An Atanassov's intuitionistic Fuzzy Kernel Clustering for Medical Image segmentation

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Abstract

This paper suggests a novel method for medical image segmentation using kernel based Atanassov's intuitionistic fuzzy clustering. The widely used fuzzy c means clustering that uses Euclidean distance has many limitations in clustering the regions accurately. To overcome these difficulties, we introduce a new method using Atanassov's intuitionistic fuzzy set theory that incorporates a robust kernel based distance function. As the membership degrees are not precise and may contain hesitation, Sugeno type fuzzy complement is used to find the non-membership values and then hesitation degree is computed. The algorithm uses all the three kernels – Gaussian, radial basis, and hyper tangent kernels. In the algorithm, for each pixel, two features are considered - pixel energy and mean and the average of the two features are taken. The method clusters the tumors/lesions/clots almost accurately especially in a noisy environment. Experiments are performed on several noisy medical images and to assess the performance of the method, the algorithm is compared with the existing non fuzzy, fuzzy, intuitionistic fuzzy methods. It is observed that the results using the proposed method that uses hyper tangent kernel seem to be much better.

Keywords: Atanassov's intuitionistic fuzzy set, hesitation degree, intuitionistic fuzzy cluster, kernel, medical image

1. Introduction

Clustering is an unsupervised segmentation where the image is segmented into different regions or groups. Segmentation subdivides the image into several regions based on the information of the objects found in the image. It is used widely in various decision making problems and especially in medical image analysis where different regions, organs, and anatomical structures of the images that are acquired from CT scan, X-rays or other imaging techniques, are segmented. Over the past two decades, many clustering techniques were proposed and these were the k means, hard c means clustering. In hard c means, each item is assigned to a single cluster. These algorithms work when the data are well separated in groups and the clustering is compact. But these algorithms will not work in real world application where the clusters overlap. For those images, pixels may belong to many clusters. Fortunately, fuzzy set theory proposed by .Zadeh[1] provides a powerful tool for such soft partitioning and so fuzzy clustering is an effective tool in segmenting the medical images. Fuzzy c-means (FCM) is a method of clustering that allows a data to belong to two or more clusters[2]. Fuzzy clustering allows a degree of membership of pixels belonging to one cluster and also expresses the different membership degrees to different

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clusters; thereby it can more objectively reflect the real world. This method, later developed by Dunn in 1973[3] and improved by Bezdek[4], is frequently used in pattern recognition. The main advantage in fuzzy c-means algorithm is that it allows pixels to belong to multiple clusters with reasonable degrees of membership grades.
FCM allows for the ability to make the clustering methods able to retain more information from the original image than the crisp or hard segmentation method Pham[5]. But the Euclidean norm in FCM does not perform for more general clusters. The disadvantage of FCM may lie in the equation for updating prototypes that is incapable to work with data which are greatly affected by noise. So the main reason for the drawback is the use Euclidean distance measures. Thus kernel based clustering algorithm is used where the Euclidean distance is replaced by a kernel that may be Gaussian, radial basis, or hyper tangent. Kannan[6] suggested robust FCM using hyper tangent kernel where they used hyper tangent distance instead of Euclidean distance. Kannan[7] also used a robust kernel function for FCM to deal with noisy data. Zhang and Song[8] proposed kernel based FCM incorporating a spatial term in the objective function. Though these methods worked well on image segmentation but due to the incorporation of spatial terms, it takes much time in running the algorithm and also it may be incorrect with images which are affected greatly by heavy noise.
There are also few methods that use Atanassov's intuitionistic fuzzy set in clustering algorithm. In fuzzy set theory, uncertainty is the degree of belongingness of an element in a set or the membership function. But the membership function is not precise. There may be some hesitation present while defining the membership function. So, due to the hesitation degree, the non-membership degree is not the complement of the membership degree as in fuzzy set, rather less than or equal to the complement of the membership degree. Atanassov[9] introduced intuitionistic fuzzy set theory (A-IFS) that considers the hesitation in the membership function. With the consideration of hesitation degree, intuitionistic fuzzy c means clustering was suggested by Chaira[10] where another function is introduced that is the intuitionistic fuzzy entropy in the objective function. She segmented tumor/ abnormal lesions in CT scan brain images. Chaira[11, 12] also suggested intuitionistic fuzzy color cluster on medical images where different color spaces – CIELab, RGB, HSV were used to show how different color spaces work in color clustering. Review on image segmentation methods was done by Kaur et al.[13] where they used IFCM[10] using radial basis kernel and Yager's generator to compute the non-membership degree, but almost no changes are observed when compared with kernel FCM. The reason may be that they used only pixel as a feature. Kuppannan[14] proposed a contrast enhancement method using intuitionistic fuzzy set theory to enhance the text documents. There is also few works on image thresholding using A-IFS by Bustince et al.[15] and medical image segmentation for rat gait analysis using interval valued fuzzy set (IVFS)[16].
In this paper, an A-intuitionistic fuzzy clustering algorithm is proposed by incorporating three kernel distance functions such as Gaussian, radial basis, and hyper tangent. Sugeno type fuzzy complement is used to find the non-membership values and then hesitation degree is computed. In the algorithm, the average of the two features - pixel energy and mean are taken. Experiments are conducted separately for three kernels to see the effect of kernel on noisy medical images.
The paper is organized as follows. Section 2 overviews the preliminary of A- intuitionistic fuzzy set. Section 3 details the proposed method. Section 4 discusses and displays the experimental results and finally conclusion is drawn in section 5.

