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Two Different Multi-Kernels for Fuzzy C-Means Algorithm for Medical Image Segmentation

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ABSTRACT

A new image segmentation using multi-hyperbolic and multi-Gaussian kernel based fuzzy c-means algorithm (KFCM) is proposed for medical magnetic resonance image (MRI) segmentation. The integration of two hyperbolic tangent kernels and two Gaussian kernels are used in the proposed algorithm for clustering of images. The performance of the proposed algorithm is tested on OASIS-MRI image dataset. The performance is tested in terms of score, number of iterations (NI) and execution time (TM) under different Gaussian noises on OASIS-MRI dataset. The results after investigation, the proposed method shows a significant improvement as compared to other existing methods in terms of score, NI and TM under different Gaussian noises on OASIS-MRI dataset.

Keywords— FCM, Segmentation, multi-Gaussian Kernel, fuzzy, multiple-kernel.

1. INTRODUCTION

In image processing and computer vision, medical image segmentation is an active research area. The process of clustering the image into non-overlapped, consistent regions is called the image segmentation. These regions are identical with respect to some features like texture, color, shape, intensity etc. Based on the features, the process of segmentation is separated into four groups: clustering (intensity), thresholding (intensity), region extraction (color or texture) and edge detection (texture). In literature, several techniques are available for medical image segmentation. The previously available literature on segmentation methods are: thresholding techniques, clustering techniques, classifiers based techniques, region growing techniques, Artificial Neural Networks (ANNs) based techniques, Markov Random Field (MRF) models atlas-guided techniques etc. Amongst the above discussed methods, the clustering based techniques show an importance in medical imaging research.

Clustering is a procedure for classifying patterns or objects in such a manner that samples of the same cluster are more comparable to one another than samples belonging to other clusters. There are two main clustering approaches: the hard clustering technique and the fuzzy clustering technique. Macqueen has proposed the k-means clustering algorithm. The k-means is one of the hard clustering techniques. The usual hard clustering techniques classify every point of the records set just to one

Cluster. As an effect, the results are often very crusty, i.e., in image clustering every pixel of the image goes to one cluster. However, in many real conditions, issues such as restricted spatial resolution, reduced contrast, partly cover intensities, noise and intensity in homogeneities decrease the efficiency of hard (crusty) clustering techniques. Fuzzy set theory has brought in the idea of incomplete membership, explained by a membership function. Fuzzy clustering, as a soft segmentation technique, has been extensively analyzed and effectively applied in image segmentation and clustering. Among the fuzzy clustering techniques, fuzzy c means (FCM) algorithm is the generally well-liked technique which is used in image segmentation due to its robust features for uncertainty and can keep much more information as compared to hard segmentation techniques. While the standard FCM algorithm works fit on most noise-free images, it is very aware to noise and other imaging artifacts, because it does not consider any data about spatial background.

Tobias and Panes have proposed a fuzzy rule-based technique also known the ruled-based neighborhood improvement system to impress spatial constraints by post processing the FCM clustering results. Noordametal have proposed a geometrically guided FCM algorithm which is a semi-supervised FCM technique. Here, a geometrical condition is used the local neighborhood of every pixel. Pham has customized the FCM objective function by counting spatial punishment on the membership functions. The punishment term leads to an iterative algorithm, which is extremely comparable to the original FCM and allows the evaluation of spatially flat membership functions. Ahmedetal have proposed the FCM where the objective function of the standard

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FCM is modified in order to recompense the intensity in uniformity and permit the labeling of a pixel to be affected by the labels in its neighborhood. The disadvantage of FCM_S is that the neighborhood labeling is computed in every iteration step which is very time-consuming.

2. METHODS

A. Fuzzy C-means Algorithm

Fuzzy c-means clustering technique is a simplification of the hard c-means algorithm yields enormously superior results in an image region clustering and object categorization. As in hard k-means algorithm, Fuzzy cleans algorithm is based on the minimization of a standard function.

Let a matrix of n data elements (image pixels), each of size s s (1) □ is represented as X x x x □ (...). 1 2 n FCM generates the clustering by iteratively minimizing the objective function given in Eq. (1).

Objective function:

$$O_m(U,C)=\sum_{i=1}^{c}\sum_{j=1}^{n}U_{ij}^{m}D^2\,(x_j,C_i) \qquad (1)$$

Constraint:

$$\sum_{i=1}^{c}U_{ij}=1; \qquad \forall_j \qquad (2)$$

Where,Uij is membership of the jth data in the ith cluster Ci , m is fuzziness of the system (m=2) and D is the distance between the cluster center and pixel.

FCM algorithm

The algorithm for the FCM based clustering is given bellow.

