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Color Textured Image Segmentation Using ICICM – Interval Type-2 Fuzzy C-means Clustering Hybrid Approach

Murugeswari Palanivelu[1,]* and and Manimegalai Duraisamy[2]

1 Department of IT, Sri Vidya College of Engineering & Technology, Sivakasi Main Road, Virudhunagar, Tamilnadu, India.
2 Department of IT, National Engineering College, K. R. Nagar, Kovilpatti, Tamilnadu, India.
* E-mail: p_murugeswari@yahoo.com

Abstract. Segmentation is an essential process in image processing because of its wild application such as image analysis, medical image analysis and pattern recognition. Color and texture are most significant low-level features in an image. Normally, color textured image segmentation consists of two steps: (i) extracting the feature and (ii) clustering the feature vector. This paper presents the hybrid approach for color texture segmentation using Haralick features extracted from the Integrated Color and Intensity Co-occurrence Matrix. Then, Extended Interval Type-2 Fuzzy C-means clustering algorithm is used to cluster the obtained feature vectors into several classes corresponding to the different regions of the textured image. Experimental results show that the proposed hybrid approach could obtain better cluster quality and segmentation results compared to state-of-art image segmentation algorithms.

Keywords: Type-2 fuzzy, color texture segmentation, IT2 fuzzy, ICICM, CCM.

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1. Introduction

The goal of the image segmentation is partitioning the image into meaningful regions which is used to further analyze the image. In computer vision and pattern recognition texture segmentation is one of the most important tasks since it plays an important role in the development of high-level image analysis such as object recognition, scene understanding, medical image analysis and remote sensing images. Texture segmentation is the identification of regions based on their texture features. Basically texture feature extraction may be based on three approaches namely (i) statistical approach (ii) structural approach and (iii) spectral approach. For texture identification many researchers have proposed number of methods, such as Gabor texture features [18], multi-channel filtering [25], wavelet transform [26], Local Binary Pattern(LBP) operators [22], co-occurrence features [10], Laws texture energy [14], Quad-tree split-and-merge [21], Markov-random field model [20], spatial temporal based Markov-random field model[30], and Fuzzy wavelet [29] . The segmentation of color textured approaches are based on (i) extracting color texture features of each color band or across different bands for segmentation and (ii) gray texture features and color features independently. Both methods are having their own merits and demerits. Gray level co-occurrence matrix was proposed in [10] by Haralick *et al.* and it is widely used for texture analysis. Color co-occurrence matrix (CCM) has been proposed by Shim and Choi [7], and in continuation of these, Modified CCM [7], Single-channel Co-occurrence Matrix [9] and Multi-channel Co-occurrence Matrix [9] have also been proposed. Integrated Color and Intensity Co-occurrence Matrix (ICICM) has been proposed by A.Vadivel *et al.* [2]. ICICM is based on integrated approach for capturing spatial variation of both color and intensity levels in the neighborhood of each pixel using HSV (Hue, Saturation and Intensity Value) color space.

Uncertain nature is present in the image segmentation; the decision making for them is done based on uncertain information. In such situation fuzzy set theory can be utilized to model and solve problems. Zadeh first introduced the Type-1 Fuzzy Set (T1FS) theory in 1965 and has been successfully applied in many areas including image processing, modeling and control, data mining, time-series prediction, etc. The clustering algorithm is used to group the image feature space into various clusters. This clustering is processed by iteratively minimizing a cost function and it is dependent on the distance of the pixels to the cluster center in the feature domain. For example; fuzzy clustering approach [19], fuzzy c-means [6], and Fuzzy based Hierarchical segmentation [5]. Generally, FCM type-1 has become the most well-known algorithm in cluster analysis. Many researchers have shown that there are limitations in the ability of T1 FSs to model and minimize the effect of uncertainties, because its membership grades are crisp. Type-2 Fuzzy set (T2FS) is characterized by Membership Functions (MFs) that are themselves fuzzy. Interval type-2 (IT2) FSs, a special case of IT2FSs, are currently most widely used because of their reduced computational cost.

An IT2FS is bounded with two T1FSs above and below, which are called Upper MF (UMF) and Lower MF (LMF) respectively and area between UMF and LMF is Footprint of Uncertainty (FOU). Now T2FS prove to model various uncertainties but it increases the computational complexity, because of its additional dimension of secondary grades for each primary membership. Example applications are Type-2 Fuzzy Clustering [1], Gaussian Noise Filter [15], Classification of coded video streams [24], Medical applications [23] and Color image segmentation [8].