2. Introduction to Atanassov's Intuitionistic Fuzzy Set (A-IFS)

A fuzzy set A in a finite set $X = \{x_1 x_{2,} ..., x_n\}$ may be represented mathematically as:

$$A = \{(x, \mu_A(x) | x \in X\}$$

where, the function $\mu_A(x): X \to [0,1]$ is measure of degree of belongingness or membership function of an element x in the finite set X and the measure of non-belongingness is $1 - \mu_A(x)$.
An A-IFS A in a finite set X may be mathematically represented as [1]:

$$A = \{(x, \mu_A(x), \nu_A(x)) \mid x \in X\} \qquad \dots (1)$$

where, the functions $\mu_A(x), \nu_A(x): X \to [0,1]$ are respectively the membership function and the non-membership function of an element x in a finite set X with the necessary condition

$$0 \le \mu_A(x) + \nu_A(x) \le 1$$

Stressing the necessity of taking into consideration a third parameter $\pi_A(x)$, known as the intuitionistic fuzzy index or hesitation degree, which arises due to the lack of knowledge or the 'personal error' in assigning the membership degree, an A-IFS A in X may be represented as:

$$A = \{(x, \mu_A(x), \nu_A(x), \pi_A(x)) | x \in X\}$$

with the condition $\pi_A(x) + \mu_A(x) + \nu_A(x) = 1$ … (2)

It is obvious that $0 \le \pi_A(x) \le 1$, for each $x \in X$.

3. The proposed technique

The image is considered fuzzy and so gray levels are imprecise. The aim is to incorporate the Atanassov's intuitionistic property. For this intuitionistic fuzzy generators are used. There are many intuitionistic fuzzy generators such as Yager[18], Sugeno[17] and also the concept of aggregation operator and negation may also be found in[19]. Sugeno's fuzzy complement is used. In this paper, Sugeno type intuitionistic fuzzy generator is used. Experiments have been performed on Yager generator but the results are not so promising and this is shown later in section 4.
Sugeno's intuitionistic fuzzy complement is written as:

$$N(\mu_{mn}) = \frac{1-\mu_{mn}}{1+\lambda.\mu_{mn}} \quad , \lambda > 0 \quad \text{where } N(1) = 0,$$

$N(0) = 1$, μ_{mn} is the membership value of the $(m, n)^{th}$ gray level of the image.

Non-membership values are calculated from Sugeno's intuitionistic fuzzy generator $N(\mu_{mn})$. Thus, with the help of Sugeno type intuitionistic fuzzy generator, IFS becomes:

$$A_\lambda^{IFS} = \{g, \mu(g), \frac{1-\mu(g)}{1+\lambda.\mu(g)} | g \in G\}$$

and the hesitation degree is:

$$\pi_A(g) = 1 - \mu_A(g) - \frac{1-\mu_A(g)}{1+\lambda.\mu_A(g)} \quad \ldots(3)$$

where g is the gray level of the image and G is a set of all gray levels.

In the clustering algorithm, two features are considered for each pixel and these are pixel energy, pixel mean. To calculate the mean, a small square window of size 3x3 is used and mean is calculated for each window. This is calculated throughout the image.
Pixel energy = pixel $g(i, j)^2$. $g(i, j)$ is the pixel value at (i, j).
Then average of the two features - energy and the mean is computed as:

Final feature = $\dfrac{g(i,j)^2 + mean}{2}$ and this feature is used in the clustering.
In the next two sections we will write briefly about intuitionistic fuzzy clustering and incorporation of kernel.

