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Flexible MKFCM Based Image Segmentation

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Abstract— Image segmentation deals with partition of images in to separate constitutes. Here, Multiple Kernel Fuzzy C-Means (MKFCM) algorithm is proposed. MKFCM is an extension of Kernel Fuzzy C-Means (KFCM). In the framework, aside from the fact that the composite kernels are used in the kernel FCM (KFCM), a linear combination of multiple kernels is proposed and the updating rules for the linear coefficients of the composite kernel are derived. The MKFCM algorithm provides us a flexible vehicle to fuse different pixel information from different kernels which are combined in the kernel space to form a new kernel. Simulations on the segmentation of synthetic and medical images demonstrate the flexibility and advantages of MKFCM algorithm. Performance of the image is found by means of Segmentation Accuracy. Various types of noises are added to the input image and the corresponding Accuracy is found.

Index Terms—Composite kernel, FCM, KFCM, MKFCM, Multiple Kernels, Segmentation Accuracy.

1 Introduction

Fuzzy C-means (FCM)-based clustering algorithm and its variants, have been widely used for Image Segmentation problems due to their simplicity and faster convergence. By carefully selecting input features such as pixel color, intensity, texture or a weighted combination of these data, the FCM algorithm can segment images to several regions [1] [3]. Recently, the FCM and other clustering based image segmentation approaches use the local spatial information of pixels in classical clustering procedures [1] [10]. Because of the local spatial information, the new FCM algorithm has demonstrated robustness over noises in images. In addition to the incorporation of local spatial information, the kernelization of FCM has made an improvement in their performance. The kernel FCM (KFCM) algorithm is an extension of FCM, which maps the original inputs into a much higher dimensional Hilbert space by some transform function. So, the data are more easily to be separated or clustered [6]. Liao et al. [12] have directly applied the KFCM in the image-segmentation problems, where the input data selected for clustering is the combination of the pixel intensity and the local spatial information of a pixel represented by the mean or the median of neighboring pixels.In KFCM, the input data is the combination of the pixel intensity and the local spatial information of a pixel which is selected for clustering. Here, multiple kernels or composite kernels are considered instead of a single fixed kernel .With multiple kernels, the kernel methods gain more flexibility on kernel selections and also reflect and fuse data from multiple heterogeneous or homogeneous sources [2].In image-segmentation problems, the inputs are the properties of image pixels, and they could be derived from different sources. For example, the intensity of a pixel is directly obtained from the image itself, but the texture information is perhaps gained from some wavelet filtering of the image [9]. Multiple-kernel methods provide us a great tool to fuse information from different sources [13] .The term "multiple kernel" in a wider sense than the one used in machine learning community. MKFCM mainly focuses more on the flexible information fusion by applications of composite kernels constructed by multiple kernels defined in different information channels. The combination of the ensemble kernel can be automatically adjusted in the learning of multiple-kernel FCM (MKFCM) or it can be settled by trial and error or cross-validation [8] [11] [13]. In MKFCM, besides the direct applications of various composite kernels in the KFCM, a new algorithm that uses a linear composite of multiple kernels is proposed and the updating rules of the linear coefficients of the combined kernel are obtained automatically. When applying the MKFCM framework in image-segmentation problems, which take advantages of local spatial information. The proposed MKFCM based algorithms demonstrate the flexibility in kernel selections and combinations, and therefore, they provide the potential of significant improvement over traditional methods on image segmentation [1] [12] [15]. MKFCM uses clustering technique, in which the intensity values are splitted in to two. That is, low level value and high level value. The values which are closest to low level value are grouped in to one and also the values belonging to the high level value are grouped in to one. There by, some differentiation appears between the segmented portion and the remaining background portion. The MKFCM algorithm is experimented in various types of noises such as salt and pepper, Gaussian, Speckle, Poisson noises to demonstrate the proposed algorithm is more robust to noise.

