# AN IMPROVED ILKFCM ALGORITHM FOR SEGMENTATION OF ANOMALIES IN LIVER CT/MR IMAGES

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**Abstract**

This project is an application of Medical Image Processing. The abdomen CT image was taken as input and anomalies in the liver was analyzed. The clustering algorithm groups the pixels based on the similarity of gray values. Here in this project an improved kernel fuzzy C-mean clustering algorithm with pixel intensity and location information (ILKFCM) is used which will segment the abdominal organs in the CT image. The proposed algorithm is insensitive to noise. The weighted fuzzy factor and the kernel distance measure by Gaussian kernel provide accurate segmentation result. The project is developed in MATLAB 2010.

***Key Words :*** **fuzzy C-mean, CT images, image segmentation**

## 1 INTRODUCTION

Medical imaging modalities can provide visual representations of the interior of a body for clinical analysis and medical intervention. Medical imaging seeks to reveal internal structures hidden by the skin and bones, as well as to diagnose and treat disease. Medical imaging also establishes a database of normal anatomy and physiology to make it possible to identify abnormalities, so helping diagnosis and planning treatment. These detailed and informative mappings can be processed to extract the information of interest instead of dealing with whole data. Imaging techniques such as computer tomography (CT), Magnetic resonance imaging (MRI) can be used for diagnosis of abdominal organ pathologies. CT can generate images with much higher spatial resolution and shorter imaging duration. MRI has the advantage of not exposing the subject to ionizing radiation.

Image segmentation is the process of partitioning an image into meaningful parts, often consisting of an object and background. The segmentation algorithm has to be selected based on the application since there is no universal algorithm. In medical imaging, Segmentation is a partitioning process of an image domain into non-overlapping connected regions that correspond to significant anatomical structures. The segmentation of abdominal organs like liver, kidney from Computed Tomography (CT)/Magnetic resonance (MR) images is an important step in many diagnostic and surgical procedures. It is also useful in building many related computer aided diagnosis, computer guided surgery systems, building anatomical atlases for the abdominal area, and many other applications.

Liver cancer or hepatic cancer is a cancer that originates in the liver. Liver tumors are discovered on medical imaging equipment present themselves symptomatically as an abdominal mass, abdominal pain, yellow skin, nausea or liver dysfunction. The leading cause of liver cancer is viral infection with hepatitis B virus or hepatitis C virus. The cancer usually forms secondary to cirrhosis caused by these viruses. Liver cancers should not be confused with liver metastases, also known as secondary liver cancer, which are cancers that originate from organs elsewhere in the body and migrate to the liver. They are formed from either the liver itself or from structures within the liver, including blood vessels or the bile duct.

## 2 PROPOSED METHODOLOGY

### 2.1 Role of Weighted Fuzzy Factor

In order to overcome the aforementioned drawbacks of various FCM variants on medical image segmentation, a weighted fuzzy factor in the FCM objective function is needed. The factor has three special characteristics as follows:

1) simultaneously considers the neighbor pixel location and the intensity information, which improves the robustness of the clustering algorithm to speckle and outliers
2) The original image is used to avoid the preprocessing steps that could cause missing image information;
3) Has few parameters that need to be tuned;

The fuzzy factor consists of two components, i.e., the spatial distance factor and the intensity distance factor. For each pixel, the location constraint factor reflects the damping extent of the neighbors with the spatial distance from the central pixel and is defined as

$$e = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\left|x(m,n)\right| \tag{1}$$

$$\omega_{sd} = \frac{1}{d_{i,j}^{s}+1} \tag{2}$$

Where the $ith$ pixel is the center of the local window $N_i$, and the $jth$ pixel belongs to the set of the neighbors falling into a window around the $ith$ pixel. The spatial Euclidean distance between the $jth$ pixel and the central pixel is denoted as $d_{ij}^{s}$.

$$d_{ij}^{i} = \frac{1}{m}\sum_{k=1}^{m}\frac{I_{N_i}(k)}{I_{Nj}(k)}, I_{Nj(k)} \neq 0 \tag{3}$$

It is worth emphasizing that the spatial distance is not sufficient to reflect the relationship between the neighbor pixel and the central pixel. Therefore, we consider the intensity distance. The Euclidean distance between two intensities has been proven to be unreliable on the FCM image since it is robust to additive noise but not to multiplicative noise. In this letter, the ratio relativity is adopted to measure the intensity distance between two pixels.