3.1. A- Intuitionistic Fuzzy c means algorithm

Conventional fuzzy C means algorithm cluster the feature vectors by searching for local minima of the following objective function:

$$J_m(U, v; X) = \sum_{i=1}^{c} \sum_{k=1}^{n} (u_{ik})^m d^2(x_k, v_i)$$

where $d(x_k, v_i)$ is Euclidean distance measure (or any distance measure) between v_i (cluster center) of each region and x_k (points in the pattern), and u_{ik} is the membership value of k^{th} data (x_k) in i^{th} cluster. c is the number of clusters, n is the number of data points. Minimization of J_m is based on suitable selection of U (membership matrix) and v using an iterative process through the following equation:

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left[\frac{d^2{}_{ik}}{d^2{}_{jk}} \right]^{\frac{1}{m-1}}},$$

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}{}^m x_k}{\sum_{k=1}^{n} u_{ik}{}^m} \forall i, k, \quad i = 1, 2, 3 \ldots c \text{ and}$$

$k = 1, 2, 3 \ldots n$

In order to incorporate intuitionistic fuzzy property in conventional fuzzy clustering algorithm, cluster centers are updated in the following manner.
Hesitation degree is initially calculated using eq. (3) and the intuitionistic fuzzy membership values (incorporating hesitation degree)[10] are obtained as follows:

$$u_{ik}{}^* = u_{ik} + \pi_{ik} \quad \ldots (4)$$

where $u_{ik}{}^*(u_{ik})$ denotes the intuitionistic (conventional) fuzzy membership of the k^{th} data in i^{th} class.

Here the intuitionistic fuzzy property is incorporated. Membership degree is accompanied by hesitation degree as the membership degree is not precise.
Substituting eq. (4) in conventional fuzzy c means method, the modified cluster center is written as:

$$v_i^* = \frac{\sum_{k=1}^{n} u_{ik}^{\ *} x_k}{\sum_{k=1}^{n} u^*_{\ ik}} \qquad \ldots (5)$$

Using eq. (5), the cluster center is updated and simultaneously the membership matrix is updated.
At each iteration, the cluster center and the membership matrix are updated and the algorithm stops when the updated membership matrix and the previous matrix i.e. $\max_{i,k} |U_{ik}^{*new} - U_{ik}^{*prev}| < \varepsilon$, ε is a user defined value and is selected as $\varepsilon = 0.03$.
Thus the criterion function in conventional FCM is modified using IFS.

3.2. Incorporation of Kernel function

To overcome the drawback of FCM in the selection of Euclidean distance, we modified the objective function by using a kernel distance function in place of Euclidean distance. The objective function is:

$$J_m(U,V) = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^{\ m} \left\|\varphi(x_k) - \varphi(v_i)\right\|^2 \quad \ldots(6)$$

where

$$\left\|\varphi(x_k) - \varphi(v_i)\right\|^2 = \langle \varphi(x_k)\varphi(x_k)\rangle + \langle \varphi(v_i), \varphi(x_k)\rangle$$
$$-2\langle \varphi(v_i), \varphi(v_i)\rangle$$

and $k = 1,2,\ldots n$ and $i = 1,2,\ldots c$. k is the data point and i is the cluster centre.

We can express kernel function, $K(x_i, v_k) = \langle \varphi(v_i), \varphi(x_k)\rangle$.

Then,
$$\left\|\varphi(x_k) - \varphi(v_i)\right\|^2 = K(x_k, x_k) + K(v_i, v_i) - 2K(x_k, v_i)$$

We express hyper tangent function as :

$K(x_k, v_i) = 1 - \tanh\left(\frac{-\left\|x_k - v_i\right\|^2}{\sigma^2}\right)$, σ is a parameter adjusted by the users.

Likewise for the Gaussian kernel, $K(x_k, v_i) = \exp(-\left\|x_k - v_i\right\| / \sigma^2)$

For radial basis kernel:

$$K(x_k, v_i) = \exp\left(-\frac{\left|x_k^{\ a} - v_i^{\ a}\right|^b}{\sigma^2}\right)$$

For these kernels, $K(x_k, x_k) = 1$ and $K(v_i, v_i) = 1$,
So, the objective function in eq. (6) reduces to:

$$J_m(U,V) = 2\sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^{\ m}(1 - K(x_k, v_i))$$

Taking the derivative of the objective function with respect to u and v and setting the derivative to zero, we have

$$u_{ik} = \frac{\left(1 - K(x_k, v_i)\right)^{\frac{-1}{m-1}}}{\sum_{j=1}^{c}\left(1 - K(x_k, v_j)\right)^{\frac{-1}{m-1}}}$$

Using A-intuitionistic fuzzy membership degree: $u_{ik}^{\ *} = u_{ik} + \pi_{ik}$

where $\pi_{ik} = 1 - u_{ik} - \frac{1 - u_{ik}}{1 + \lambda . u_{ik}}$,

the cluster center is written as:

$$v_i^* = \frac{\sum_{k=1}^{n} \mu^{*\ m}_{\ ik} K(x_i, v_k)\left(1 + \tanh\left(\frac{-\left\|x_k - v_i\right\|^2}{\sigma^2}\right)\right) x_k}{\sum_{k=1}^{n} \mu^{*\ m}_{\ ik} K(x_i, v_k)\left(1 + \tanh\left(\frac{-\left\|x_k - v_i\right\|^2}{\sigma^2}\right)\right)}$$

For the Gaussian and radial basis kernel, the cluster centers are:

$$v_i^* = \frac{\sum_{k=1}^{n} \mu^{*\ m}_{\ ik} K(x_i, v_k) x_k}{\sum_{k=1}^{n} \mu^{*\ m}_{\ ik} K(x_i, v_k)}$$

$'m'$ is chosen as 2.
The procedure follows like conventional fuzzy c means clustering with new cluster centers and membership function.

