Robust Image Segmentation Using Fuzzy C-Means Clustering With Spatial Information Based on Total Generalized Variation

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ABSTRACT Fuzzy c-means clustering (FCM) has proved highly successful in the manipulation and analysis of image information, such as image segmentation. However, the effectiveness of FCM-based technique is limited by its poor robustness to noise and edge-preserving during the segmentation process. To tackle these problems, a new objective function of FCM is developed in this work. The main innovation and results of this paper are outlined as follows. First, a regularization operation performed by total generalized variation (TGV) is used to guarantee noise smoothing and detail preserving. Second, a weight factor incorporated into the spatial information term is designed to form nonuniform membership functions, which can contribute to the assignment of each pixel for the highest membership value. In addition, a regularization parameter is used to balance the respective importance of penalty between whole image and each neighborhood. The main advantage of this technique over conventional FCM-based methods is that it can reconstruct image patterns in heavy noise with only a small loss. We perform experiments on both synthetic and real images. Compared to state-of-the-art FCM-based methods, the proposed algorithm exhibits a very good ability to noise and edge-preserving in image segmentation.

INDEX TERMS Fuzzy c-means clustering, image segmentation, local spatial information, total generalized variation, nonuniform membership function.

I. INTRODUCTION Image segmentation focuses on the process of partitioning an image into meaningful regions, which has emerged as a fundamental topic for diverse applications in image understanding and computer vision [1]–[3]. During the past several decades, a variety of clustering techniques have been developed for their applications to image segmentation [4]. In these clustering algorithms, Fuzzy c-means (FCM) approach has been attracting significant attentions in this emerging area and has become increasingly important to elucidate image structures because they may identify the belongingness of each pixels with a certain fuzzy membership degree which cannot be revealed easily by hard clustering methods [5].

The success of FCM mechanism dealing with segmentation process is mainly due to its more flexibility to handle the uncertainties in image information, such as unclear boundaries or ambiguous restrictions between their regions. Although good performances have been achieved in the development of FCM segmentation algorithms, the segmentation for noise images and imaging artifacts remains a largely unsolved problem [4]. To overcome these limitations, many improved versions have been developed and formalized in many different ways.

One way to improve the segmentation effect is by adding a spatial regularization term. Ahmed et al. [6] first proposed the FCM algorithm with spatial neighborhood
information (FCM_S) to increase the robustness to noise, which has been the basis of several techniques in many ways. A shortcoming of FCM_S is its high computational complexity because this algorithm computes the neighborhood term in each iteration step. To deal with this problem, Chen and Zhang [7] developed FCM_S1 and FCM_S2 to reduce the execution time compared with FCM_S since mean and median filtering are used instead of the neighborhood term. Sziłágyi et al. [8] given the enhanced FCM algorithm to solve the same problem, its low computational time is achieved by performing a linear weighted image based on histogram instead of pixels. As a continued work, a modified version of the enhanced FCM has been published in [9] with forming a nonlinearly weighted image. In a novel fuzzy way, Krinidis and Chatzis [10] defined a factor in terms of both spatial and gray level to handle the influence of penalty parameter selection, termed as fuzzy local information c-means (FLICM). Base on this strategy, Gong et al. [11] incorporated kernel distance into the objective function to enhance its robustness to noise, termed as FCM with local information and kernel metric (KWFLICM). To improve segmentation performance in a novel fuzzy way, Yang et al. [12] developed a robust FCM (RFCM) algorithm based on a new objective function to deal with the pixel assignment problem. Zhao et al. [13] proposed a modified version to improve the noise insensitivity through a combination of spatial information and kernel induced distance, termed as kernel generalized fuzzy c-means clustering with spatial information (KGFCMS). To be more robust to noise in brain magnetic resonance images, Elazab et al. [14] introduced adaptively regularized kernel FCM (ARKFCM) based on local contextual information and kernel functions. To handle inherent drawbacks existed in level set methods, Li et al. [15] proposed a new level set formulation by using fuzzy region competition for selective image segmentation, named as selective level set method (Selective-LSM). With remarkable success, Lei et al. [16] given a more feasibility model called fast and robust FCM (FRFCM) to achieve good segmentation results, which adopts morphological reconstruction and membership filtering. Other FCM-based methods used to segment image regions can be found in [17]–[27].

The above-mentioned methods have a strong mathematical basis and achieve efficient results for different types of images. But despite the efforts spent, it is still an open question whether the strengths of the strategies are sufficient to identify patterns under heavy noise. However, unsatisfactory results might emerge when dealing with this type of images. For example, kernel based FCM algorithms have been widely applied to noise reduction in image segmentation by performing an arbitrary nonlinear mapping from the original feature space to a space of higher dimensionality. In practical applications, however, overall the performance obtained by kernelized FCM is not very impressive in clustering classifications compared to FCM [27]. In addition, these methods exhibit highly sensitivity to the selection of specific values of the kernel parameters to some extent. So the task for accurate and reliable methods to automatically determine the boundaries and patterns of large noise images still needs to be solved today.

To address the challenges in a more precise way, one of our intuitions is that if a model can effectively suppress noise and artifacts and produce visually pleasing edge profiles, we can get more accurate segmentation when treating image. Another object of this paper is to investigate the unimodal property of membership functions and its application to optimal assignment of each pixel. To accomplish these two purposes, this paper proposed a robust fuzzy clustering with total generalized variation (TGV) [28]–[30] and weight factor based on spatial information to achieve a high segmentation precision. The main contributions behind our segmentation method can be summarized as follows:

1) To improve the high-amplitude noise immunity and edge preservation in the process of segmentation, we present a regularization scheme to retain the image quality by incorporating the new concept of TGV. The well-behaved solutions of higher-order derivatives achieved in TGV regularization make it capable of yielding visually pleasant images with more continuous boundaries and less patchy artifacts. By introducing this term into the objective function, our segmentation scheme is more robustness to heavy noise and outliers than existing FCM algorithms.

