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CLINICAL DIAGNOSIS OF MALIGNANT MELANOMA USING SPATIALLY COHERENT FUZZY CLUSTERING TECHNIQUE

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Abstract - Dermoscopic images have great potential in the early diagnosis of malignant melanoma, but their interpretation is time consuming and subjective, even for trained dermatologists. The Fuzzy clustering techniques are used for segmentation of lesions are Fuzzy C Means Algorithm (FCM), Spatially Coherent Fuzzy Clustering Algorithm. The segmented images are compared with the ground truth image using various parameters such as False Positive Error (FPE), False Negative Error (FNE), Coefficient of similarity, Spatial overlap and their performance is evaluated.

Keywords: Fuzzy C Means, Spatially Coherent Fuzzy Clustering Algorithm, FPE, FNE, Coefficient of similarity, Spatial overlaps.

I. INTRODUCTION

Image segmentation is the process of partitioning a digital image into a non-overlapped homogeneous regions with respect to some characteristics, such as gray value, motion, texture, etc. Image segmentation is used in various applications like medical imaging, locating objects in satellite images, face recognition, traffic control systems, and machine vision, etc. [2]. They can be classified into regions based approaches [4, 5] and edge detection based approaches [6]. In the present work, we focus on the region based approach using a fuzzy clustering algorithm (soft clustering), instead of hard clustering strategies.

In the hard clustering, each data point is assigned to only one cluster, while in soft clustering each data point belongs to all clusters with different degrees of membership, thus taking a better account for poor contrast, overlapping regions, noises, and intensity in homogeneities. To overcome the misclassification errors due to noise, many extensions of the FCM algorithm have been proposed [7]. Some of the methods combine the pixel-wise fuzzy classification with preprocessing (noise cleaning in the original image) [9].

This paper is an extended version of the conference paper [7], which proposes an improved FCM-based algorithm for accurate and noise-robust image segmentation. In the new method we present two improvements. First, to create a method that is more robust to noise, we incorporate local neighborhood information not only in the similarity measure, but also into the membership function. Second, to design a method that accurately segment edges and line elements without smoothing, we consider anisotropic neighbourhood based on phase congruency features.

II. METHOD

2.1 Fuzzy c-means algorithm

The fuzzy c-means algorithm is a fuzzy clustering method based on the minimization of a quadratic criterion, where clusters are represented by their respective centers. For a set of data patterns $X = \{x1, x2. . . xN\}$ the fuzzy c-means clustering algorithm allows to partition the data space, by calculating the center of the cluster, the membership function, and by minimizing the objective function with respect to the center and membership function.

Firstly, the centers of classes are fixed to find the membership degrees. Secondly, the membership degrees are fixed to find the centers. These two steps are alternately repeated until convergence $||C_i^{(k)} - C_i^{(k-1)}|| < \epsilon$, is attained. The Mathematical expression for Euclidean Distance, Membership function and Objective function are as follows:

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$$d^2(X_j, V_i) = \| X_j - V_i \| \quad (1)$$

$$U_{ij} = \frac{1}{\sum_{K=1}^{C} \left(d(x_j, v_{ij}) \mid d(x_j, v_k) \right)^{2/m-1}} \quad (2)$$

$$J_m(U, V) = \sum_{j=1}^{N} 1 \sum_{i=1}^{C} u_{ij}^{\ m} d^2(X_j, V_i) \quad (3)$$

In image segmentation, *xi* is the gray value of the *ith* pixel, *N* is the number of pixels of the image, *C* is the number of the regions (clusters), *d*2 (*xi*, *cj*) is the Euclidian distance between the pixel *xi*, *and* the center *cj*, Uij is the membership degree of pixel *xi* in the *jth* cluster and m is the degree of fuzziness (m>1).

2.2 Proposed method

This method proceeds as

- Initialization of the classification of the pixels
- Segmentation of the image using Spatially coherent Fuzzy clustering method.