Inspired by the Gaussian mapping function, we use a natural logarithm function to map the relativity into the intensity distance factor, which is defined as

$$\omega_{id} = 1-\log(d_{ij}^{I}) \tag{4}$$

$$\omega_{ij} = \omega_{sd}.\omega_{id} \tag{5}$$

In(4), the constant 1 guarantees that intensity distance factor$w_{id}$ is nonnegative, as well as $w_{ij}$ in (5). The incorporation of a fuzzy factor into the FCM has been studied in [9], [10], and [14]. The major contributions of this letter on the fuzzy factor are the following: The pixel intensity distance and the spatial distance are simultaneously taken into consideration, which makes use of more local information, and the weighted fuzzy factor is robust to speckle noise, which makes a contribution to FCM image segmentation. Hence, the discrepancy of the neighboring pixels can be accurately estimated by using the spatial constraint and the local intensity relationship.

## 2.2 ILKFCM algorithm

By incorporating $w_{ij}$ into the objective function of the FCM, we now propose a kernel fuzzy C-means clustering algorithm with pixel intensity and location information (the FCM) for SAR image segmentation. The objective function is defined in terms of

$$J_m = \sum_{i=1}^{N} \sum_{k=1}^{c} \left[ u_{ki}^m \left\| \phi(p_i) - \phi(v_{k)}) \right\|^2 + G_{ki} \right] \quad (6)$$

where$N$ is the number of pixels, $c$ is the number of clusters with $2 \le c \le N$, and $u_{kj}$ is the membership degree of the $kth$ pixel to the Parameter m is a weighting exponent on each fuzzy membership and determines the amount of fuzziness of the clustering result. According to practical experience, here, we set $m = 2$ for the following experiments. The feature vectors of the $kth$ pixel and $kth$ cluster center are represented in terms of $(p_i)$ and $(v_k)$, respectively. Symbol is the Euclidean norm, and $\phi(.)$ is an implicit nonlinear map. The inner product between $\phi(p_i)$ and $\phi(v_k)$ in the feature space is $\phi(p_i)^T \phi(v_k) = K(p_i, v_k)$ Through the kernel substitution, we get

$$\begin{aligned} \left\| (\phi(p_i) - \phi(v_{k)}) \right\|^2 &= (\phi(p_i) - \phi(v_{k)}))^T (\phi(p_i) - \phi(v_{k)})) \\ &= \phi(p_i)^T - \phi(p_i) - \phi(v_k)^T - \phi(p_i) - \phi(p_i)^T \phi(v_k) + \phi(v_k)^T \phi(v_k) \\ &= K(p_i, p_i) + K(v_k, p_i) - 2K(p_i, v_k) \end{aligned} \quad (7)$$

This way, a new class of non-Euclidean distance measures in the original feature space is obtained. For simplicity, we consider the Gaussian radial basis function (GRBF) kernel, and then, (7) can be rewritten as $2(1 - K(p_i, v_k))$ Kernel distance $K(p_i, v_k)$ is defined as

$$K(p_i, v_k) = \exp\left( -\frac{\left\| p_i - v_k \right\|^2}{\sigma} \right) \quad (8)$$

where $\sigma$ is the bandwidth of the GRBF kernel. Similar to the work in [10], the parameter is set on the basis of the distance variance of all feature vectors. Let be the distance from feature vector $(p_i)$ to feature average $p^{-}$. Then we can get the mean distance of $D_i$ as follows:

$$\overline{D} = \frac{1}{N} \sum_{i=1}^{N} D_i \quad (9)$$

$$\sigma = \left( \frac{1}{N-1} \sum_{i=1}^{N} (D_I - \overline{D})^2 \right)^{1/2} \quad (10)$$

Thus, the ILKFCM iteration is given as follows.