2) The FCM-based segmentation is performed by assigning each pixel to the class that holds the largest membership value, so membership functions should be unimodal. To obtain unimodal membership functions, a weight factor is defined to modify the FCM objective function. The unimodal property of the membership functions achieved in the proposed method could manage to enhance its crisp membership values.

The remainder of the paper is organized as follows. Section II briefly describes the motivation for our work. The proposed algorithm is introduced in Section III. Experimental results are presented in Section IV and conclusions are drawn in Section V.

II. MOTIVATION

Now, let us first briefly describes the standard FCM algorithms. FCM is a staple of unsupervised machine learning which allows one piece of data to belong to two or more clusters, which assigns a degree of membership for every cluster number and a dataset, the method iterates to minimize the objective function to deal with the pixel assignment problem. To accomplish these two purposes, this paper proposed a robust fuzzy clustering with total generalized variation (TGV) [28]–[30] and weight factor based on spatial information to achieve a high segmentation precision. The main contributions behind our segmentation method can be summarized as follows:

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and $V = \{v_j\}$ denotes cluster center. Using the Lagrange multiplier method, we may obtain a local minimum for $J$ if we update $U$ and $V$ alternatingly according to the algorithm (1) at each step $k$

$$v_j^{(k+1)} := \frac{\sum_{i=1}^{N} (u_{ij}^{(k)})^m x_i}{\sum_{i=1}^{N} (u_{ij}^{(k)})^m},$$  
(2)

$$u_{ij}^{(k+1)} := \left( \frac{C}{\sum_{i=1}^{N} \frac{1}{\|x_i - v_j^{(k+1)}\|^2} } \right)^{-\frac{1}{m}}.$$  
(3)

### A. MOTIVATION OF INTRODUCING THE REGULARIZER

Although the standard FCM works well on most noise-free images and blurring, it is sensitive to noise and other imaging artifacts. By comprehensively considering the drawback of FCM, to increase FCM robustness to noise, Ahmed et al. [6] modified the standard FCM by adding a spatial penalty term to the objective function defined in (1) as follows:

$$J(U, V) = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \|x_i - v_j\|^2 + \frac{\alpha}{N_R} \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \sum_{r \in N_i} \|x_r - v_j\|^2,$$  
(4)

where $N_i$ represents the neighborhood window centered in pixel $i$, $N_R$ denotes the pixel number of every window and parameter $\alpha > 0$ here is used to control the effects of penalty. In a similar way to the standard FCM algorithm, the objective function $J$ can be minimized under the constraint of $U$. The optimization of the membership function $U$ and cluster centers $V$ involve the use of the technique of Lagrange multipliers which leads to the expression

$$v_j^{(k+1)} := \frac{\sum_{i=1}^{N} (u_{ij}^{(k)})^m x_i}{\sum_{i=1}^{N} (u_{ij}^{(k)})^m},$$  
(5)

$$u_{ij}^{(k+1)} := \left( \frac{C}{\sum_{i=1}^{N} \frac{1}{\|x_i - v_j^{(k+1)}\|^2} } \right)^{-\frac{1}{m}}.$$  
(6)

A shortcoming of FCM_S is its time expense as the computation of the neighborhood terms will be executed at every iteration step. To reduce the computational complexity of FCM_S, Chen and Zhang [7] introduce a new algorithm called FCM_S1 and FCM_S2 whose neighbourhood terms are substituted by mean filtering and median filtering, respectively. The objective functions of these two variants is written as follows:

$$J(U, V) = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \|x_i - v_j\|^2 + \alpha \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \|x_i - v_j\|^2.$$  
(7)

In another way, Krimidis and Chatzis defined a novel fuzzy factor to measure local similarity:

$$J(U, V) = \sum_{i=1}^{N} \sum_{j=1}^{C} \left( u_{ij}^m \|x_i - v_j\|^2 + G_{ij} \right),$$  
(8)

while the fuzzy factor is defined as

$$G_{ij} = \alpha \sum_{i \neq r} 1 \frac{1}{d_{jr}} \left( 1 - u_{ij}^m \right) \|x_r - v_j\|^2.$$  
(9)

Although the modified versions of FCM have produce excellent performance for image segmentation, in dealing with heavy noise they will result in loss of important image details such as boundaries or edges of image. In practice, we expect to solve the problem by describing an image using regularization techniques [30], i.e.,

$$y = F(x) + \eta,$$  
(10)

where $\eta$ is assumed to be noise and $F$ is an ill-posed forward operator representing the degradation process. In general, recovering $x$ from its measurements requires the following optimization problem

$$\min_x \| F(x) - y \|^2 + \lambda R(x),$$  
(11)

where $\| F(x) - y \|^2$ denotes fidelity term and $R(x)$ is regularization penalty.

Motivated by this, we introduce a regularization model to FCM to yield high quality images with clear boundaries and less block artifacts. In this study, the TGV regularization was adapted under the FCM framework for image segmentation. The main property of TGV is its capability of incorporating smoothness from the first up to the $h$-th derivative, thus effectively attenuating the staircase effect present in the solution of (11). In other words, TGV regularization involves and balances higher-order derivatives, yielding good image reconstruction results produced by highlighting objects edges while smoothing regions in the image. In Section III.B, we will present this regularization in detail.