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2 Proposed Methodology

The block diagram for the proposed methodology is given in Fig 1. First the input image was given to the MATLAB. The input image may be medical or synthetic image. The image was corrupted by adding some types of noises. Before adding clusters in the image, image enhancement was done, by which clear details of an image is highlighted. Clusters differentiate the segmented portion and the remaining background portion.

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Finally, by using MKFCM algorithm, the image is segmented.

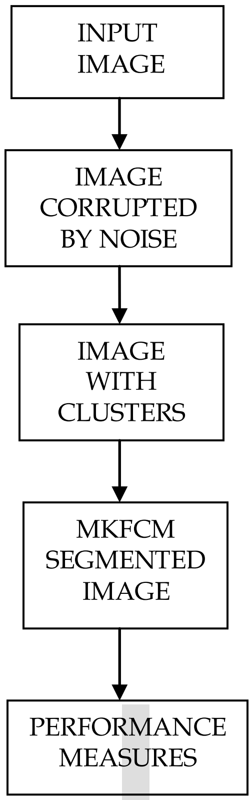

Fig 1. Proposed Methodology

2.1 Input Image

The input image may be Brain Tumour Image is given to the MATLAB as input. The original size of the image is 256 X 256. Here, the input image is resized and its size is 200 X 200.

2.2 Image Corrupted by Noise

The input image is corrupted by adding some types of noises. Noises like Gaussian noise, Salt and pepper noise,Poisson noise,Speckle noise are added to the image.Salt and pepper noise is otherwise known as impulsive noise.In Salt and pepper noise,the segmentation is made by number of iterations and epsilon value.Salt and pepper noise having dark pixels in bright regions and bright pixels in dark regions.In Gaussian noise,it is independent of signal intensity and pixel value.In Speckle noise,increase in the gray level of granular noise.In Poisson noise,it is nothing but the artificial noise is added to the image.The above noises are added to the input image to avoid leakage when segmenting.In the below figure,Salt and pepper noise is added.

2.3 Image Enhancement

Before obtaining clustered image, there was a need for Image Enhancement.Image Enhancement is to highlight the fine details of an image.

2.4 Image with Clusters

In image with clusters, the intensity value of the image is grouped in to two levels. Low level value and High level value. For instance, low level value is zero and high level value is 255 means, the values nearby the intensity value zero, are grouped in to one and the values nearby the value 255 are grouped in to one. Thereby, applying clusters in an image. So, the tumour part and the remaining background of the image is differentiated. Clustering is otherwise known as the grouping of high dimensional data space. Objects are grouped in to one. Thus the clusters are applied and tumour portion are identified.

2.5 MKFCM Segemented Image

The combination of multiple kernels is proposed and the updating rules for the linear coefficients of the composite kernel are derived as well. MKFCM algorithm provides us a new flexible vehicle to fuse different pixel information in image-segmentation problems. That is, different pixel information represented by different kernels is combined in the kernel space to produce a new kernel. We can easily fuse the texture information into segmentation algorithms by just adding a kernel designed for the texture information in the composite kernel.

3 Steps in MKFCM Algorithm

Step 1: Select initial class prototype.
Step 2: Update all memberships.
Step 3: Obtain the prototype of clusters in the forms of weighted Average.
Step 4: Repeat step 2-3 till termination.

The membership function can be defined as,

$$u_{ik} = \frac{(1/(1-k(x_k, v_i)))1/(m-1)}{\sum\limits_{j=1}^{c} (1/(1-k(x_k, v_i)))1/(m-1)} \qquad (1)$$

Where k represents reference cluster.u_{ik} represents degree of membership of ith pixel in the kth cluster.m is the weighting component which should be larger than one.v_i represents centre of the ith cluster.x_k represents the prototype of the cluster.

$$j_{m(u,v)} = \sum_{i=1}^{c} . \sum_{k=1}^{n} u_{ik} \, \| \varphi(x_i) - \varphi(v_i) \| \qquad (2)$$

The above equation represents the objective membership function. U is an N × C membership matrix whose elements are the degrees of membership; and V = [v1 v2 · · · vC] is an l × C matrix whose columns correspond to cluster centers.j_m could be minimized using iterations. MKFCM uses the squared-norm to measure the inner product with an appropriate 'kernel' function.