- ***Step 1:*** Set the number*c*of the clusters, fuzzificationparameter *m*, and stopping condition *ε*.
- ***Step 2:*** Randomly initialize the fuzzy cluster prototypes,set loop counter *b* = 0.
- ***Step 3:*** Scan the image, and calculate weighted fuzzyfactor $w_{ij}$ and the kernel distance of the feature vectors, as depicted in (5) and (8), respectively.
- ***Step 4:*** Update the partition matrix using (9).
- ***Step 5:*** Update the cluster prototypes using (10).
- ***Step 6:*** If $\{U^{(b)} - U^{(b+1)}\} \leq \xi$ then stop; otherwise,set loop counter $b = b + 1$ and go to Step 4, where $U = \{U_{ki}\}$ is the membership degree matrix.

When the algorithm has converged, a defuzzification process takes place in order to convert fuzzy partition matrix *U* to the crisp segmented image. This procedure assigns the $ith$ pixel to the $kth$ cluster with the highest membership $\phi(p_i)^T \phi(v_k) = K(p_i, v_k)$.

## 3 EXISTING METHODOLOGY

The general methods of SAR image segmentation have four categories, graph partitioning techniques clustering algorithms model-based methods and morphologic strategies . Fuzzy C-means (FCM) is one of the most widely used fuzzy clustering algorithms in image segmentation, which has robust characteristics for ambiguity and can retain much more information than hard segmentation methods . However, it is very sensitive to noise and other imaging artifacts, since it does not consider anyinformation about spatial context.

To address this problem, many improved FCM algorithms that incorporate local spatial information have been proposed. Ahmed *et al.*proposed FCM_S, which modified the objective function of the FCM by introducing the spatial neighborhood term. Cai*et al.*proposed the fast generalized FCM algorithm. In this method, a local similarity measure that combines both the spatial and gray level information is introduced to form a nonlinearly weighted sum image. Clustering is performed based on the gray level histogram of the summed image. To avoid the parameter selection that is involved in the aforementioned methods, Krinidis and Chatzis proposed a robust fuzzy local information C-means (FLICM) algorithm, which incorporates a fuzzy factor into the objective function of the FCM, considering the local spatial information. Besides, FLICM is free of any parameter. More recently, Gong *et al.*proposed an improved FLICM algorithm (the KWFLICM) by introducing a tradeoff weighted fuzzy factor and a kernel metric, which can accurately estimate the damping extent of neighboring pixels.

Although the aforementioned algorithms have got satisfactory results for the segmentation of synthetic, natural, and magnetic resonance images, they do not consider the special characteristic of noise in the medical image. Therefore, they are not suitable for medical image segmentation.

## 4 RESULTS

4.1 Input Image

**Figure 4.1: Input Image**

The above fig shows the image of the liver, which is given as input
4.1 Output Images

**Segmented Output Image nc=3**

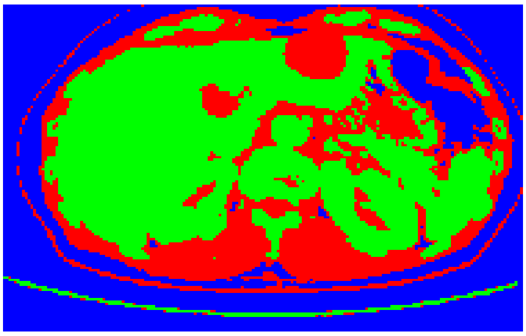

**Figure 4.2: nc=3**

The above figure is the segmented image with nc=3 represented by 3 different colour.