In this paper, a new Extended IT2 Fuzzy C-Means (Extended IT2FCM) clustering algorithm is proposed which is applied to segment the color texture images. The main contribution of this paper is the extended method presented in [3] applied to an interval type-2 fuzzy clustering. The focus of this model is on fuzzifier m by defining two fuzzifiers m_1 and m_2 in the interval type-2 fuzzy clustering algorithm and finding best parameter values for color image segmentation in the ICICM model. The rest of the paper is organized as follows: In section 2 the proposed Extended IT2FCM is presented, in section 3 several numerical values for parameters are discussed to validate the proposed method, and in section 4 conclusions is presented.

2. Methodology

The proposed hybrid approach segments the color texture image into different regions using Haralick features extracted from ICICM. The images obtained from benchmark (http://mosaic.utia.cas.cz) database images are in RGB (Red, Green, and Blue) color model. HSV color space is suitable for calculating the ICICM. So RGB color image is converted into HSV color space and then ICICM is calculated. From this

ICICM, the texture features are extracted. Finally, the images are segmented using Extended Interval type-2 fuzzy c-means clustering approach.

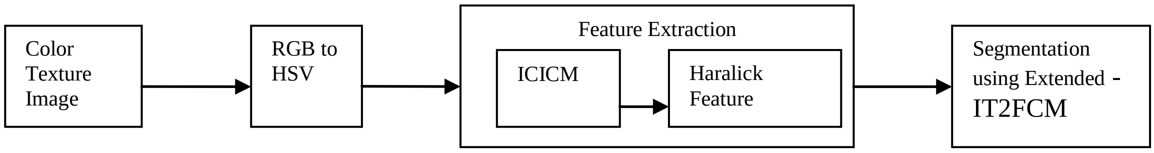

Fig. 1. Proposed hybrid approach.

2.1. Generation of ICICM

A. Vadivel *et al.* [2] proposed an integrated approach for capturing spatial variation of both color and intensity levels in the neighborhood of each pixel using HSV color space. In their paper they have estimated the amount of color and intensity variation between each pixel and its neighbor using weight function. Suitable weighted constraints are satisfied while choosing the weight function for effectively relating visual perception of color and the HSV color space properties. Therefore ICICM is generalization of grayscale co-occurrence matrix and color-occurrence matrix technique. The advantage of ICICM is the color and intensity variations are represented in a single composite feature. Some of the useful properties of the HSV color space and their relationship to human color perception are utilized for extracting this feature.

The generation of ICICM algorithm is summarized below:

1) ICICM is a two-dimensional matrix, which consists of four sub matrices and it can be represented as follows:

$$\begin{pmatrix} ICICM_{CC} & ICICM_{CI} \\ ICICM_{IC} & ICICM_{II} \end{pmatrix} \tag{1}$$

where
ICICMCC – color perception of pixel p and color perception of its neighbor *Np*;
ICICMCI – color perception of pixel p and gray level perception of its neighbor *Np*;
ICICMIC – gray level perception of pixel p and color perception of its neighbor *Np*;
ICICMII – gray level perception of pixel p and gray level perception of its neighbor *Np*.

2) Determine the dimension of the matrix ICICM by the number of quantization levels of HL and GL as follows:

$$HL = \left\lfloor \frac{2\pi}{Q_H} \right\rfloor + 1 \tag{2}$$

$$GL = \left\lfloor \frac{255}{Q_I} \right\rfloor + 1 \tag{3}$$

where Q_H and Q_I are quantization factors for Hue and Intensity.

3) Calculate each component of ICICM as follows:

$$ICICM_{CC}(i,j)_{i=0..HL-1;j=o..HL-1} = \left(\left(hl_p, hl_{N_p}\right) = (i,j)\right) \tag{4}$$

$$ICICM_{CI}(i,j)_{i=0..HL-1;j=o..GL-1} = \left(\left(hl_p, gl_{N_p}\right) = (i,j)\right) \tag{5}$$

$$ICICM_{IC}(i,j)_{i=0..GL-1;j=o..HL-1} = \left(\left(gl_p, hl_{N_p}\right) = (i,j)\right) \tag{6}$$

$$ICICM_{II}(i,j)_{i=0..GL-1;j=o..GL-1} = \left(\left(gl_p, gl_{N_p}\right) = (i,j)\right) \tag{7}$$

4) Update the ICICM using weight function:

$$W_{col}(S,I) = \begin{cases} S^{r_1 *(255|I)^{r_2}}, & for\ I \neq 0 \\ 0, & for\ I = 0 \end{cases} \tag{8}$$

where r_1 and r_2 are constants, the value of r_1 and r_2 depend on the particular applications.