Input: Raw image; Output: Segmented image;

- Randomly initialize the (c=3 clusters) cluster centers C_i .
- The distance D between the cluster center and pixel is calculated by using Eq. (3).

$$D^2(x_j,C_i)=\left\|x_j-C_i\right\|^2 \qquad (3)$$

0The membership values are calculated by using Eq. (4).

$$\mathrm{U_{ij}}=\frac{(D(x_j,C_i))^{-1/(m-1)}}{\sum_{k=1}^{c}(D(x_j,C_k))^{-1/(m-1)}} \qquad (4)$$

Update the cluster centers

$$C_i=\frac{\sum_{j=1}^{n}U_{ij}^{m}x_j}{\sum_{j=1}^{n}U_{ij}^{m}} \qquad (5)$$

The iterative process starts:

1. Update the ij U by using Eq. (4).
2. Update the i C by using Eq. (5).
3. Update the D using Eq. (3).
4. If; (0.001) new old CC □□ □ □ □ then go to step1
5. Else stop Assign every pixel to a precise cluster for which the membership value is maximal.

B. Kernel Based FCM

Kernel version of the FCM algorithm and its objective function are given bellow:

$$O_m(U,C)=\sum_{i=1}^{c}\sum_{j=1}^{n}U_{ij}^{m}(1-K(x_j,C_i)) \quad (6)$$

Objective function:

Thus, the revise equations for the essential conditions for minimizing (,) m O U C are given bellow:

$$C_i=\frac{\sum_{j=1}^{n}U_{ij}^{m}K(x_j,C_i)x_j}{\sum_{j=1}^{n}U_{ij}^{m}K(j,C_i)} \;; i=1,2,\dots C \quad (6)$$

$$U_{ij}=\frac{(1-K(x_j,C_i))^{-1/(m-1)}}{\sum_{k=1}^{c}(1-K(x_j,C_i))^{-1/(m-1)}}; \qquad (7)$$

i=1,2,…C,j=1,2,…n

We identify the essential conditions for minimizing (,) m O U C are revise Esq. (6) and (7) only when the kernel function K is selected to be the Gaussian function with 22 (,) exp(‖ ‖) j i j i K x C x C □ □ □ □ . Different kernels can be selected by replacing the Euclidean distance for different conditions. However, a Gaussian kernel is appropriate for clustering in which it can essentially make the essential conditions. The above proposed KFCM algorithm is very sensitive to the noise conditions. To solve this difficulty Chen and Zhang have introduced the KFCM techniques which are utilized the spatial data by bring α parameter.

C. Multi Kernel FCM

The overall framework of MKFCM goals to reduce the goal characteristic:

$$Q=\sum_{i=1}^{c}\sum_{j=1}^{m}u_{ij}^{m}\left|\left|\varphi_{com}(x_j)-\varphi_{com}(o_i)\right|\right|^2 \qquad (8)$$

To enhance the Gaussian-kernel-based KFCM-F by way of including a nearby facts time period in the goal feature

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$$Q = \sum_{i=1}^{c}\sum_{j=1}^{m} u_{ij}^{m}\left(1 - k(x_j, o_i)\right) + \alpha \sum_{i=1}^{c}\sum_{j=1}^{m} u_{ij}^{m}(1 - k(\bar{x}_j, o_i))$$

(9)

Whereas x_j is the intensity of pixel j.
Where k_1 is still the Gaussian kernel for pixel intensities

$$k_1(x_i, x_j) = \exp\left(-|x_i - x_j|^2 / r^2\right)$$

k_2 is a polynomial kernel for the spatial information

$$k_2(x_i, x_j) = (x_i x_j + d)^2$$

If $k_{com} = k_1 + \alpha k_2$ is the composite kernel, the minimized goal feature of the MKFCM is derived as

$$Q = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} ||\varphi_{com}(x_j) - o_i||^2 \qquad (10)$$

For example, the input photo information x_j is set to be $x_j = [x_j, x_j, s_j] \in R3$, the same as the third variant of MKFCM, then the composite kernel is designed as

$$k_L = w_1^b k_1 + w_2^b k_2 + w_3^b k_3$$

3. EVALUTION MEASURES

Segmentation is that the usage of outstanding algorithms (Noises-'Gaussian' & 'Salt &Pepper').

Gaussian noise:

Foremost sources of Gaussian noise in digital pictures stand up throughout acquisition e.g. detector noise thanks to negative illumination and/or extreme temperature, and/or transmission e.g. electronic circuit noise.

Salt-and-pepper noise:

An image containing salt-and-pepper noise might have dark pixels in bright regions and vivid pixels in dark regions. This manner of noise is also as a result of analog-digital converter errors, bit errors in transmission, and so on.