In the experimentation, the parameter λ in Sugeno type generator is taken as 0.5. With $\lambda = 0.5$, the results are seen to be better. With $\lambda < 0.5$, clustered image contains lot of noise. With $\lambda = 1$, the clustered image still contains little bit noise. But with $\lambda = 0.5$, the clustered image is very clear. Results are shown in Fig. 1.

About the kernels, $\sigma = 0.6$ is used for Gaussian, hyper tangent, and radial basis kernels. On experimenting on many images, we find that with $0.7 < \sigma < 0.6$, the images are not properly clustered. For radial basis, the constants $a = 0.9, b = 1$ are selected.

4. Results and Discussion

Tests are performed on several medical images. Seven sets on CT scan brain images are shown where the images are segmented into three clusters. Out of 7 images, two images are normal images i.e., without noise and five images are noisy images where Gaussian noise is added. It is observed that the algorithm works well in noisy environment. To show the efficacy of our method, our results are compared with i) conventional FCM, ii) intuitionistic fuzzy c means cluster, iii) kernel based fuzzy c means cluster (KFCM) algorithm, iv) K means clustering algorithm.

As has been said earlier, the proposed algorithm is tested using Yager's generator with hyper tangent kernel (as with Sugeno's intuitionistic fuzzy generator, hyper tangent kernel gives better result). Figs. 2, 3 show the results using Yager's intuitionistic fuzzy generator. Fig. 2 shows a clear clot using the proposed method but the clot is not prominent using Yager's generator. Fig. 3 shows a clear tumor with less noise as compared to Yager's generator.

Figure 4 is a CT brain image. It is observed that IFCM, IFCM with Gaussian kernel, and IFCM with radial basis kernel contain noise in the clustered images. Results with FCM, K means clustering, Kernel FCM, and Intuitionistic FCM with hyper tangent kernel are almost similar but the result with intuitionistic fuzzy hyper tangent kernel in Fig. 4(g) contains very little noise in the upper left part of the image.

Figure 5 is a CT brain image. It is observed that FCM, IFCM, K means, and kernel FCM contain little amount of noise. Fig. 5(h) is the result with radial basis kernel that contains lot of noise. Results with IFCM with the kernels using hyper tangent and Gaussian in Figs. 5(f, g) are almost similar and contain very little noise.

Figure 6 is a CT brain image. It is observed that in all the methods i.e. FCM, IFCM. KFCM, K means, the clustered image contains noise. But, in intuitionistic fuzzy kernels based methods using Gaussian, radial basis kernels in Figs. 6(f)-(h), it is observed that the clustered images contains less noise as compared to FCM, KFCM, IFCM, and K means cluster methods. But intuitionistic fuzzy cluster with hyper tangent kernel and radial basis kernel in Fig. 6(g) are much better with almost no noise present and looks very clear.

Figure 7 is a CT brain image mixed with Gaussian noise. It is observed that in all the methods i.e. FCM, IFCM, KFCM, K means cluster, intuitionistic fuzzy cluster with Gaussian and radial basis kernels, clustered images contains lot of noise. But the intuitionistic fuzzy method with hyper tangent kernel in Fig. 7(g) is much better with very little amount of noise in the form of spots only at the centre and the clustered image looks very clear.

Figure 8 is a CT brain image. It is observed that in all the methods i.e. FCM, IFCM, K means cluster, and KFCM, clustered images contain noise. But in intuitionistic fuzzy kernels based methods in Figs. 8(f)-(h), it is observed that using all the three kernels, clustered images contain less noise as compared to FCM, IFCM, KFCM, and K means. But intuitionistic fuzzy cluster with hyper tangent kernel in Fig. 8(g) is much better with minimum noise as there are very less number of spots in the centre.

Figure 9 is a CT brain image. It is observed that in all the methods i.e. FCM, IFCM. KFCM, K means, the clustered image contains noise. Intuitionistic fuzzy cluster with radial basis kernel in Fig. 9(h) does not cluster the image. Intuitionistic fuzzy cluster with Gaussian kernel in Fig. 9(f) is clear but the clot region is not clear. But intuitionistic fuzzy cluster with hyper tangent kernel in Fig. 9(g) is the best with very little noise. The clot in the clustered image is almost prominent against a clear background.