5) Compute the intensity weight of a pixel as a complement of the color weight as given below:

$$W_{int}(S,I) = 1 - W_{col}(S,I) \tag{9}$$

2.2. Haralick Feature

Haralick features are considered for extracting the properties from texture images. Haralick introduced 14 texture features extracted from CCM [10]. These features are statistical measures on the CCM of an image which allow reduction of information quantity of each matrix. Palm used 8 of these 14 Harlaick features namely homogeneity, contrast, correlation, variance, inverse difference moment, entropy, correction 1 and 2. Uma *et al.* [4] used only 5 of these 14 Haralick features contrast, correlation, variance, inverse difference moment and angular second moment, in order to reduce the size of the feature space. Generally each image coded in a color space, therefore it is needed to calculate 3 CCM matrices and so N_f = 3 x 14 Haralick features are extracted from these matrices. The total number (N_f) of candidate color texture features is very high, since it is needed to reduce the feature space. Therefore, in the proposed method ICICM is calculated and 1 x 5 Haralick features are extracted from this matrix. Therefore total number (N_f) of candidate color and texture features is reduced significantly.

$$Angular\ second\ moment = \sum_i \sum_j p(i,j)^2 \tag{10}$$

$$Constrast = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{i=1}^{N_g} \sum_{j=0}^{N_g} p(i,j) \right\}, |i = j| = n \tag{11}$$

$$Correlation = \frac{\sum_i \sum_j (i,j)p(i,j) - \mu_x \mu_y}{\sigma_{x\ \sigma_y}} \tag{12}$$

$$Inverse\ Difference\ Moment = \sum_i \sum_j \frac{p(i,j)}{1 + (i-j)^2} \tag{13}$$

$$Variance = \sum_i \sum_j (p(i,j) - \mu)^2 p(i,j) \tag{14}$$

2.3. Extended IT2FCM

The pixels on textured image are highly correlated; therefore, the spatial relationship of neighboring pixels is an important characteristic that can increase the performance of segmentation approaches. This spatial relationship is important in clustering but it is not utilized in a standard FCM algorithm. The aim of this paper is to develop space-partitioning algorithm that is able to return meaningful results even when applied to composite and complex natural scenes that have large variations in color and texture. To achieve this we propose a new clustering strategy called Extended IT2FCM whose implementation can be viewed as extension of IT2FCM. The main idea behind Extended IT2FCM is to minimize an objective function J based on hybrid approach which is extracting Haralick features from ICICM.

- When adding the spatial information, the feature partition will be formulated as the minimization of a new objective function given by;

$$J_{m_1(U,v)} = \sum_{i=1}^{N} \sum_{j=1}^{C} u_j(x_i)^{m_1} d_{ji}^2 + \alpha \sum_{i=1}^{N} \sum_{j=1}^{C} \frac{1}{n} \sum_{\delta \epsilon w} u_j(x_i)^{m_1} d_{ji+\delta}^2 \tag{15}$$

$$J_{m_2(U,v)} = \sum_{i=1}^{N}\sum_{j=1}^{C} u_j(x_i)^{m_2} d_{ji}^2 + \alpha \sum_{i=1}^{N}\sum_{j=1}^{C}\frac{1}{n}\sum_{\delta \epsilon w} u_j(x_i)^{m_2}\, d_{ji+\delta}^2 \tag{16}$$

α – is selected experimentally
w – Set of neighbors that exist in a window around a central pixel.

- The Interval Type-2 Fuzzy Membership becomes

$$\overline{u}_j(x_i) = \begin{cases} \dfrac{\sum_{k=1}^{C}\left(\left(d_{ji}/d_{ki}\right) + \alpha\left(d_{ji}/d_{ki}\right)\delta\right)^{2/(m_1-1)}}{\sum_{k=1}^{C}\left(\left(d_{ji}/d_{ki}\right) + \alpha\left(d_{ji}/d_{ki}\right)\delta\right)^{2/(m_1-1)}}, & if\, \dfrac{1}{\sum_{k=1}^{C}\left(d_{ji}/d_{ki}\right)} < \dfrac{1}{C} \\ \dfrac{\sum_{k=1}^{C}\left(\left(d_{ji}/d_{ki}\right) + \alpha\left(d_{ji}/d_{ki}\right)\delta\right)^{2/(m_2-1)}}{\sum_{k=1}^{C}\left(\left(d_{ji}/d_{ki}\right) + \alpha\left(d_{ji}/d_{ki}\right)\delta\right)^{2/(m_2-1)}}, & otherwise \end{cases} \tag{17}$$