2.2.1. Initialization using particle swarm optimization (PSO)

In order to optimize the initialization step of the FCM clustering algorithm, a PSO metaheuristic is used to find the best initial positions of the centers of clusters, as performed by [30] for PCM clustering algorithm. Particle swarm optimization (PSO) is a population-based stochastic optimization algorithm proposed for the first time by Eberhart and Kennedy [10], inspired by bird flocking and fish schooling. The problem is tackled by considering a population (particles), where each particle is a potential solution to the problem. The evolution of the swarm is governed by the following equations ((4) and (5)).

$$V^{(k+1)} = w.V^{(k)} + C_1.rand_1.\left(pbest^{(k)} - X^{(k)}\right) + C_2.rand_2.\left(gbest^k - X^{(k)}\right), \quad (4)$$

$$X^{(k+1)} = X^{(k)} + V^{(k+1)} \quad (5)$$

Where:
X: is the position of the particle,
V: is the velocity of the particle,
w: is the inertia weight,
pbest: is the best position of the particle,
gbest: is the global best position of the swarm,
*rand*1, *rand*2: are random values between 0 and 1

*c*1, *c*2: are positive constants which determine the impact of the personal best solution and the global best solution in the search process, respectively,

k: is the iteration number.

The use of metaheuristics always induces a problem of adjusting parameters. The values of the parameters of the equation (4) used are given in table1. Concerning the stopping condition, we used two criteria, if one of them is verified the algorithm stops:

The non-significant improvement of the objective function after *nerp* iterations:

$$\forall k \in [0, nb_{maxiter}], \forall n \in \left[k, k + n_{erp}\right]: \ |J^{(n+1)} - J^{(n)}| < \epsilon_{ep} \ (6)$$

The maximum number of iterations *nbmaxiter*.

The parameters *ep*, *nbmaxiter*, *nerp* and the number of particles are determined experimentally in order to have a good compromise between the convergence time of the algorithm and the quality of the final solution, which will be used as initial configuration (centers of classes) for the clustering algorithm.

Table1: The parameters' values used in the PSO initialization

Parameters	Values
c1 = c2	1.70
w	Adaptive [0.4, 0.9]
ep	10−6
nbmaxiter	200
nerp	10
Number of particles	12

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1.2.2. Spatially coherent fuzzy clustering method

We improve the performance of the standard FCM algorithm by integrating local neighbourhood information along with the PSO initialization method.

Neighborhood Configuration:

Phase Congruency is used to detect the neighborhood information. Phase Congruency is a method to detect any feature type in the image such as line, step edges, etc. It is more efficient than the smoothing technique.

The Local Energy Model model for Phase Congruency was developed by Morrone et al. [11]. Other work on this model of feature perception can be found in Morrone and Burr [13], Owens et al. [14], Venkatesh and Owens [15], and Kovesi [8]. The local, complex valued, Fourier components at a location x in the signal will each have an amplitude A (x) and a phase angle □n (x). The magnitude of the vector from the origin to the end point is the Local Energy, $|E(x)|$. The measure of phase congruency developed by Morrone et al. [10]

$$PC1(x) = \frac{|E(x)|}{\sum_n A_n(x)} \qquad (7)$$

FCM objective function, is significantly influenced by the choice of the similarity measure D_{ij}, Which is used for computing the membership degree values u_{ij}, and u_{ij} are further used for computing the cluster centers v_i. Thus, in each iteration of the algorithm we adjust both the similarity measure and the membership degree values, in two separate steps, using the information of neighboring pixels. In the first step we calculate the neighborhood weighted similarity measure as follows:

$$D_{ij}^{*} = (1-\alpha S_{ij})\, \|x_j - v_i\|^2 \qquad (8)$$

Where w_{ij} [0, 1] is the similarity measure weight, which depends on the local neighborhood attraction weight S_{ij} □ [0, 1] and the parameter α [0, 1] that controls the relative importance of the neighbourhood attraction. The local neighbourhood attraction weight S_{ij} is defined as:

$$S_{ij} = \frac{\sum_{r\in\Omega j} u_{ir}\, a_{jr}\, d_{jr}^{-2}}{\sum_{r\in\Omega j} a_{jr}\, d_{jr}^{-2}} \qquad (9)$$