Figure 10 is a CT brain image. It is observed that in all the methods i.e. FCM, IFCM, and KFCM, K means, clustered images contain noise. Intuitionistic fuzzy cluster with radial basis kernel does not cluster the image properly as shown in Fig. 8 (h). Fig. 10(g) is the clustered image using intuitionistic fuzzy cluster with Gaussian kernel but the clot is little bit vague. Fig. 10(f) is the result using intuitionistic fuzzy cluster with hyper tangent kernel, shows a clear and prominent blood clot without any noise.

Overall, the clustered image using intuitionistic fuzzy cluster with hyper tangent kernel gives better result.

Table 1 shows the number of iterations for all the methods. It is observed that kernel FCM and the kernel IFCM takes almost same number of iterations, but kernel IFCM works much better in a noisy environment.

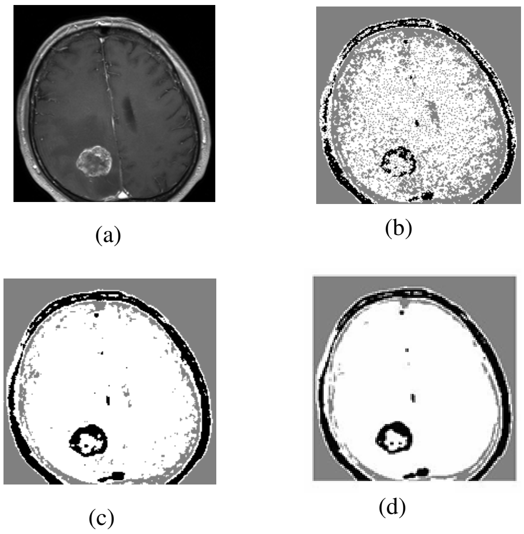

Fig.1 a) Original image, b) lambda=0.2, c) lambda = 1, d) lambda=0.1

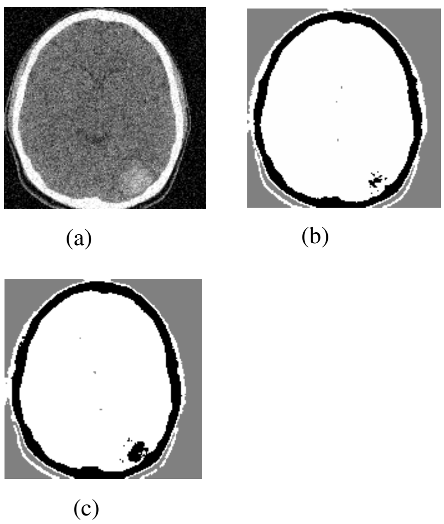

Fig. 2. a) Original image, b) IFCM with Gaussian kernel using Yager's generator with hyper tangent kernel , c) IFCM with hyper tangent kernel with Sugeno's generator

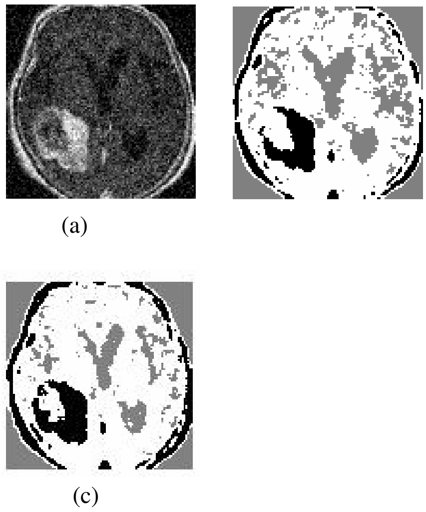

Fig. 3. a) Original image, b) IFCM with Gaussian kernel using Yager's generator with hyper tangent kernel, c) IFCM with hyper tangent kernel using Sugeno's generator