$$\underline{u}_j(x_i) = \begin{cases} \dfrac{\sum_{k=1}^{C}\left(\left(d_{ji}/d_{ki}\right) + \alpha\left(d_{ji}/d_{ki}\right)\delta\right)^{2/(m_1-1)}}{\sum_{k=1}^{C}\left(\left(d_{ji}/d_{ki}\right) + \alpha\left(d_{ji}/d_{ki}\right)\delta\right)^{2/(m_1-1)}}, & if\, \dfrac{1}{\sum_{k=1}^{C}\left(d_{ji}/d_{ki}\right)} \geq \dfrac{1}{C} \\ \dfrac{\sum_{k=1}^{C}\left(\left(d_{ji}/d_{ki}\right) + \alpha\left(d_{ji}/d_{ki}\right)\delta\right)^{2/(m_2-1)}}{\sum_{k=1}^{C}\left(\left(d_{ji}/d_{ki}\right) + \alpha\left(d_{ji}/d_{ki}\right)\delta\right)^{2/(m_2-1)}}, & otherwise \end{cases} \tag{18}$$

- Updating cluster centers

$$v_j = \frac{v_L + v_R}{2} \tag{19}$$

- Type reduction and hard-partitioning can be obtained as follows:

$$u_j(x_i) = \frac{u_j^R(x_i) + u_j^L(x_i)}{2}, \quad j = 1, \dots\dots C \tag{20}$$

$$u_j^R(x_i) = \frac{\sum_{l=1}^{M} u_{jl}(x_i)}{M} \tag{21}$$

where $u_{jl}(x_i) = \begin{cases} \overline{u}_j(x_i), & if\ x_{il}\ uses\ \overline{u}_j(x_i) for\ v_j^R \\ \underline{u}_j(x_i), & \text{otherwise} \end{cases}$, and

$$u_j^L(x_i) = \frac{\sum_{l=1}^{M} u_{jl}(x_i)}{M} \tag{22}$$

where $u_{jl}(x_i) = \begin{cases} \overline{u}_j(x_i), & if\ x_{il}\ uses\ \overline{u}_j(x_i) for\ v_j^L \\ \underline{u}_j(x_i), & \text{otherwise} \end{cases}$.

When we apply any algorithm in texture segmentation we have to consider two texture properties: homogeneity property and texture bounder property. In homogenous regions, the spatial functions simply strengthen the original membership and the clustering result remains unchanged. But, for a texture bounder property, the formula reduces the weighting of a noisy cluster by the labels of its neighboring pixels. As a result, misclassified pixels from noisy regions or spurious blobs can easily be corrected. Clustering is a two-pass process at each iteration. In the first pass, calculate the membership function in the spectral domain. In the second pass, the membership information of each pixel is mapped to the spatial domain. The iteration is stopped when the maximum difference between two cluster centers at two successive iterations

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is less than a threshold. After the convergence, defuzzification is applied to assign each pixel to a specific cluster whose membership is maximum value.

3. Experimental Result

The proposed hybrid approach is tested on a large number of benchmark database images (http://mosaic.utia.cas.cz) and natural color texture images in order to evaluate its performance with respect to the identification of parameter values and experimental result is compared with Type-1 FCM, IT2FCM, and Extended IT2FCM. Two set of experiments have been carried out: In the first set, after the Haralick features are extracted in CCM the clustering approach is performed using (i) Type-1 FCM, (ii) IT2FCM and (iii) Extended IT2FCM. The second set of experiment is carried out by extracting the Haralick features in ICICM and then clustering approach is performed using (i) Type-1 FCM, (ii) IT2 FCM and (iii) Extended IT2 FCM.

3.1. Evaluation of Segmentation Result

A large number of experiments were carried out to analyze the performance of the proposed color texture segmentation algorithm using MATLAB tool. Figure 3 shows the sample test images taken from the http://mosaic.utia.cas.cz**,** benchmark database and natural images. To demonstrate the capability of the proposed method, four images (namely Txt_1.png, Txt_2.png, Rimg_1.jpg, Rimg_2.jpg) are evaluated in detail to highlight the advantage of the proposed approach. The performance of Extended IT2FCM approach is evaluated by comparing the algorithmic efficiency and the segmentation results with Type-1 FCM, IT2FCM and Extended IT2FCM.

Txt_1.png Txt_2.png Rimg_1.jpg Rimg_2.jpg

Fig. 2. Sample test images.

The ICICM method's effectiveness is based on two factors, which are the quantization levels (HL & GL) and choice of parameter r_1 and r_2. We have extended a fuzzy set into an IT2FCM by incorporating two different values of fuzzifier m (m_1 and m_2). Therefore the proposed method has six parameters namely HL & GL, r_1 & r_2 in ICICM algorithm and m1 and m2 in Extended IT2FCM algorithm. We have considered four different combination of hue and intensity levels HL & GL. For example the combination (4, 2) means that the color weight - color weight will update a (2, 2) area, intensity weight-color weight updates (4, 4) area, color weight-intensity weight updates (4, 2) area and intensity weight-intensity weight updates (2, 4) area of ICICM. Next, to determine the best combination of r_1 and r_2 we experimented three set of values (.05, .8), (.1, .85) and (.15, .9). Three possible combinations of m_1 and m_2 is experimented (.4, .6), (.7, .9) and (.8, 1.0) with ICICM parameters.