Score Calculation For comparison segmentation results of varied algorithms with a quantitative live; we tend to use the assessment rating S_{ik} outlined as:

$S_{ik} = (A_{ik} \Lambda A_{refk}) / A_{ik} U A_{refk}()$. (11)

Whereas A_{ik} represents the set of pixels happiness to the k^{th} magnificence determined via the i^{th} set of rules and A_{refk} represents the set of pixels happiness to the k^{th} magnificence among the reference divided image.

TO CALCUTE THE ENERGY:

DICE:

The Dice constant (cube), to boot referred to as the overlap index, is that the most used metric in corroboratory clinical amount segmentations. Additionally to the direct comparison between automatic and ground truth segmentations, it's miles common to use the cube to degree dependableness (repeatability).

$$DICE = \frac{2|s_g^1 \cap s_t^1|}{|s_g^1| + |s_t^1|} = \frac{2TP}{2TP + FP + FN} \qquad (12)$$

SENSITIVITY:

Sensitivity (also referred to as verity advantageous rate, the take into consideration, or risk of detection in a very few fields) measures the proportion of positives which could be properly diagnosed per se (e.g. the share of sick those who square measure properly recognized as having the condition).
Mathematically, this might be expressed as:

$$sensitivity = \frac{\text{number of true positives}}{\text{number of true positives} + \text{number of false negatives}}$$

SPECIFICITY:

Specificity (additionally referred to as the real negative charge) measures the proportion of negatives which may be effectively recognized per se (e.g. the share of healthy of us that square measure expeditiously known as not having the circumstance).
Mathematically, this will even be written as:

$$specificity = \frac{\text{number of true negatives}}{\text{number of true negatives} + \text{number of false positive}}$$

In that setting:
True positive=ill individuals properly diagnosed as sick.
False positive=healthy humans incorrectly diagnosed as sick.
True negative=healthy kinsmen effectively recognized as healthful.
False negative= sick humans incorrectly diagnosed as healthy.
In popular, positive = recognized and negative = rejected.
Therefore:
True positive = effectively known.
False positive= incorrectly known.

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True negative = effectively rejected.
False negative = incorrectly rejected.

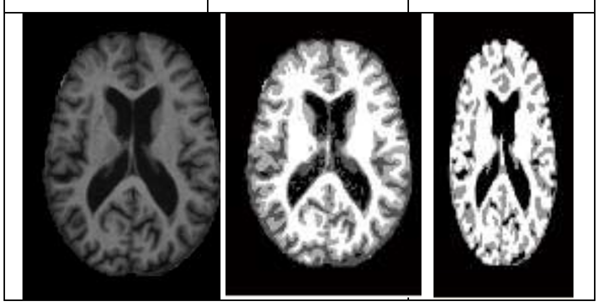
4. EXPERIMENTAL RESULTS

In order to verify the effectiveness of the proposed algorithm, experiments were conducted on two brain MRIs [27]. The performance of the proposed algorithm is compared with the other existing FCM variant methods in terms of score, number of iterations (NI) and computational time (CT) on OASIS-MRI dataset.

All the algorithms have been implemented using MATLAB software.

Test case 1

Input Image	Segmented Output Image (Proposed)	Segmented Output Image (Existing)

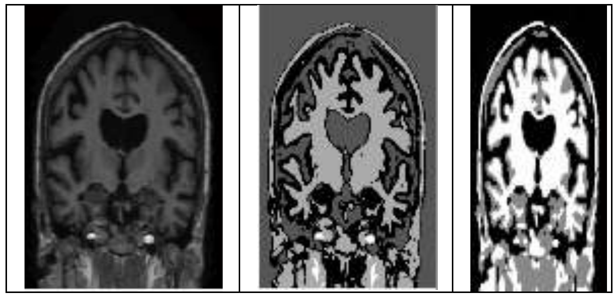


Performance comparison (Test case 1)

Parameter	Proposed Approach	Existing approach
Dice coefficient	0.687	0.59
Sensitivity	0.85	0.79
Specificity	0.94	0.75

Test case 2

Input Image	Segmented Output Image (Proposed)	Segmented Output Image (Existing)



Performance comparison (Test case 2)

Parameter	Proposed Approach	Existing approach
Dice coefficient	0.85	0.79
Sensitivity	0.92	0.76
Specificity	0.90	0.81

5. CONCLUSIONS

In this paper, new image segmentation algorithms (FCM, KFCM and MFCM) which are increasing the performance and decreasing the computational complexity is proposed. The algorithm utilizes the multi-hyperbolic tangent function and multi-Gaussian kernels. The proposed algorithm is applied on brain MRI which degraded by Gaussian noise. The segmentation results demonstrate that the proposed algorithm shows the robustness under different noises as compared to other existing image segmentation algorithms from FCM family.

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