### B. MOTIVATION OF INTRODUCING THE WEIGHT FACTOR

In general, the modified versions of FCM by adding the spatial term can be formulated as follows:

$$J(U, V) = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m d^2(x_i, v_j) + \sum_{i=1}^{N} \sum_{j=1}^{C} G_{ij},$$  
(12)
where \( G_{ij} \) is the fuzzy factor or the spatial penalty term, 
\( d^2(x_i, v_j) \) denotes a distance measure between object \( x_i \) and cluster center \( v_j \).

In FCM_S and FCM_S1/2, it can be seen that the membership \( u_{ij}^m \) of the spatial penalty term shows the same tendencies with respect to the membership values of the first term. For FLICM, the membership \( u_{ij}^m \) of the first term and the penalty \((1 - u_{ij}^m)\) of the fuzzy factor are in the opposite trend.

In fuzzy clustering, we expect to find minima of a distance between the object \( x_i \) and the cluster center \( v_j \) by a term \( u_{ij}^m \) that quantifies a higher value. In fact, when the pixel \( x_i \) is assigned to cluster \( v_j \) with the higher membership value \( u_{ij}^m \) in the first term \( \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m d^2(x_i, v_j) \), we can reasonably assume that noise has a little influence on this pixel, and the second term \( \sum_{i=1}^{N} \sum_{j=1}^{C} G_{ij} \) affecting the reconstruction of patterns should be reduced. On the contrary, we take into account the influence of the neighboring pixels on the central pixel. Motivated by this idea, we define the weight factor, i.e.,

\[
w_{ij} = u_{ij}^m(1 - u_{ij}^m).\]  

Fig. 1 reveals the relationship between \( w_{ij} \) and \( u_{ij} \).

**FIGURE 1.** Relationship between \( w_{ij} \) and \( u_{ij} \) \((m = 2)\).

As shown in Fig. 1, when \( u_{ij} \) becomes smaller than 0.5, the second term weighted by \( w_{ij} \) is rewarded a bigger contribution to overcomes the impact of noise data. If \( u_{ij} \) is smaller than 0.5, the impact of the second term on image outline and detail will be decreased. This property can help achieve the nonuniform or unimodal property of the membership functions such that they are suitable well for noisy image segmentation.

### III. METHODOLOGY

Motivated by the above descriptions, we develop the proposed method by introducing regularization technique and a weighted fuzzy factor. The details of the proposed algorithm, termed as TGVFCMS for short, will be described in this section.

#### A. BASIC FRAMEWORK OF THE PROPOSED METHODOLOGY

The proposed TGVFCMS performs clustering on the spatial information, the objective function is formulated as

\[
J(U, V) = \sum_{i=1}^{N} \sum_{j=1}^{C} d^2(x_i, v_j) + \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \cdot G_{ij}^2, \tag{14}
\]

while the fuzzy factor is defined as

\[
G_{ij}^2 = \frac{\gamma}{N_R} \sum_{r \neq i} w_{rj} \| x_r - v_j \|^2, \tag{15}
\]

where \( x_r \) denotes the neighbor pixels falling into a window \( N_i \) around \( x_i \). \( \xi_j \) is the TGV regularization for \( x_i \), and the parameter \( \gamma \) control the effect of neighbors term. Then we can calculate the center vector \( \{v_j\} \) and the membership function \( \{u_{ij}\} \) for each step \( k \):

\[
v^{(k+1)}_j := \frac{\sum_{i=1}^{N} \left( u^{(k)}_{ij} \right)^m \xi_i}{\sum_{i=1}^{N} \left( u^{(k)}_{ij} \right)^m}, \tag{16}
\]

\[
u^{(k+1)}_{ij} := \left( \sum_{i=1}^{C} \left( \| \xi_i - v^{(k+1)}_j \|^2 + G_{ij}^2 \right) \right)^{-1} \left( \sum_{i=1}^{C} \frac{\| \xi_i - v^{(k+1)}_j \|^2 + G_{ij}^2}{\| \xi_i - v^{(k+1)}_j \|^2 + G_{ij}^2} \right). \tag{17}
\]

Thus, the TGVFCMS algorithm as the iteration processes is listed in Table 1. In the case of TGVFCMS, a fixed \( 3 \times 3 \) window is used in experiments and the controller parameter \( \gamma \) is set to 0.2.

**TABLE 1.** Process of TGVFCMS.

| Algorithm 1: The process of TGVFCMS |
|-------------------------------------|
| **Input:** the cluster number \( C \), the weight fuzzy coefficient \( m \), the penalty parameter \( \alpha \), the window size \( N_i \), the termination criterion \( \epsilon \) |
| **Output:** the cluster centers \( \{v^{(k+1)}_j\} \), the membership functions \( \{u^{(k+1)}_{ij}\} \) |
| **Begin** |
| 1. Initialize the cluster centers \( v^{(0)}_i \) and the membership functions \( u^{(0)}_{ij} \); |
| 2. Set the loop counter \( k=0 \); |
| 3. Calculate the TGV regularization \( \xi_i \) and the distance measurements \( \| \xi_i - v^{(k)}_j \| \) and \( \| x_r - v^{(k)}_j \| \), respectively; |
| 4. Update the cluster centers using (16); |
| 5. Update the partition matrix using (17); |
| 6. If \( \| u_{ij}^{(k+1)} - u_{ij}^{(k)} \| \leq \epsilon \) then stop, otherwise \( k = k+1 \) go to step 3; |
| **End** |