The first set of experiment are carried out to extract the Haralick feature in CCM, then clustering approach is performed using Type-1 FCM, IT2FCM and Extended IT2FCM with various combination values of HL & GL, r_1 & r_2 and m_1 & m_2. The experimental segmentation results are depicted in Fig. 3. Figure 3(a) shows the segmentation results using the Type-1 FCM algorithm. Here the algorithm over segments the image and boundary are lost. Figure 3(b) presents segmentation based on IT2FCM; here it shows that number of segments is reduced, but the pixels of different texture are grouped together. This improper grouping among different texture regions lost the homogeneity property of textures. Figure 3(c) presents segmentation based on Extended IT2FCM, which shows that homogeneous regions are extracted with less number of misclassifications.

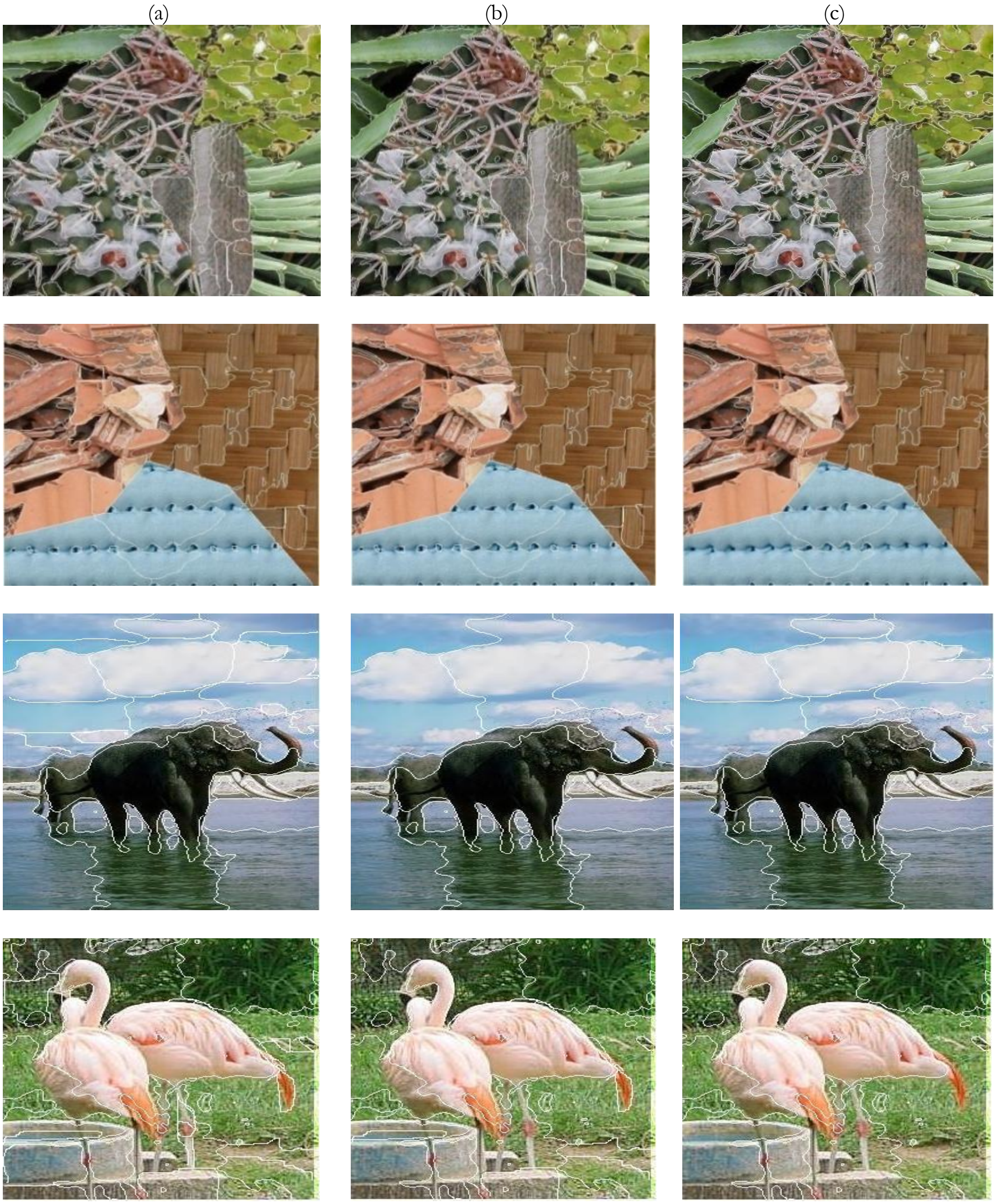

Fig. 3. Segmentation Result- Extracting the Haralick feature in CCM, then clustering approach is performed using (a) Type-1 FCM, (b) IT2FCM, and (c) Extended IT2FCM.