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The Gaussian kernel function is defined as,

$$k(x,y)=\exp(-\|x-y\|^2/2\sigma^2) \quad (3)$$

The weighted average function is defined as,

$$v_i=\frac{\sum_{k=1}^{n} u_{ik}.k(x_k,v_i)x_k}{\sum_{k=1}^{n} u_{ik}^{m}.k(x_k,v_i)} \quad (4)$$

Kernel induced metric is defined as,

$$d(x,y)\triangleq\|\phi(x)-\phi(y)\|=\sqrt{2(1-k(x,y)} \quad (5)$$

Termination criterion is defined as,

$$\|v_{new}-v_{old}\|<\varepsilon \quad (6)$$

Assign each pixel to a specific cluster for which a membership value will be maximal.The value of the epsilon will be 0.001.It is the stopping condition.

4 Results and Discussion

The simulations in this section do not intend to prove that the MKFCM-based image segmentation is inherently better than other KFCM-based image segmentation methods. They are used to demonstrate the MKFCM's significant flexibility in kernel selections and combinations and the great potential of this flexibility could bring to image-segmentation problems. Under the framework of MKFCM, changing the Gaussian kernel for local spatial information, and is straightforward, and the corresponded learning algorithm is not changed. By doing so, the segmentation results are improved. We can easily fuse the texture information into segmentation algorithms by just adding a kernel designed for the texture information in the composite kernel. As in the MR image-segmentation and Synthetic image-segmentation, simply adding a Gaussian kernel function of the texture descriptor in the composite kernel of MKFCM leads to better segmentation results. To sum up, the merit of MKFCM-based image-segmentation algorithms is the flexibility in selections and combinations of the kernel functions. After combining the different kernels in the kernel space (building the composite kernel), there is no need to change the computation procedures of MFKCM. There is also another advantage of reflecting and fusing iformation from various heterogeneous or homogeneous sources.