#### B. TGV REGULARIZATION

One of the important aspects of our TGVFCMS method is its robustness to noise and its ability to edge-preserving. In order to restore the image that satisfies people’s needs, regularization techniques are usually applied. Particularly, the desirable properties of TGV regularization up to a certain
order of differentiation make it of a useful tool to measure image characteristics, such as noise removing and sharp edge preserving. To eliminate the undesired noise and artifacts from the FCM-based methods, in this study the TGV regularization was adapted in the smoothing term of our TGVFCMS. Let us first define the framework of TGV as follows:

$$ \text{TGV}^k_{\alpha}(u) = \sup \left\{ \int_{\Omega} u \text{div}^2 v dx \mid v \in C^2_c(\Omega, \text{Sym}^k(\mathbb{R}^d)), \right.$$

$$\text{div}^2 v \leq \alpha \right\}, \quad (18)$$

where $l = 0, 1, \ldots, k - 1$, and $k \in \mathbb{N}$ indicates an order of TGV, and $\alpha = (\alpha_0, \alpha_1, \ldots, \alpha_{k-1})$ denotes the positive weights to TGV. Sym$^k(\mathbb{R}^d)$ represents the space of symmetric $k$-tensors. For each component $\eta \in M_k$. The $l$-divergence of a symmetric $k$-tensor field is given by

$$\text{div}^l v \eta = \sum_{\gamma \in M_l} \frac{1}{\gamma !} \partial_i v_{\eta + \gamma}, \quad (19)$$

where $M_k$ is the multi-index of order $k$

$$M_k = \left\{ \eta \in \mathbb{N}^d \mid \sum_{i=1}^d \eta_i = k \right\}. \quad (20)$$

The $\infty$-norm for symmetric $k$-vector fields is given as

$$\| v \|_{\infty} = \sup_{x \in \Omega} \left( \sum_{\eta \in M_k} \frac{k!}{\eta!} v_{\eta}(x)^2 \right). \quad (21)$$

The first-order gradient and the high-order gradient achieved in (18) are both constrained to be sparse, which can obviously reduce the staircase artifacts.

Here, we take into account the second order TGV, i.e.,

$$\text{TGV}^2_{\alpha}(u) = \sup \left\{ \int_{\Omega} u \text{div}^2 v dx \mid v \in C^2_c(\Omega, S^{d \times d}), \right.$$

$$\| v \|_{\infty} \leq \alpha_0, \| \text{div} v \|_{\infty} \leq \alpha_1 \right\}. \quad (22)$$

where $C^2(\Omega, S^{d \times d})$ denotes the vector space of compactly supported under the set of symmetric matrices $S^{d \times d}$. Particularly, the respective definitions for the divergence and norms can be calculated as follows:

$$\text{div} v = \sum_{j=1}^d \frac{\partial v_{ij}}{\partial x_j}, \quad \text{div}^2 v = \sum_{j=1}^d \frac{\partial^2 v_{ij}}{\partial x^2_j} + 2 \sum_{i<j} \frac{\partial v_{ij}}{\partial x_i \partial x_j} \quad (23)$$

and

$$\| v \|_{\infty} = \sup_{x \in \Omega} \left( \sum_{i=1}^d |v_{ij}(x)|^2 + 2 \sum_{i<j} |v_{ij}(x)|^2 \right)^{1/2}$$

$$\| \text{div} v \|_{\infty} = \sup_{x \in \Omega} \left( \sum_{i=1}^d \sum_{j} \left| \frac{\partial^2 v_{ij}}{\partial x_j^2}(x) \right| \right)^{1/2} . \quad (24)$$

The definition of (22) is generalized to solve a minimization problem as follows [29], [31]:

$$\text{TGV}^2_{\alpha}(u) = \min_v \int_{\Omega} |\nabla u - v| dx + \alpha_0 \int_{\Omega} |\varepsilon(v)| dx, \quad (25)$$

where minimum solution is taken over all vector fields on $\Omega$ and $\varepsilon(v) = (\nabla v + \nabla u^T)/2$ indicates the symmetrized derivative. Here, the definition of (25) shows that $\nabla^2 u$ contributes less than $\nabla u = v$ to smooth regions. In the edge neighbors, $\nabla^2 u$ is locally ‘larger’ than $\nabla u$ in these regions, and minimization could work well with $v = 0$. Thus, provides a way to achieve the balance between the first and second derivative (via the ratio of positive weights $\alpha_0$ and $\alpha_1$). For practical purposes, the two weights $\alpha_0$ and $\alpha_1$ are tuned to 0.1 and 0.15, respectively.

Through the definition of second-order TGV, the proposed TGVFCMS can yield results that are more robust to noise and detail-preserving. Fig. 2 shows the fuzzy partition matrix of each considered method by using a synthetic image contaminated with Gaussian noise (the mean value is zero, and the variance is 35%). Note that fuzzy partition matrix is important for subsequent clustering and image segmentation. This test image includes four patterns (four intensity value are 0, 85, 170 and 255 respectively). What we can see in Fig. 2 is that the fuzzy partition matrices achieved in RFCM, KGFCMS, KWFLICM, ARKFCM, Selective-LSM and FRFCM are sensitive to noise, and the boundaries between different patterns are not well defined. It is clear that the proposed method almost perfectly reconstructs the four patterns of input image in terms of fuzzy partition matrix.