The second set of experiments were carried out to extract the Haralick features in ICICM, and then clustering approach is performed using Type-1 FCM, IT2FCM and Extended IT2FCM with various combination values of HL & GL, r_1 & r_2 and m_1 & m_2. The experimental segmentation results are depicted in Fig. 4. Figure 4(a) is the segmentation results using the Type-1 FCM algorithm. Here the algorithm under segments the image and boundary are not clear. Figure 4(b) presents segmentation based on IT2FCM, where it shows that number of misclassified pixel is reduced comparing the results obtained by Type-1 FCM. Figure 4(c) shows result of the proposed approach has applied. It shows that the segment accuracy is increased by reducing misclassification of pixels in the boundary region; also homogenous regions are properly segmented with very good pixel level clarity. Table 1 shows number of segments produced by different algorithms.

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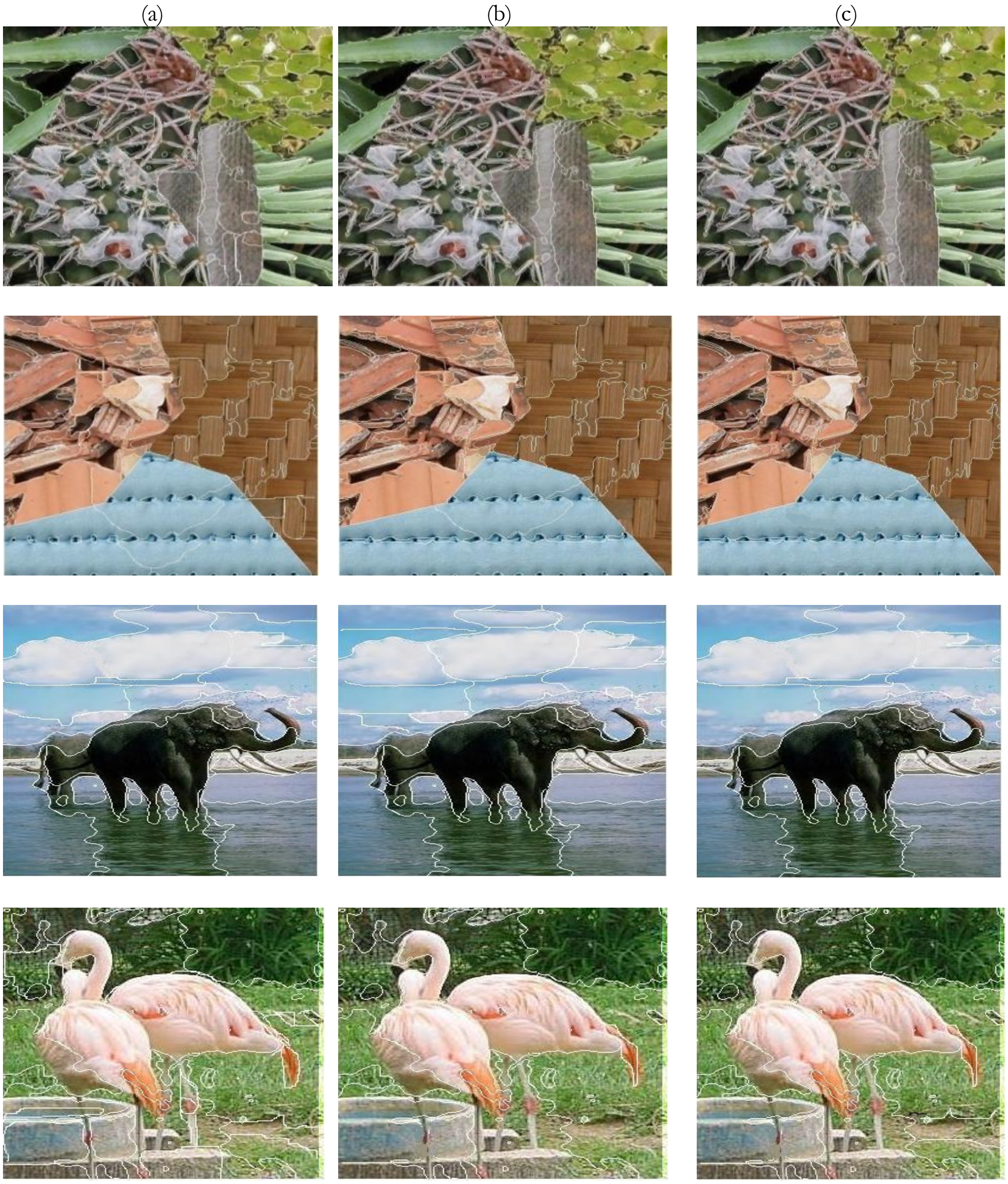