Where Ω_j Is a set of neighbors with index r in a n × n square window, surrounding the study element with index j,u_{ir} is the membership degree of the neighbouring element r to the cluster i. The intense attraction is the absolute intensity difference between the study pixel and its neighbor. The distance attraction d_{jr} is the Manhattan distance between the element j with coordinates (p_j, q_j) and its neighbour r with coordinates (p_r, q_r) .

After calculating the new similarity measure D_{ij}^{*} , we update the membership values using u_{ij}. Then, in the second step we use again the local neighbourhood information to adjust the updated membership values in the following way:

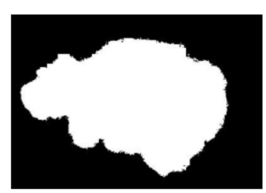
$$u_{ij}^{*} = \frac{u_{ij}\, M_{ij}^{\beta}}{\sum_{k=1}^{c} u_{kj}\, M_{kj}^{\beta}} \qquad (10)$$

$$M_{ij} = \frac{\sum_{r\in\Omega j} u_{ir}\, d_{jr}^{-2}}{\sum_{r\in\Omega j} d_{jr}^{-2}} \qquad (11)$$

Where u_{ij}^{*} is the new membership value, C is the number of clusters, M_{ij} is the spatially weighted membership degree mean. The squared reciprocal distance d_{jr}^{-2} is used, because the neighbours close to the central element should influence the result more, while more distant neighbours should have a lower weight. Illustrations or pictures: All illustrations or pictures should be clear black and white/color prints. Supply the best quality illustrations or pictures possible.

III. RESULTS

A real dermoscopic (Malignant Melanoma (256 x 400)) image is obtained from the database to evaluate the performance of various fuzzy clustering techniques. The input digital image is segmented using various Fuzzy Clustering techniques. The results obtained are then compared with the segmentation results that were performed manually to explore the accuracy of the proposed fuzzy based algorithm.



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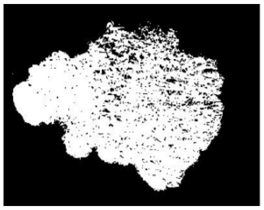

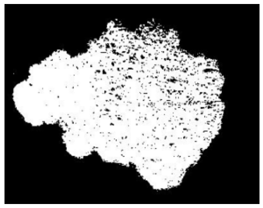

Fig 1 is the input malignant melanoma image.
Fig 2 is ground truth image.
Fig 3 is the segmented image using Fuzzy C Means Algorithm.
Fig4 is the segmented image using Spatially Coherent Fuzzy Clustering Technique.

For obtaining the more accurate result in performance analysis, various parameters are to be considered. For the performance analysis the ground truth image (Fig. 2) is considered.

IV. PERFORMANCE ANALYSIS

In order to evaluate the accuracy of the fuzzy based segmentation some of the segmentation performance parameters based on ground truth (Fig: 2) based evaluation are shown. The four important parameters used to determine the accuracy of the proposed algorithm are false positive and negative error, spatial overlap, and coefficient of similarity.