**Segmented Output Image  nc=4**

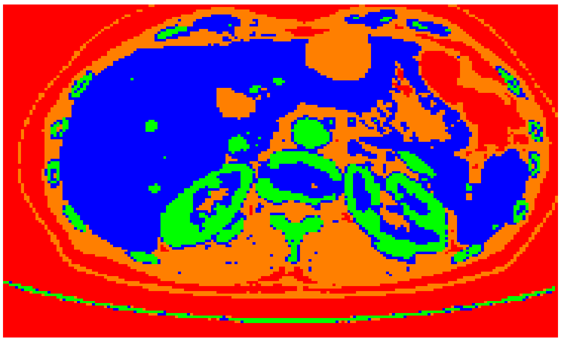

**Figure 4.3: nc=4**

The above figure is the segmented image with nc=4  represented by 4 different colour

**Segmented Output Image  nc=5**

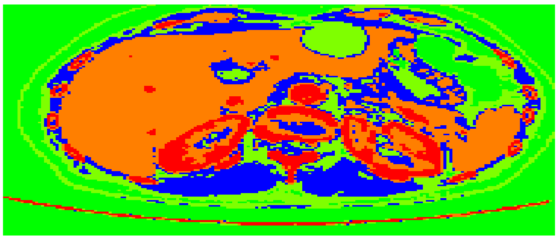

**Figure 4.4: nc=5**

The above figure is the segmented image with nc=5 represented by 5 different colour

**Segmented Output Image nc=6**

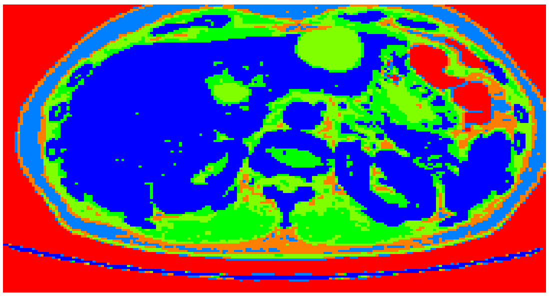

**Figure 4.5: nc=6**

The above figure is the segmented image with nc=6 represented by 6 different colour.

**Segmented Output Image nc=7**

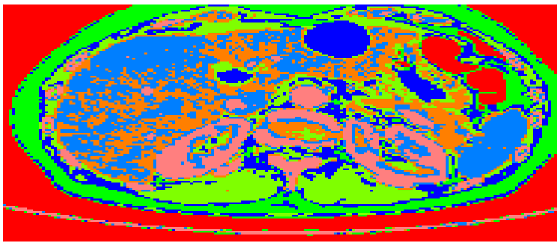

**Figure 4.6: nc=7**

The above figure is the segmented image with nc=7 represented by 7 different colour

**Segmented Output Image nc=8**

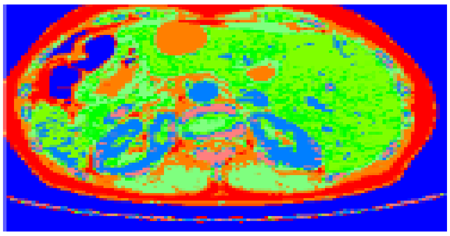

**Figure 4.7: nc=8**

The above figure is the segmented image with nc=8 represented by 8 different colour

**Segmented Output Image nc=9**

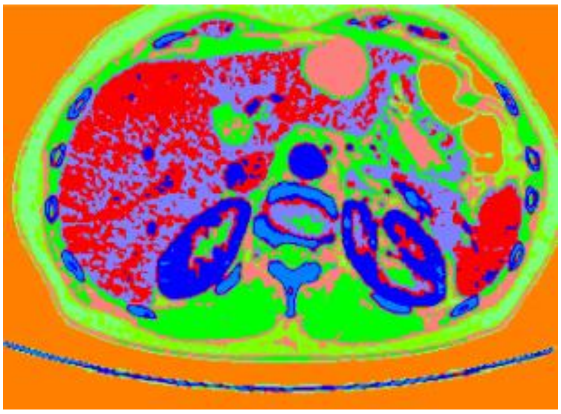

**Figure 4.8: nc=9**

The above figure is the segmented image with nc=9 represented by 9 different colour.

## 5 CONCLUSION

In this project an improved kernel fuzzy C-means clustering algorithm with pixel intensity and location information (ILKFCM) is used that produce better results than conventional FCM algorithm. In future the work will be concentrating in the tumor segmentation and classification will also be done.

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