Fig. 4. Segmentation Result-Extracting the Haralick feature in ICICM, then clustering approach is performed using (a) Type-1 FCM, (b) IT2FCM, and (c) Extended IT2FCM.

Table 1. Number of segments produced by different algorithms.

Methods	Type-1 FCM		IT2 FCM		Extended IT2FCM	
Images	CCM	ICICM	CCM	ICICM	CCM	ICICM
Txt_1.png	16	12	14	10	12	09
Txt_2.png	16	14	13	11	11	10
Txt_3.png	14	12	11	09	12	08
Rimg_1.jpg	10	08	09	07	08	06
Rimg_2.jpg	11	09	11	09	06	06

Table 2 summarizes the various parameter settings in the ICICM & Extended IT2FCM and corresponding number of segment count (four combinations of HL & GL, three combinations of r_1 & r_2 and three combinations of m_1 & m_2) and numerical results. According to the numerical values depicted in Table 1, we find that when HL = 4 & GL = 4, r_1 = .05 & r_2 = .8 and m_1 =.7 & m_2 =.9, it produces the good number of segments in the experimental image.

Table 2. Various parameter settings in the ICICM & Extended IT2FCM and corresponding no. of segment count (four combinations of HL & GL, three combinations of r_1 & r_2 and three combinations of m_1 & m_2).

Parameters					**Number of Segment Count**			
HL = 2 GL = 2	r_1	r_2	m_1	m_2	Txt_1.jpg	Txt_2.jpg	Rimg_1.jpg	Rimg_2.jpg
	.05	**.8**	**.4**	**.6**	13	14	10	09
	.05	.8	**.7**	**.9**	13	14	10	09
	.05	.8	**.8**	**.1**	11	12	09	08
	.1	**.85**	.4	.6	13	11	09	07
	.1	.85	.7	.9	12	11	10	07
	.1	.85	.8	.1	12	12	09	09
	.15	**.9**	.4	.6	13	12	08	08
	.15	.9	.7	.9	13	12	07	08
	.15	.9	.8	.1	12	11	07	06
HL = 4 GL = 4	**.05**	**.8**	**.4**	**.6**	12	11	09	09
	.05	.8	**.7**	**.9**	12	11	09	08
	.05	.8	**.8**	**.1**	11	10	07	08
	.1	**.85**	.4	.6	10	10	06	07
	.1	.85	.7	.9	09	10	06	07
	.1	.85	.8	.1	09	11	07	08
	.15	**.9**	.4	.6	10	10	07	06
	.15	.9	.7	.9	11	11	06	07
	.15	.9	.8	.1	12	11	06	07
HL = 2 GL= 4	**.05**	**.8**	**.4**	**.6**	13	13	08	09
	.05	.8	**.7**	**.9**	13	13	06	09
	.05	.8	**.8**	**.1**	12	12	06	08
	.1	**.85**	.4	.6	12	12	07	07
	.1	.85	.7	.9	12	11	07	06
	.1	.85	.8	.1	11	11	06	07
	.15	**.9**	.4	.6	13	10	07	06
	.15	.9	.7	.9	13	12	07	06
	.15	.9	.8	.1	11	12	06	07
HL = 4 GL = 2	**.05**	**.8**	**.4**	**.6**	10	11	08	08
	.05	.8	**.7**	**.9**	11	11	06	08
	.05	.8	**.8**	**.1**	11	12	06	07
	.1	**.85**	.4	.6	11	13	07	08
	.1	.85	.7	.9	12	12	08	08
	.1	.85	.8	.1	12	12	08	06
	.15	**.9**	.4	.6	11	11	06	07
	.15	.9	.7	.9	10	13	06	07
	.15	.9	.8	.1	10	11	07	06

The efficiency of the Extended IT2FCM approach and other approaches are compared with the execution time. The execution time for these clustering approaches is tabulated in Table 3. The execution time of the proposed approach is relatively less than Type-1 FCM and IT2FCM.

Table 3. Execution time (in seconds) various clustering approaches.