![Figure 2. Descriptions of fuzzy partition matrix of the RFCM, KGFCMS, KWFLICM, ARKFCM, Selective-LSM, FRFCM and TGVFCMS methods when they are applied to the synthetic image contaminated with Gaussian noise (the mean value is zero, and the variance is 35%).](image-url)
C. NONUNIFORM MEMBERSHIP FUNCTIONS

In a way, the distributions of membership functions determine the assignment of each pixel to a cluster. When we designate a pixel as a given cluster, the corresponding membership value should be as close to 1 as possible, and the belonging of other pixels to this cluster in terms of membership values should be closer to 0. In fact, the distribution of membership values can be described quantitatively by histogram. If the histogram has two apparent peaks, we can achieve a good image segmentation; Otherwise, it is difficult if the histogram is uniform. The nonuniform or unimodality achieved in our TGVFCMS mainly relies on the weight factor $w_{ij}$, as shown in (15). Herein, let us observe the nonuniform using the example in Fig. 2. The histograms of membership values for different patterns are shown in Fig. 3. For the histogram of Class I, RFCM exhibits highest membership values around 0.48, while the highest values generated by KGFCMS, KWFLICM, ARKFCM, Selective-LSM and FRFCM are close to 0. Compared to other methods, there are two obvious peaks for each pattern in our proposed algorithm and the highest membership values with respect to each class are as close to 1 as possible.

IV. EXPERIMENTAL RESULTS

We conduct the segmentation experiments from two aspects. First, we evaluate the performance of the proposed method on two synthetic images, one natural image, two medical images, and one remote-sensing image. In the second place, two datasets are used to systematically assess the segmentation results. In order to set up the general form of comparative experiments, the TGVFCMS as well as six state-of-the-art FCM-based methods RFCM [12], KGFCMS [13], KWFLICM [11], ARKFCM [14], Selective-LSM [15] and FRFCM [16], are applied to the test data mentioned above. In Selective-LSM, the regions bounded by colour contour lines denote its segmentation results. For all algorithms, we set the fuzziness index $m = 2$. All the methods are implemented in MATLAB and performed on a computer with Intel(R) Core(TM) i7-9700F, CPU@ 3.00GHz, 32G RAM and Microsoft Windows 10.

A. RESULTS ON THE SYNTHETIC IMAGES

We first carry out some experiments to compare the segmentation performances of these algorithms on two synthetic images. The first image includes four patterns, and the second image includes three classes. The advantage for using synthetic images rather than real image data for validating segmentation methods is that synthetic data includes prior knowledge of the true types and control over image parameters such as modality and noise.

In this subsection, we use the segmentation accuracy (SA) [16] as the evaluation indices. SA is defined as the sum of correctly classified pixels divided by the total number of pixels:

$$SA = \frac{1}{c} \sum_{i=1}^{c} A_i \cap C_i$$  \hspace{1cm} (26)

where $c$ is the number of clusters, $A_i$ denotes the pixels belonging to the $i$th class found by algorithm, and $C_i$ denotes
In Fig. 4, we test the algorithms’ performances when the first synthetic image corrupted by Gaussian noise with 10%, 20%, 30%, 35%, 40% and 45% variance, respectively. What we can see in Fig. 4 is that RFCM, KGFCMS and ARKFCM are sensitive to noise with different levels, and the boundaries between different regions are not well defined. KWFLICM, Selective-LSM and FRFCM generate satisfactory results when noise level $\leq 35\%$, $\leq 30\%$ and $\leq 30\%$, respectively; while these three methods obtain poor results when noise is presented in heavy level. The results achieved by TGVFCMS show that the region uniformity is good and the boundaries between regions are clear, although some subtle textures were lost when noise level is 45%. Fig. 5 illustrates the segmentations of the first synthetic image contaminated with Salt & Pepper noise (30%, 40%, 50% and 60%). The segmented regions achieved in RFCM, KGFCMS, KWFLICM, ARKFCM, Selective-LSM and FRFCM are respectively affected by the Salt & Pepper noise to different extents, while TGVFCMS obtains more consistent and homogenous in the presence of noise, compared to the corresponding algorithms. The segmentation accuracies in terms of SA obtained by considered methods for the first synthetic image are listed in
Table 2. Segmentation accuracy (SA%) of seven methods on the first synthetic image with different level of Gaussian noise and Salt & Pepper noise.

| Noise Level          | RFCM   | KGFCMS | KWFLICM | ARKFCM | Selective-LSM | FRFCM | TGVFCMS |
|----------------------|--------|--------|---------|--------|---------------|-------|---------|
| Gaussian noise       |        |        |         |        |               |       |         |
| 10%                  | 90.02  | 57.95  | 99.95   | 98.12  | 99.84         | 99.92 | 98.20   |
| 20%                  | 83.83  | 78.32  | 99.77   | 57.80  | 99.60         | 99.72 | 97.77   |
| 30%                  | 78.99  | 48.77  | 99.07   | 56.82  | 66.42         | 56.42 | 97.46   |
| 35%                  | 73.51  | 56.34  | 55.75   | 81.33  | 69.45         | 55.88 | 97.08   |
| 40%                  | 67.74  | 58.88  | 58.94   | 38.94  | 69.62         | 57.00 | 96.00   |
| 45%                  | 61.50  | 53.58  | 59.26   | 42.39  | 69.56         | 57.37 | 83.49   |
| Salt & Pepper noise  |        |        |         |        |               |       |         |
| 30%                  | 77.16  | 47.27  | 99.47   | 60.24  | 69.48         | 99.67 | 99.17   |
| 40%                  | 69.01  | 41.23  | 97.71   | 96.39  | 69.47         | 99.57 | 99.06   |
| 50%                  | 61.90  | 45.48  | 92.33   | 91.83  | 69.06         | 81.07 | 98.90   |
| 55%                  | 54.23  | 34.43  | 81.11   | 83.90  | 66.76         | 97.96 | 98.61   |