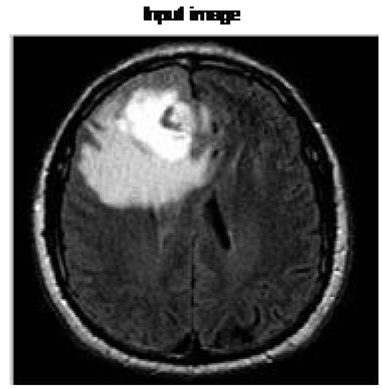

Fig 3.1 Input Image

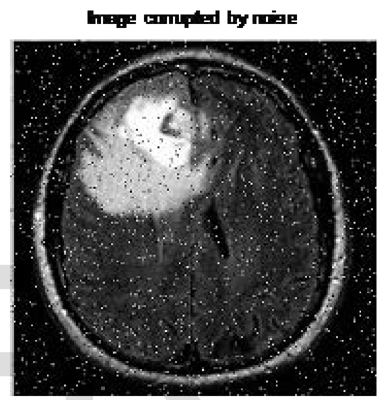

Fig 3.2 Image corrupted by noise

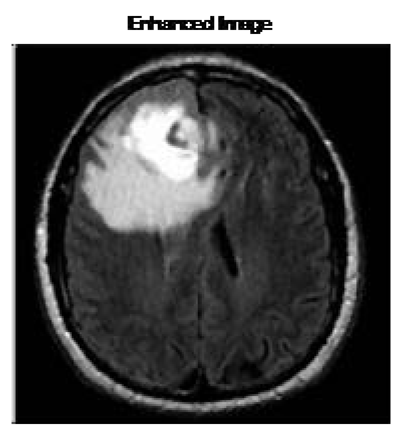

Fig 3.3 Enhanced Image

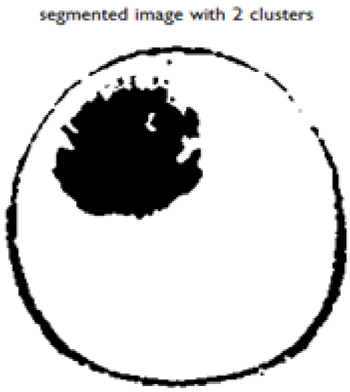

Fig 3.4 Image with clusters

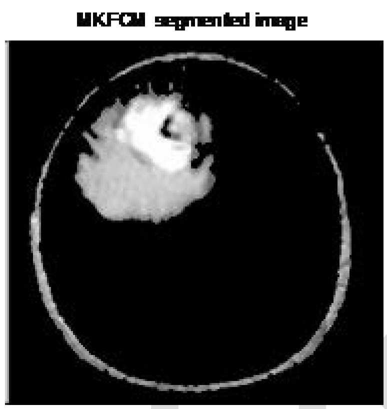

Fig 3.5 MKFCM segmented Image

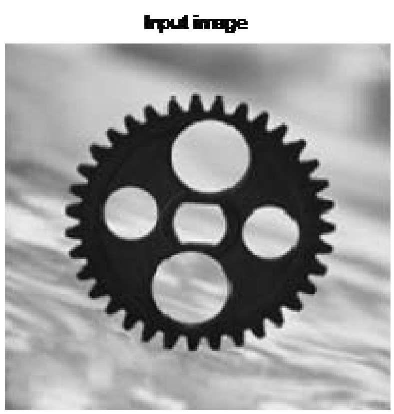

Fig 3.6 Input Image

Fig 3.7 Image corrupted by noise

Fig 3.8 Enhanced Image

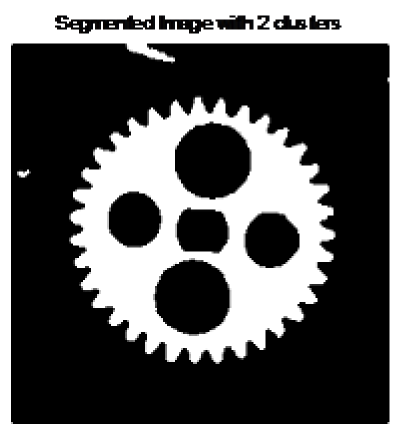

Fig 3.9 Image with clusters

Fig 3.10 MKFCM Segmented Image

5 Performance Analysis

The performance of the segmented image can be measured by means of accuracy. Accuracy can be calculated by using the below formula,

$$SA = \frac{\text{number of correctly classified pixels}}{\text{Total number of pixels}}$$

It is in the size of 64 x 64 pixels. Different noises, including "Gaussian noise", "Salt and pepper noise", "Speckle noise", "Poisson noise", are added to the image.

TABLE 1
Segmentation Accuracy

Noises	Segmentation accuracy
Salt & pepper	93.1030
Gaussian	94.0887
Speckle	92.3965
Poisson	93.0313

Segmentation accuracy for diffent types of noises on Brain tumour image

TABLE 2
Segmentation Accuracy

Noises	Segmentation accuracy
Salt & pepper	86.7996
Gaussian	90.8569
Speckle	82.3212
Poisson	86.5921

Segmentation accuracy for diffent types of noises on Synthetic image

6 Conclusion

In this paper, an MKFCM methodology has been proposed and applied as the framework for image-segmentation problems. The kernels are selected for different pieces of information. Aside from the fixed composite kernels, a new method that uses a linear combination of multiple kernels is proposed, and the updating rules of the linear coefficients of the composite kernel are derived.In the MKFCM framework, the texture information is easily fused in to the segmentation algorithm by just adding the Gaussian kernel designed for the texture in formation in the composite kernel (combination of spectral and spatial information). In both medical and synthetic image segmentation, just add the kernel function of the texture descriptor in the composite kernel which leads to a better segmentation results. The proposed algorithms provide a significant flexibility in selecting and combining different kernel functions. The information of the image is gathered from multiple heterogeneous or homogeneous data, a source is combined in the kernel space. Simulations on synthetic and Brain tumour images show the flexibility and the advantages of MKFCM in image-segmentation problems.

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