Methods	**Type-1 FCM**		**IT2FCM**		**Extended IT2FCM**	
Images	CCM	ICICM	CCM	ICICM	CCM	ICICM
Txt_1.png	24.0	20.0	18.3	15.2	**16.4**	**13.1**
Txt_2.png	22.2	21.1	19.2	17.9	**15.3**	**12.2**
Rimg_1.jpg	16.3	14.6	14.2	11.3	**10.9**	**9.6**
Rimg_2.jpg	18.4	16.3	14.8	12.4	**11.4**	**10.2**

3.2. Evaluation on Cluster Quality

To evaluate the cluster quality, several important cluster validity measures have been proposed by researchers. K. Siang Tan *et al.* [5] used two evaluation functions to evaluate the cluster quality. The first benchmark is Bezdek's partition coefficient [22], where the membership function is IT2FCM, so the evaluation function is defined as follows:

$$V_{PC} = \frac{1}{N}\,\frac{\sum_{i=1}^{N}\sum_{j=1}^{M}\left(\overline{u_{ji}}+\underline{u_{ji}}\right)^2}{2} \tag{23}$$

This benchmark is used to measure the fuzziness of a clustering result and the VPC value can take on any value ranging from 0 to 1. From the context of validation, a good clustering algorithm must produce a better clustering result that is less fuzzy with larger VPC value.

The second benchmark is the Xie and Beni function [23], where the membership function is IT2FCM, so the evaluation function is defined as follows:

$$V_{XB} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M}\left(\overline{u_{ji}}(x_i) + \underline{u_{ji}}(x_i)\right)^2 - c_j^2}{2 * N \min_{\forall j \neq k}\left\{c_j - c_k^2\right\}} \tag{24}$$

According to Xie and Beni, the VXB should decrease monotonically when the cluster number is close to the number of pixels in the image and furthermore, a better clustering result should produce smaller VXB value. The VPC values of the Type-1 FCM, IT2FCM and Extended IT2FCM approaches are tabulated in Table 4. It shows that the proposed approach produces relatively larger VPC values than other approaches, which shows that the general cluster distribution is better than the other approaches.

Table 4. Comparison results for different algorithms using ICICM in V_{PC} and V_{XB}.

Methods	**Type-1 FCM**		**IT2FCM**		**Extended IT2FCM**	
Images	V_{PC}	V_{XB}	V_{PC}	V_{XB}	$\mathbf{V_{PC}}$	$\mathbf{V_{XB}}$
Txt_1.png	.625	.160	.698	.128	**.798**	**.091**
Txt_2.png	.678	.192	.687	.122	**.854**	**.098**
Txt_3.png	.589	.172	.654	.143	**.721**	**.072**
Rimg_1.jpg	.716	.231	.752	.182	**.859**	**.082**
Rimg_2.jpg	.634	.201	.678	.162	**.756**	**.072**

The VXB values of the Type-1 FCM, IT2FCM and Extended IT2FCM approaches are tabulated in Table 5. It shows that the proposed approach produces relatively smaller VXB values than other approaches.

Table 5. Comparison results for different algorithms using ICICM segment count.

Methods	**Type-1 FCM**		**IT2 FCM**		**Extended IT2FCM**	
Images	CCM	ICICM	CCM	ICICM	CCM	ICICM
Txt_1.png	16	12	14	10	12	09
Txt_2.png	16	14	13	11	11	10
Txt_3.png	14	12	11	09	12	08
Rimg_1.jpg	10	08	09	07	08	06
Rimg_2.jpg	11	09	11	09	06	06

4. Conclusion

In this paper, a new hybrid approach of Haralick feature extraction from ICICM and Extended IT2FCM for color-texture image segment is presented. The advantages of Extended IT2FCM are to generate accurate color descriptor using ICICM and the spatial information is also included in the clustering process. In the conventional method it is needed to calculate 3 CCM matrices and Haralick features are extracted from these matrices so the size of the feature space is high. But in the proposed method feature space is reduced because the 1X5 Haralick features are extracted from ICICM matrix. Therefore, from the experiment it is found that the computational complexity of Interval Type-2 fuzzy is slightly more compared to Type-1 Fuzzy, but the computation time is reduced because feature space is reduced.

The proposed method is evaluated and compared with conventional Type-1 FCM and IT2FCM. The performance of the developed color texture segmentation algorithm has been evaluated on a large number of benchmark database images and natural images. The parameter value of HL = 4 and GL = 4 and r_1 = .05 and r_2 = .8 in ICICM and the parameter value of IT2FCM m_1 = .7 and m_2 = .9 produce the good number of segments in the experimental image. The results show that the proposed method is able to produce accurate segmentation results. Applying and analyzing the performance of Extended IT2FCM in content based image retrieval system and segmentation of medical images can be focused for future work.

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