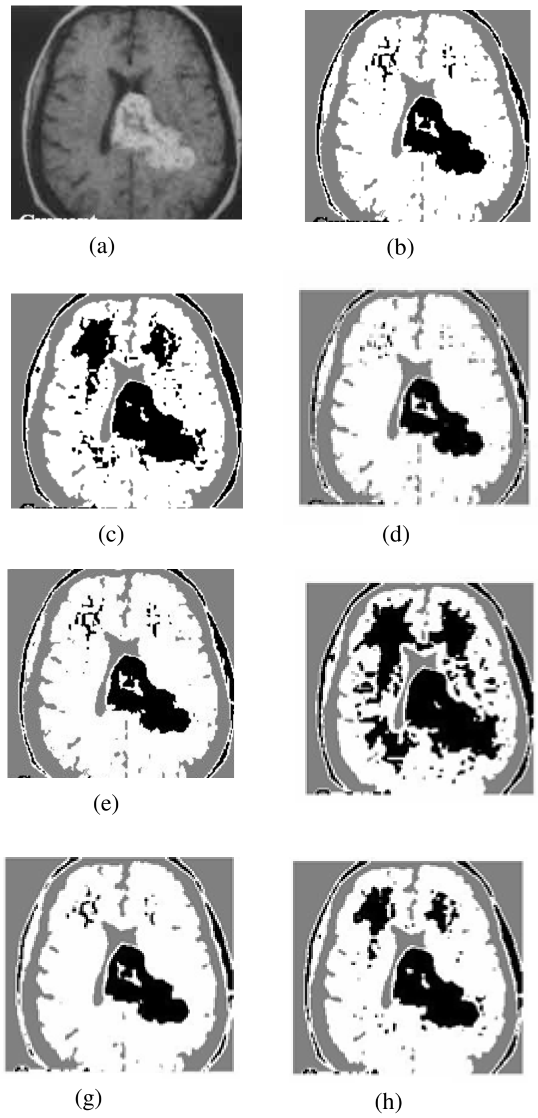

Fig. 4. a) Original image, b) FCM, c) IFCM, d) kernel FCM, e) K means algorithm, f) IFCM with Gaussian kernel, g) IFCM with hyper tangent kernel, h) IFCM with radial basis kernel

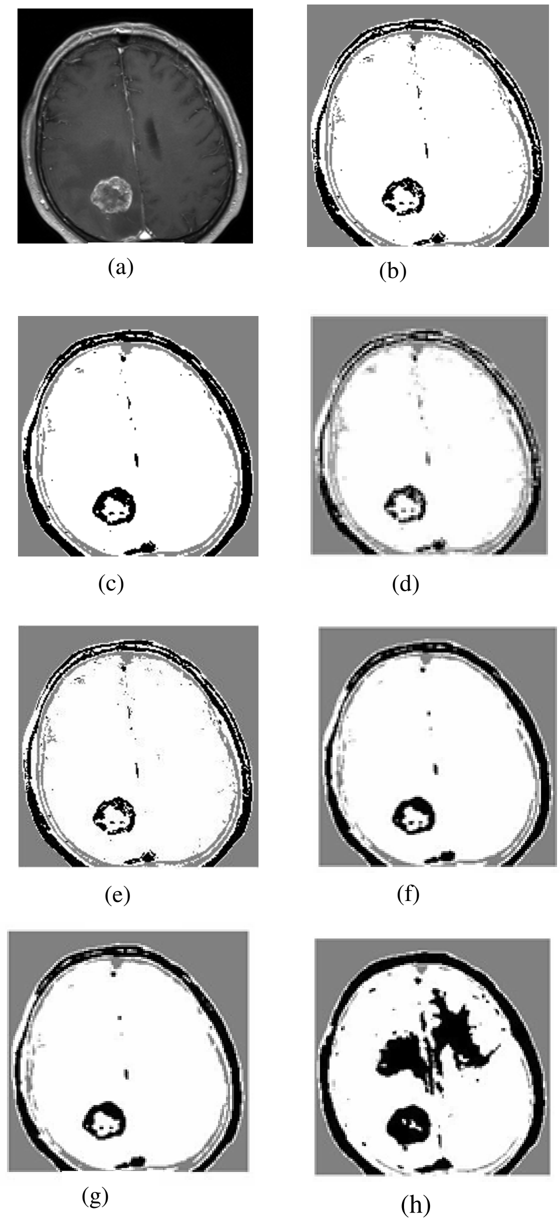

Fig. 5. a) Original image, b) FCM, c) IFCM, d) kernel FCM, e) K means algorithm , f) IFCM with Gaussian kernel, g) IFCM with hyper tangent kernel, h) IFCM with radial basis kernel

