operates on a neighborhood defined by $\boldsymbol{NBx_j}$is used to append spatial weight into the proposed MKPCM algorithm to make the noise performance of the algorithm effectual. This function is represented with h_{ij} and is expresses as

$$h_{ij} = \sum_{k\in NB_{x_j}}\sum_{l\in NB_{x_j}} \frac{1}{2\pi\sigma^2} e^{\frac{k^2+l^2}{2\sigma^2}} M_{k,l} \quad (6)$$

This function possess similar characteristics as that of M_{ij} and is used to increase the weight of it. The weight induced membership function is given by

$$M'_{ij} = \frac{M_{ij}^{m} h_{ij}}{\sum_{k=1}^{c} M_{ij}^{m} h_{ij}} \quad (7)$$

Using this updated membership function the $\boldsymbol{J_{MKPCM}}$ can be treated as$\boldsymbol{J_{MKSPCM}}$.

***Algorithm of the MKSPCM**:*

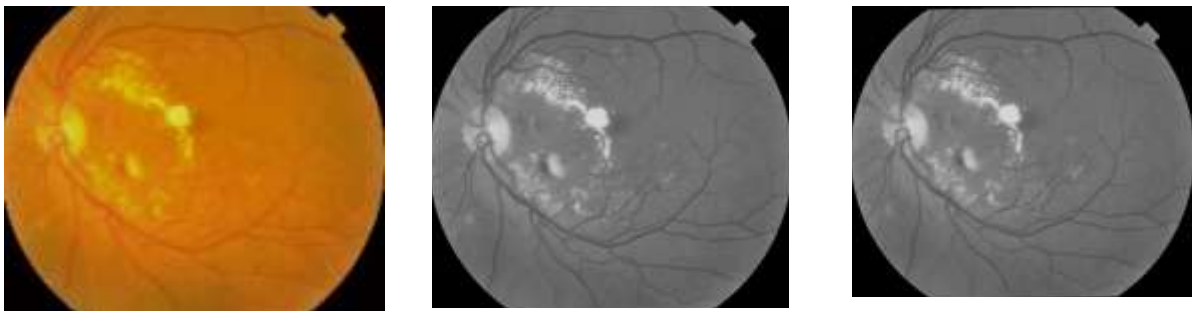
1. Fix the initial cluster count '*C*' (with *m*>0) and arbitrarily set the cluster centers C_i
2. Using eq(2) calculate the initial membership function, $\boldsymbol{M_{ij}}$
3. Using eq(4) compute the kernel function, $\boldsymbol{K(x_j, c_i)}$
4. Using eq(5) compute the possibilistic constraint $\boldsymbol{\eta_i}$
5. Using eq(6) compute the spatial function $\boldsymbol{h_{ij}}$(use equation 11)
6. Using eq(7) update the membership function $\boldsymbol{M_{ij}}$ with induced spatial constraint $\boldsymbol{h_{ij}}$
7. Update Objective function J_{MKSFCM} (use eq1)

Repeat the steps 3 to 7 iteratively until $|J^t - J^{t-1}| < \varepsilon$. Here ε is minimum value (say 0.0001)

Single and dual laplacian kernels are induced into these proposed MKPCM, MKSPCM and the performance evaluation of the methods is done statistically.

IV. EXPERIMENTAL RESULTS

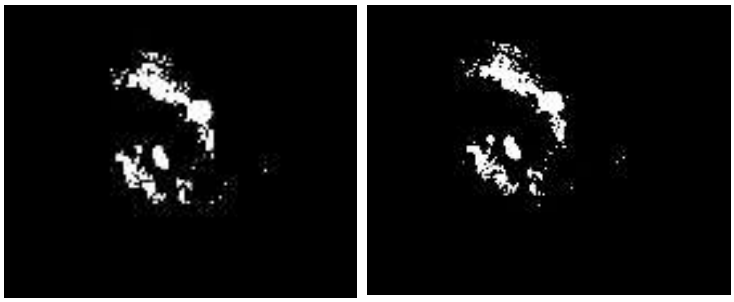
Exudates are easily recognized using a digital ophthalmoscope. They appear as yellow or white spots accumulated in the retinal fundus. A typical DR image is represented in figure 1(a). Hard exudates near to macular region is observed.