Fig. 6 shows our experiment when these algorithms are applied to the second synthetic test image corrupted by Gaussian noise with 10%, 20%, 30%, 40%, 45%, 50% and 55% variance. From Fig. 6, KWFLICM, Selective-LSM and FRFCM obtain good results for image corrupted by noise with level 10%, 20% and 30%. Although the segmentations it can be concluded that our method can consistently reach higher accuracy.
The results in terms of SA on the second synthetic image by using considered methods are recorded in Table 3. By comparing with the other methods, nearly all pixels are classified correctly by TGVFCMS so that the algorithm turns out to be robust to Gaussian noise and Salt & Pepper noise. This suggests that the proposed algorithm outperforms the compared algorithms on this kind of test data.

Fig. 8 presents the iterations of object functions of different methods when they are applied to these two synthetic images. From Fig. 8, we find that the iterations of Selective-LSM, FRFCM and TGVFCMS are more than those of other methods. What is more, the needed iterations of these three methods are only 10 iterations. The performance of Selective-LSM is mainly due to the use of the level set method. FRFCM gets the results by employing the modification of membership partition to save less iterations. So the converge property of these three methods is much better than those of other methods.
However, there is a jump in each object function curve of Selective-LSM and FRFCM in some cases. In contrast, our TGVFCMS tends to converge very fast and gets the steady state as presented in Fig. 8.

Following the analysis above, Table 4 lists the computational complexity of different methods. From this table, we can see that KWFLICM has highest computational complexity due to its introduction of two additional loops on the neighborhood. On the contrary, the RFCM method is fastest because its constraints do not require loop in local information. ARKFCM is also fast due to the pre-filtering of local information. KGFCMS needs more computational cost than ARKFCM because this algorithm adds another constraint to its object function. FRFCM employs grayscale histogram to accelerate the executing of cluster algorithm, so it works well with less implementation time. Selective-LSM takes the level set method into account, so the extra computational complexity of this method depends on the convergence of its energy function. Our proposed method incorporates the regulation scheme by introducing TGV, the additional computational cost is viewed by the convexity of TGV energy function. It should be noted that TGV behaves well in convex regularization function, so the proposed algorithm can fast convergence to steady state.

### TABLE 4. Computational complexity of seven methods.

| Method         | Computational Complexity                                                                 |
|----------------|------------------------------------------------------------------------------------------|
| RFCM           | $O(N + N\times C \times T)$                                                              |
| KGFCMS         | $O(N(1 + W^2) + N\times C \times T)$                                                     |
| KWFLICM        | $O(N(1 + W^2) + N\times C \times T^2)$                                                   |
| ARKFCM         | $O(N \times W^2 + N\times C \times T)$                                                   |
| Selective-LSM  | $O(N \times T_{ls} + N\times C \times T)$                                               |
| FRFCM          | $O(N \times W^2 + N\times C \times T)$                                                   |
| TGVFCMS        | $O(N \times (T_{gs} + W^2) + N\times C \times T)$                                         |

$\uparrow N$ is the pixel number, $C$ denotes the cluster number, $T$ indicates the iteration number of fuzzy clustering, $W$ is the window size, $T_{ls}$ indicates the iteration number of level set method, $T_{gs}$ denotes the iteration number of TGV regularization.

### B. RESULTS ON THE NATURAL IMAGE

The second type of case is a diversely illuminated image “Hill”, which exposes more intricate details. In this experiment, 6-level clustering was applied to extract the intrinsic details present in the image. The segmentation results of different methods on the natural image corrupted by Gaussian noise with 10%, 20%, 30%, 40% and 45% variance are shown in Fig. 9. As this test image contains diversely illuminated regions and more intricate details, RFCM, KGFCMS, ARKFCM, Selective-LSM and FRFCM generate misclassified points in the segmented image and give unsatisfactory results. In contrast, TGVFCMS yield clear boundaries between regions and the region uniformity achieved by this algorithm is good. The superiority of the proposed TGVFCMS with good robustness is observable in this figure.
C. RESULTS ON THE MEDICAL IMAGES

Now, we present segmentation experiments by using considered methods, when applied on two medical images. The first example is real MR slices of four patterns, which contains four classes of tissues: whiter matter, gray matter, cerebrospinal fluid and background. The CT-liver image includes three patterns, specially: lesion, surrounding tissues and background.

Fig. 10 and Fig. 11 present the comparison of segmentation results among considered methods on these two medical images corrupted by Gaussian noise with 10%, 20%, 30%, 40% and 50% variance.

The results shown in Fig. 10 demonstrate that the RFCM, KGFCMS, KWFLICM, ARKFCM, Selective-LSM and FRFCM methods give bad performance in the presence of noise and cannot correctly classify different tissues. Visually, TGVFCMS acquires satisfying segmentation results, although some subtle details are lost in the presence of heavy noise (variance = 40% and variance = 50%). From the zoom in areas, we can see that our
method can better distinguish the white matter from other parts.

Fig. 11 shows the results of applying different methods for the segmentation of CT-liver image. By comparing with other algorithms, TGVFCMS achieve satisfactory results and the boundaries between the true regions obtained by this technique are well defined.

**D. RESULTS ON THE REMOTE-SENSING**

To demonstrate the generalization capability of the proposed TGVFCM, we choose a remote-sensing image as test data. The remote-sensing image contains three patterns: airplane, shadow and ground.