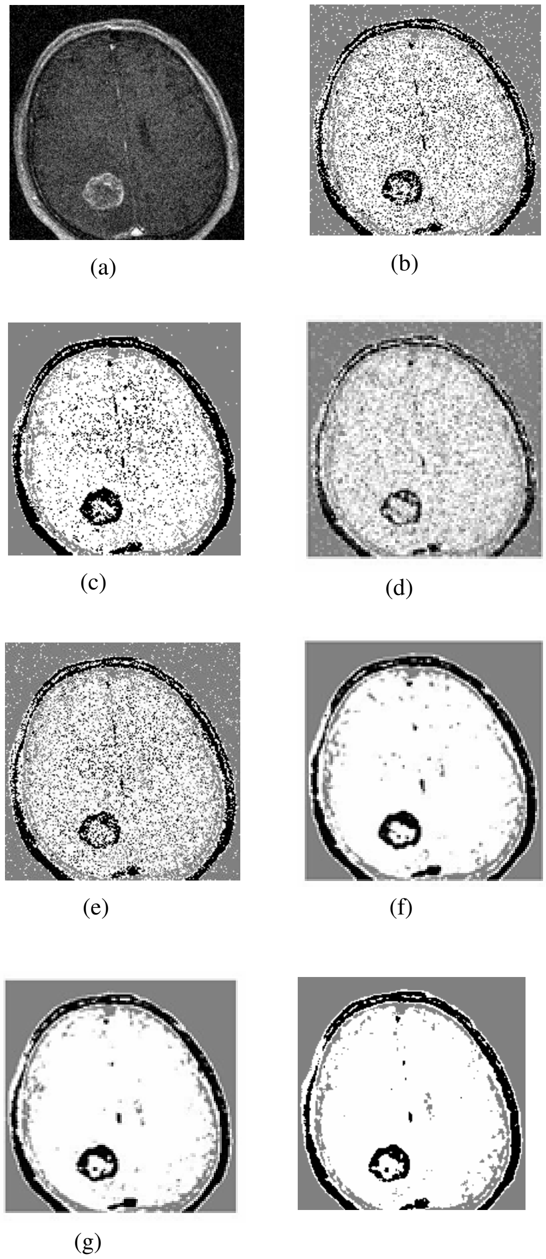

Fig. 6. a) Original image, b) FCM, c) IFCM, d) kernel FCM, e) K means algorithm, f) IFCM with Gaussian kernel, g) IFCM with hyper tangent kernel, h) IFCM with radial basis kernel

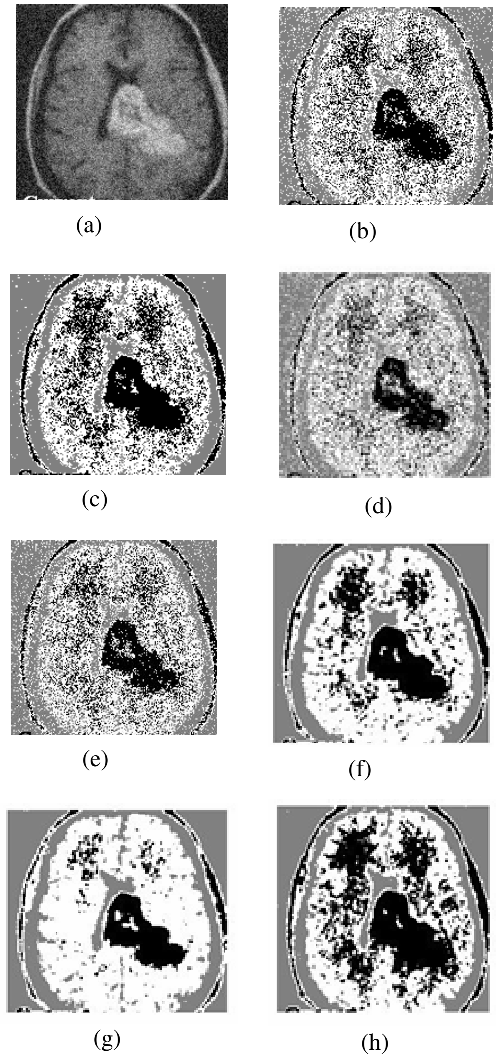

Fig. 7. a) Original image, b) FCM, c) IFCM, d) kernel FCM, e) K means algorithm, f) IFCM with Gaussian kernel, g) IFCM with hyper tangent kernel, h) IFCM with radial basis kernel

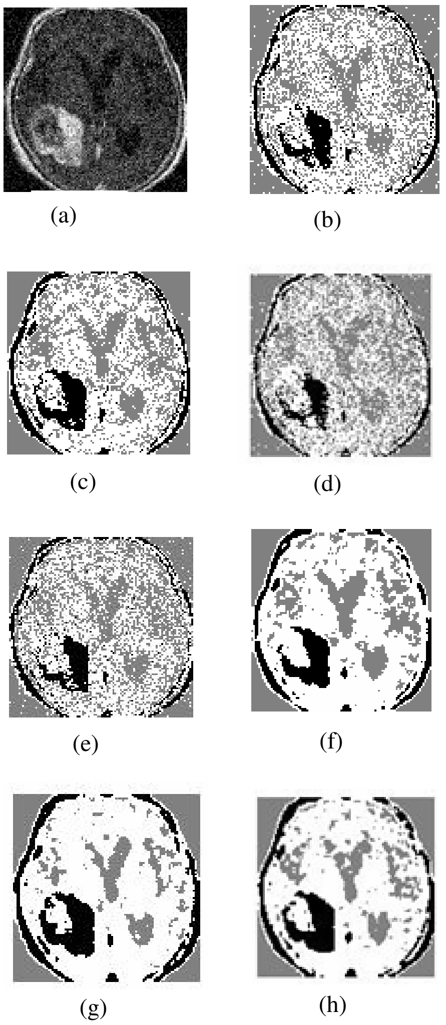

Fig. 8. a) Original image, b) FCM, c) IFCM, d) kernel FCM, e) K means algorithm, f) IFCM with Gaussian kernel, g) IFCM with hyper tangent kernel, h) IFCM with radial basis kernel