(a) **(b)** **(c)**

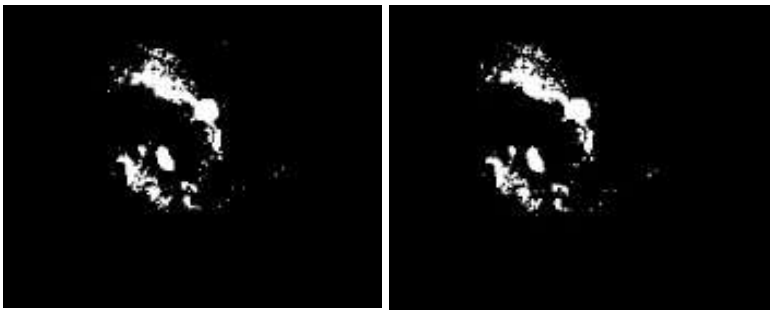
Figure 1: (a) a typical DR image (Courtesy: Suthrama Eye Hospital, Madanapalle, A.P. India); (b) its green component; (c) median filtered output.

Figure 1(b) is the extracted green component from figure 1(a) and is preprocessed using median filtration for noise suppression. The filtered output is represented by figure 1(c). It can be observed that the resultant image is enhanced a bit and the edge information is preserved well.



(a) **(b)**

Figure 2: (a) and (b) are the outputs of L1KPCM and L2KPCM respectively



(a) **(b)**

Figure 3: (a) and (b) are the outputs of L1KSPCM and L2KSPCM respectively

The output images obtained by L1KPCM and L2KPCM are represented by Figure 2 (a), (b). Whereas the output images of L1KSPCM and L2KSPCM are represented by figure 3 (a), (b). From these results it can be observed that the proposed methods

are successful in extracting the lesion features. These results are used to compile the following statistical function using clinician's ground truths. The statistical parameters used in this work are given by

$$Sensitivity = \frac{TP}{TP+FN} \quad (8)$$

$$Specificity = \frac{TN}{TN+FP} \quad (9)$$

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (10)$$

- True Positive(TP) : Count of correctly classified exudate pixels
- True Negative(TN): Count of correctly classified non-exudate pixels
- False Positive(FP): Misclassified count of non-exudates treated as exudates
- False Negative(FN) : Misclassified count of exudates treated as non-exudates

The proposed methods has achieved the Sensitivity, Specificity and Accuracy as:
L1KPCM - 90.22%, 99.09% and 94.31%; L2KPCM – 90.12%, 99.18% and 94.01%; L1KSPCM – 93.13%, 99.23% and 95.32%; L2KSPCM – 93.15%, 99.20% and 94.55% respectively.

V. CONCLUSION

From the experimental results it can be observed that the proposed methods are quite successful in extracting the finest details of lesions present in the DR fundus image. The beauty of this exists with the extrication of BVs without the need of any intermediate step. The OD is selectively segregated for to preserve the segmentation accuracy and avoid the chance of unnecessary false alarms. Thus the misclassification rate is minimized. The algorithms are simulated in a personal computer equipped with intel core i5 5200 2.20GHz CPU and Raspberry pi 3 Model B with 1GB RAM, quad core 1.2 GHz processor kit using octave 4.0 and Matlab application software. It is observed that the raspberry kit is taking 4.8 to 5.2 times more run time than compared to the PC for simulating the algorithms. Graphical evaluation of the statistical values for the proposed methods is done, in which the respective statistical feature obtained from individual DR images used is represented. Also it can be observed that the proposed methods tries to converge these statistical features to the maximum. Compared to the existing methods, the proposed methods had proven its significance statistically.

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