The results of the compared methods on the remote-sensing image are shown in Fig. 12. It can be seen that RFCM, KGFCMS, KWFLICM, ARKFCM, Selective-LSM and FRFCM exhibit comparatively unsatisfactory performance, while TGVFCMS maintains the clear image edges and does not create isolated pixels.

**E. RESULTS ON BERKELEY SEGMENTATION DATASET**

In order to comprehensively evaluate the performance of considered methods, we conducted experiments on the
Berkeley Segmentation Dataset (BSDS500) that comprises 500 files by using considered methods. It has been shown that KWFLICM, Selective-LSM and FRRCM outperforms its counterparts with respect to segmentation accuracy, respectively. In this work, the performance of TGVFCMS has been compared with only these three algorithms.

For comparison with these three methods in the presence of heavy noise, the segmentation performance was evaluated by eight measures: Precision, Recall, Accuracy, $F_1$-score [32]; Global Consistency Error (GCE) [33]; Probabilistic Rand Index (PRI) [34]; Variation of Information (VoI) [35]; Boundary Displacement Error (BDE) [36].

To which $S$-score are defined as follows

\[
\text{Precision} = \frac{TP}{TP + FP},
\]

\[
\text{Recall} = \frac{TP}{TP + FN},
\]

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP},
\]

\[
F_1 - \text{score} = \frac{2 \times TP}{2 \times TP + FN + FP}.
\]

These four metrics have been widely used for evaluating the performance of image segmentation, see [32] for more details.

Let $S_{\text{ground truth}}$ and $S_{\text{test}}$ be the ground truth and the segmentation for an image, respectively. GCE provides a score to which $S_{\text{ground truth}}$ and $S_{\text{test}}$ are mutually consistent. The definition of GCE is expressed in the following manner:

\[
\text{GCE} \left( S_{\text{ground truth}}, S_{\text{test}} \right) = \frac{1}{N} \min \left\{ \sum_i E \left( S_{\text{ground truth}}, S_{\text{test}}, p_i \right), \sum_i E \left( S_{\text{test}}, S_{\text{ground truth}}, p_i \right) \right\},
\]

where $E \left( \cdot \right)$ indicates local refinement error, $N$ is the pixel number.

PRI gives a measurement of the fraction of pixel pairs whose labels are consistent between $S_{\text{ground truth}}$ and $S_{\text{test}}$. The similarity in terms of PRI is

\[
\text{PRI} \left( S_{\text{ground truth}}, S_{\text{test}} \right) = \frac{N}{2} \left\{ \frac{N}{2} - \frac{1}{2} \left( \sum_i \left( \sum_j n_{ij} \right)^2 - \sum_i \left( \sum_j n_{ij} \right)^2 - \sum_i \sum_j n_{ij}^2 \right) \right\},
\]

where $n_{ij}$ denotes the pixel number of the $i$th cluster in $S_{\text{ground truth}}$ and the $j$th cluster in $S_{\text{test}}$.

BDE counts the average displacement error of boundary pixels between $S_{\text{ground truth}}$ and $S_{\text{test}}$. The BDE metric is defined as follows:

\[
\text{BDE} \left( S_{\text{ground truth}}, S_{\text{test}} \right) = \frac{\sum_{i} d \left( p_i, S_{\text{ground truth}} \right)}{N_1} + \frac{\sum_{j} d \left( p_j, S_{\text{test}} \right)}{N_2}/2,
\]

where the operator $d \left( \cdot \right)$ denotes the distance between the pixel $p_i$ of $S_{\text{test}}$ and its closest boundary pixel $p_j$ of $S_{\text{ground truth}}$.

Table 5 and Table 6 summarize the segmentation results of considered methods on BSDS500 images corrupted by Gaussian noise with 50% variance and Salt & Pepper noise with 60% density, respectively. The analysis of these evaluation metrics in Table 5 and Table 6 shows that the TGVFCMS algorithm performs better than the other techniques, giving consistently improved segmentation accuracy. In other words, our method exhibits a competitive result for these metrics based on different criteria and comparatively to state-of-the-arts. Table 7 shows the execution times (in seconds) of considered algorithms on the images of BSDS500. It clear that FRFCM consumes less time than other methods due to its modified membership partition. Although the running time using TGVFCMS is higher than FRFCM, the time-consumption obtained by the proposed algorithm is acceptable as compared to KWFLICM and Selective-LSM.

**TABLE 5.** Performance validation of four methods on BSDS500 when all 500 images are corrupted by Gaussian noise with 50% variance.

| Method        | Precision | Recall | Accuracy | $F_1$-score | GCE  | PRI  | Vol  | BDE |
|---------------|-----------|--------|----------|-------------|------|------|------|-----|
| KWFLICM       | 0.4993    | 0.5327 | 0.6821   | 0.4736      | 0.2443| 0.6516| 1.2687| 29.23|
| Selective-LSM | 0.4852    | 0.7567 | 0.6110   | 0.5390      | 0.2357| 0.6523| 1.2419| 29.41|
| FRFCM         | 0.5887    | 0.6153 | 0.7465   | 0.5581      | 0.2382| 0.6677| 1.2334| 28.19|
| TGVFCMS       | 0.7581    | 0.7723 | 0.8684   | 0.7450      | 0.1633| 0.7918| 0.8743| 22.99|
TABLE 6. Performance validation of four methods on BSDS500 when all 500 images are corrupted by Salt & Pepper noise with 60% density.