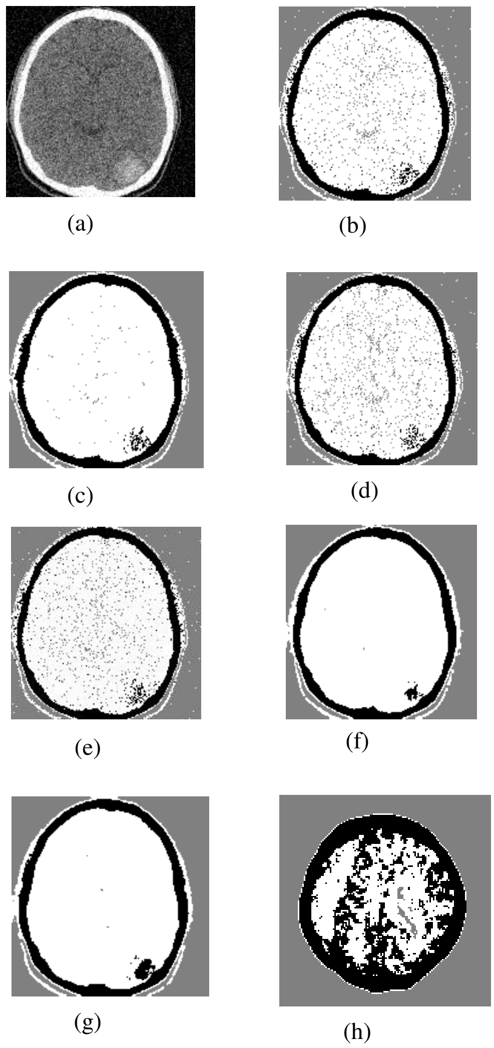

Fig. 9. a) Original image, b) FCM, c) IFCM, d) kernel FCM, e) K means algorithm, f) IFCM with Gaussian kernel, g) IFCM with hyper tangent kernel, h) IFCM with radial basis kernel

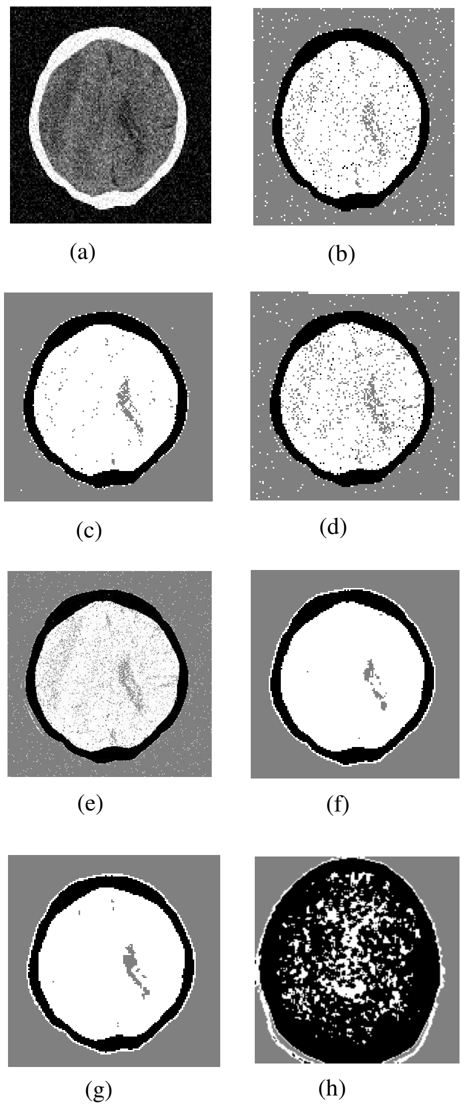

Fig.10. a) Original image, b) FCM, c) IFCM, d) kernel FCM, e) K means algorithm, f) IFCM with Gaussian kernel, g) IFCM with hyper tangent kernel, h) IFCM with radial basis kernel

5. Conclusion

In this paper, an A-intuitionistic fuzzy clustering algorithm is proposed where kernel distance function are used instead of Euclidean distance function. The incorporation of kernel distance in A-intuitionistic fuzzy cluster has a good effect on noisy images. Average of the pixel features such as the mean and energy is used in the algorithm. Sugeno type fuzzy complement is used to create an intuitionistic fuzzy image. Results on the medical images show that the proposed A-intuitionistic fuzzy method using hyper tangent kernel performs much better than the existing FCM and kernel based FCM, intuitionistic fuzzy cluster methods and also intuitionistic fuzzy cluster using Gaussian and radial basis kernel function. The number of iterations in KFCM and the proposed technique are almost similar but the proposed technique works much better on noisy images.

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Table. 1: No. of iteration in different methods

	No. of iterations	No. of clusters
Standard FCM	30	3
IFCM	18	3
Kernel FCM	13	3
IFCM with Gaussian kernel	12	3
IFCM with hyper tangent kernel	14	3
IFCM with radial basis kernel	12	3