





The Gaussian function  $\eta_i$  are estimated using,

$$\eta_i = K \frac{\sum_{k=1}^n u_{ik}^m 2(1 - K(x_k, v_i))}{\sum_{k=1}^n u_{ik}^m} \quad (2)$$

The fuzzy membership function  $u_{ik}$  is that the edges connecting the inner data points in a cluster may have a larger “degree of belonging” to a cluster than the “peripheral” edges (which, in a sense, reflects a greater “strength of connectivity” between a pair of data points). For instance, the edges (indexed  $i$ ) connecting the inner point in a cluster (indexed  $k$ ) are assigned  $u_{ik} = 1$  whereas the edges linking the boundary points in a cluster have  $u_{ik} < 1$ .

Each cluster is represented by a data point called a cluster center, and the method searches for clusters so as to maximize a fitness function called net similarity. The method is iterative and stops after maximum iterations (default of 500). It automatically determines the number of clusters, based on the input  $p$ , which is an  $N \times 1$  matrix of real numbers called preferences. A good choice is to set all preference values to the median of the similarity values. The number of identified clusters can be increased or decreased by changing this value accordingly.

The objective function in the clustering problem becomes more general so that the weights of data points are being taken into account, as follows:

$$S(C) = \sum_{k=1}^K \left( \sum_{i=1}^{|C_k|} u_{i(j)k}^m k \lambda k + \sum_{j=1}^n \gamma_{jk} (C_k) \right) \quad (3)$$

where  $C$  denotes the decomposition of the given clusters,  $C_1, \dots, C_K$  are not-necessarily disjoint clusters in the decomposition  $C$ ,  $\gamma$  denotes the modulating argument,  $S(C)$  denotes the total strength of connectivity cluster, designates, as in the edge connectivity of cluster, the weight  $u_{i(j)k}$ ,  $k$  is the membership degree of  $i(j)$  containing data point  $j$  in cluster  $k$ , and finally, it is the fitness of cluster  $j$  to cluster  $k$ .

### 3.3. Level Set Segmentation

The fuzzy using pixel classification with level set methods utilizes dynamic variational boundaries for image segmentation. Segmenting images by means of active contours is well known approach instead of parametric characterization of active contours. Level set methods embed them into a time dependent PDE function. It is

possible to approximate the evolution of active contours implicitly by tracking the zero level set.

The level set evolution of active contour implicitly tracking the zero level set  $\Gamma(t)$ ,

$$\begin{cases} \phi(t, x, y) < 0 & (x, y) \text{ is inside } \Gamma(t) \\ \phi(t, x, y) = 0 & (x, y) \text{ is at } \Gamma(t) \\ \phi(t, x, y) > 0 & (x, y) \text{ is outside } \Gamma(t) \end{cases} \quad (4)$$

### 3.4. Fuzzy With Level Set Algorithm

Both fuzzy algorithms and level set methods are general-purpose computational model that can be applied to problems of any dimensions. A new fuzzy level set algorithm is proposed for automated medical image segmentation. The algorithm automates the initialization and parameter configuration of the level set segmentation, using Kernel Fuzzy clustering.

A new fuzzy level set algorithm automates the initialization and parameter configuration of the level set segmentation, using spatial kernel fuzzy clustering. It employs a KFCM with spatial constraints to determine the approximate contours of interest in a medical image. Benefitting from the flexible initializations, the enhanced level set function can accommodate KFCM results directly for evolution. The enhancement achieves several practical benefits. The objective function now is derived from spatial fuzzy clustering directly. The level set function will automatically slow down the evolution and will become totally dependent on the smoothing term.

## 4. IMPLEMENTATION

Step 1: Infuzzy clustering process, the input MRI image and number of clusters are to be initialized. In this process, fuzzy objective function, membership function and weights are calculated. To separate the partition matrix with help of cluster centroid value, the distance matrix is used to find the similarity index value of black and white pixels of the image. In the last iteration, the final partitioned objective function is derived.

Step 2: Contour plot is defined to separate the background and foreground region in the image. The regions of object in binary images are found using initial contour and perimeter functions.

Step 3: 2-D convolution process, Gaussian filter function creates an image smoothness value which returns the central part of the image convolution.

Step 4: The image pixel directions are estimated with the help of gradient function which can either be scalars to specify the spacing between points in each direction or