| Method         | Precision | Recall | Accuracy | F\_score | GCE  | PRI   | Vol  | BDE  |
|----------------|-----------|--------|----------|----------|------|-------|------|------|
| KWFLICM        | 0.4198    | 0.4500 | 0.6421   | 0.3904   | 0.2748 | 0.5981 | 1.4281 | 31.44 |
| Selective-LSM  | 0.3659    | 0.7142 | 0.5285   | 0.4437   | 0.2807 | 0.5442 | 1.5160 | 33.98 |
| FRFCM          | 0.4588    | 0.5904 | 0.6421   | 0.4708   | 0.2817 | 0.6034 | 1.4311 | 30.35 |
| TGVFCMS        | 0.7465    | 0.6995 | 0.8257   | 0.6839   | 0.1760 | 0.7557 | 0.9457 | 23.54 |

TABLE 7. Comparison of execution times (in seconds) of four methods on BSDS500.

| Images Corrupted by Gaussian Noise with 50% Variance | Images Corrupted by Salt & Pepper Noise with 60% Density |
|-----------------------------------------------------|--------------------------------------------------------|
| Method                                             | KWFLICM | Selective-LSM | FRFCM | TGVFCMS | KWFLICM | Selective-LSM | FRFCM | TGVFCMS |
|Execution Times                                     |         |               |       |         |         |               |       |         |
| Example I                                          | 83920   | 13550         | 1285  | 6046    | 84088   | 14897         | 722   | 5937    |
| Example II                                         |         |               |       |         |         |               |       |         |
| Example III                                        |         |               |       |         |         |               |       |         |
| Example IV                                         |         |               |       |         |         |               |       |         |
| Example V                                          |         |               |       |         |         |               |       |         |
| Example VI                                         |         |               |       |         |         |               |       |         |

FIGURE 13. Comparison of segmentation results on six images chosen from BSDS500. (a) Original images. (b) Images corrupted by Gaussian noise (50% variance). (c)-(f) Segmentations of KWFLICM, Selective-LSM, FRFCM and TGVFCMS when images are contaminated with Gaussian noise (50% variance), respectively. (g) Images corrupted by Salt & Pepper noise (60% density). (h)-(k) Segmentations of KWFLICM, Selective-LSM, FRFCM and TGVFCMS when images are contaminated with Salt & Pepper noise (60% density), respectively.

In general, the proposed TGVFCMS is best among all these four methods when we comprehensively considering the performance and the running time.

Fig. 13 is examples when these methods applied on six images chosen from BSDS500. The outperformance of the TGVFCMS in Fig. 13 agrees with the results that have been shown in Table 5 and Table 6.

F. RESULTS ON THE AERIALS VOLUME OF THE USC-SIPI IMAGE DATABASE

In this section, we applied the TGVFCMS method and the other three methods considered in above section to the Aerials volume of the USC-SIPI Image Database. The Aerials volume contains 38 images with 37 color and 1 monochrome. It should be noted that ground truth data is not available in Aerials volume. All the same, we carry out a further experiment on images of the Aerials volume by using considered methods. The segmentation results of KWFLICM, Selective-LSM, FRFCM and TGVFCMS are detailed in Supplementary Materials S1 File. Fig. 14 displays the segmentation results when these methods applied on three images of the Aerials volume. The proposed TGVFCMS could detect the main objects, although there are still some isolated pixels. The region uniformity and the boundary localization of the TGVFCMS are both satisfactory.
G. DISCUSSIONS AND FUTURE WORKS

This paper focused on the FCM-based image segmentation in different types of data. As mentioned in segmentation experiments, RFCM, KGFCMS, KWF LICM, ARKFCM, Selective-LSM and FRFCM exhibit satisfactory performances for images with low level noise to some extent. However, when noise levels increased, they cannot effectively remove the noise and retain useful details in segmentation. By comparing with RFCM, KGFCMS and ARKFCM, the KWF LICM, Selective-LSM and FRFCM methods generate good results for images of simple patterns, such as synthetic images. In dealing with images expressed by complex patterns (MR image) or diversely illuminated layers (BSDS500 images), KWF LICM, Selective-LSM and FRFCM become incapable of revealing data structure in the presence of heavy noise.

In terms of segmentation accuracy and visual effect, our newly proposed method was shown better than the existing FCM applications in the area. Further research can be conducted to improve on segmentation accuracy of our algorithm. Firstly, Gustafson-Kessel algorithm by utilizing the Mahalanobis distance can be incorporated in our existing objective function for the sake of completeness. Secondly, the accuracy of image segmentation can also be improved by employing more complementary features such as the geometric characteristics of object. Finally, feature normalization and weighting methods can also be investigated for enhancement of pattern values in image segmentation.

V. CONCLUSION

Image segmentation has been an active area of research in the fields of computer vision and pattern recognition for the past two decades. Specially, the fuzziness nature of fuzzy c-means through a minimization of a quadratic objective function to reveal structure in image data has drawn increasing interest in this area. In this paper, we have presented a novel fuzzy based algorithm that is able to incorporate spatial information, TGV regularization and weighted fuzzy factor into the image segmentation. The proposed method is formulated by modifying the objective function of the fuzzy clustering algorithm by the smoothing term that utilizes total generalized variation to regularize target pixels and the penalty term that takes into account the weighted fuzzy factor to balance the influence of the neighboring pixels on the center pixels. These two strategies make the proposed scheme capable of reducing heavy noise and preserving more important details. Experimental results demonstrate that the proposed method provide better segmentation results by comparing with its counterparts. Our further and ongoing works include complex scene classification in our algorithms, adaptive determination for the clustering number and other applications.

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