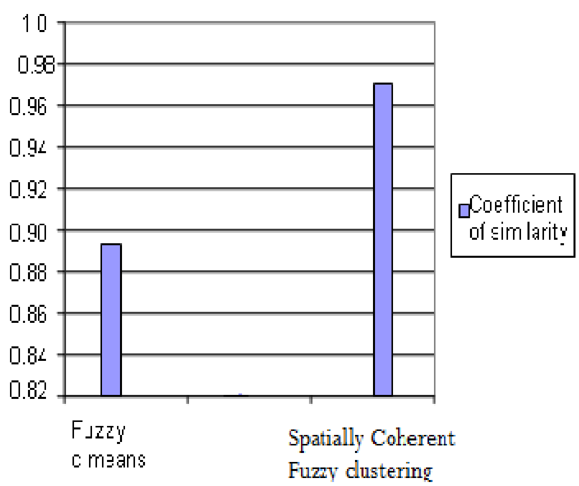

Fig 5: Coefficient of similarity of different Clustering methods

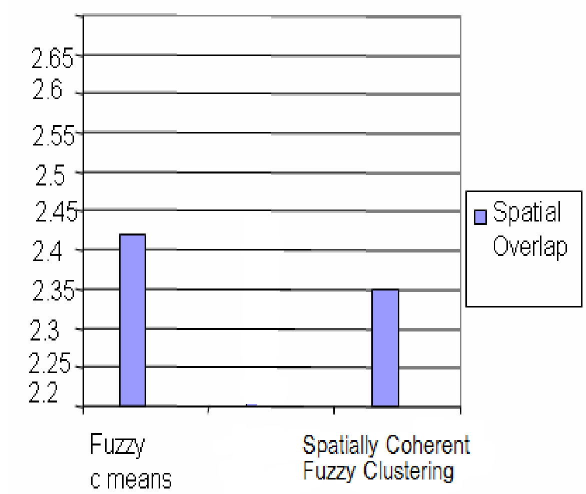

Fig 6:Spatial Overlap for different clustering methods

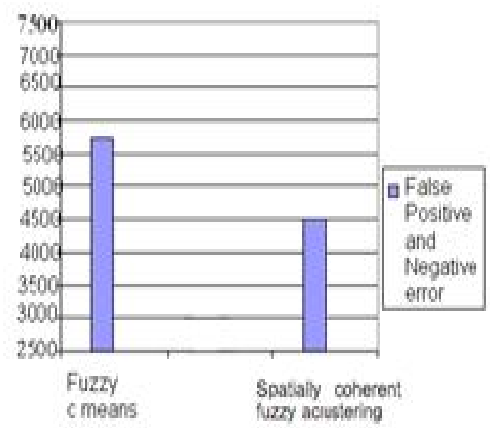

Fig 7: False Negative and Positive errors for different clustering methods

Fig .5-7 shows the result of performance analysis of various fuzzy clustering techniques. The best (low value) false positive and false negative error is obtained by the Spatially Coherent Fuzzy Clustering method. Also, the measure of similarity (value near to one) and the Coefficient of similarity hold well in Spatially Coherent Fuzzy Clustering method. Thus the experimental results obtained by employing the Spatially Coherent Fuzzy Clustering algorithm reveals that it has better performance over the other two clustering techniques. Furthermore, the Spatially Coherent Fuzzy Clustering

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algorithm eliminates the effect of noise greatly. This in turn increases the segmentation accuracy of the clustering algorithm. The experimental results indicate that our method has the highest accuracy in segmentation comparing with other methods.

V. CONCLUSION

The project proposes and evaluates the performance of various fuzzy clustering techniques for the segmentation of skin lesions in dermoscopic images. The fuzzy technique provides better segmentation when compared to the various existing methods. The various Fuzzy clustering techniques employed in this work are Fuzzy C Means, Spatially Coherent Fuzzy Clustering. Experiments are conducted on real medical image to evaluate the performance of the proposed algorithm.

The Spatial coherent Fuzzy Clustering approach provides better performance and can handle uncertainties that exist in the data efficiently and useful for the accurate lesion segmentation in a computer aided diagnosis system to assist the clinical diagnosis of melanoma. The standard approach in automatic dermoscopic image analysis usually has three stages: 1) Image Segmentation; 2) Feature Extraction; and 3) Lesion Classification. The present work deals with the segmentation stage, which is one of the most important since it affects the accuracy of the subsequent steps.. The work can be continued with the subsequent steps in the melanoma detection such as feature extraction, and lesion classification.

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