An Adaptive Color Texture Segmentation Using Similarity Measure of Symbolic Object Approach

Dr. G. Uma Maheswari[1], Dr. K. Ramar[2], Dr. D. Manimegalai[1], V. Gomathi[1] and G. Gowrision[3]

[1] *National Engineering College, Kovilpatti, Tamilnadu*
[2] *Einstein College of Engineering, Tirunelveli, Tamilnadu*
[3] *Institute of Road and Transport Technology, Erode*

Abstract

Texture segmentation is the process of partitioning an image into regions with different textures containing similar group of pixels. Texture is an important spatial feature, useful for identifying object or region of interest. In texture analysis the foremost task is to extract texture features, which efficiently embody the information about the textural characteristics of the image. This can be used for the segmentation of different textured images. This paper presents a new approach for color texture segmentation using Haralick's features extracted from color co-occurrence matrices. The originality of this approach is to select the most discriminating color texture features extracted from the color co-occurrence. Symbolic Object Approach is used for achieving texture segmentation.

Key Words: *Color co-occurrence matrix, Haralick's features, texture segmentation, symbolic object approach*

1. Introduction

Image segmentation is a core problem in image analysis and computer vision. In recent years, research work has been focused on color image segmentation, since grayscale images can not satisfy the needs in many situations. Color image segmentation divides a color image into a set of disjoint regions which are homogeneous with respect to some properties consistent with human visual perception, such as colors or textures. The essential objective of segmentation is to decompose an image into parts which should be meaningful for certain applications. Texture is an important spatial feature, useful for identifying object or region of interest. Texture analysis, a part of image processing, has proved itself in the field of classifying images over the time. Texture is defined as a structure composing of a large number of more or less ordered, similar elements or patterns. Image textures can be qualitatively evaluated as having one or more of the properties like fineness, coarseness, smoothness, granulation, randomness, irregularity etc.

Many texture or color segmentation methods have been proposed in the past couple of decades. Most of them are based on two basic properties of the pixels in relation to their local neighborhoods

- Discontinuity
- Similarity

Approaches based on discontinuity partition of an image by detecting isolated points, lines and edges are known as edge detection techniques. On the other hand, region based

approaches including region growing, region splitting, region merging, and their combination group merge similar pixels into different homogeneous regions.

Color texture segmentation is to separate the image into a set of disjointed regions which are homogeneous with respect to some properties such as color and texture. A similarity measure is an important metric for determining the degree of similarity between two objects.

Kaufman and Rousseeuw [1] presented some examples to illustrate traditional similarity measure applications in hierarchical cluster analysis. Since Zadeh [2] originated the idea of fuzzy sets, many different similarity measures between fuzzy sets have been proposed in the literature. Zwick et al [3] reviewed geometric distance and Hausdorff metrics presenting similarity measures among fuzzy sets. Pappis and Karacapilidis [4] proposed three similarity measures based on union and intersection operations, the maximum difference, difference and sum of membership grades. Wang [5] presented two similarity measures between fuzzy sets and between elements. Liu [6] and Fan and Xie [7] provided the axiom definition and properties of similarity measures between fuzzy sets. Turksen and Zhong [8] applied similarity measures between fuzzy sets for approximate analogical reasoning. Buckley and Hayashi [9] used a similarity measure between fuzzy sets to determine whether a rule should be fired for rule matching in fuzzy control and neural networks. Chidananda Gowda and Diday [10] proposed a hierarchical, agglomerative, symbolic clustering methodology based on new similarity measure using the “position”, “span” and “content” of symbolic objects. The symbolic representation of the classes can be used for creating knowledge base of expert systems. Gowda and Diday [11] presented dissimilarity and similarity measures based on “position”, “span” and “content” of symbolic objects. The distance measure is used in the area of conventional hierarchical clustering of symbolic data. More work can be found in the field of conceptual hierarchical clustering of symbolic data. Texture classification is to assign an unknown sample image to one of the set of known texture classes. Manimegalai [12] proposed new texture classification using symbolic object approach due to similarity and dissimilarity measures. This proposed segmentation is a sequel to the classification proposed by Manimegalai[12].

This paper is organized as follows. The methodology is presented in section 2 and the experimental results are discussed in section 3 and section 4 concludes the work.

2. Proposed Methodology

The proposed method segments the color texture image into different texture regions using symbolic object approach. The texture images are obtained from the standard Vistex database. The images obtained from these databases are in RGB color model. In order to measure the color difference properly, image colors are represented in a modified color space LUV. Then, color co-occurrence matrix is calculated. From the color co-occurrence matrix, Haralick’s features are extracted. Finally, the images are segmented using symbolic object approach. Figure 1 shows the proposed architecture for color texture segmentation.

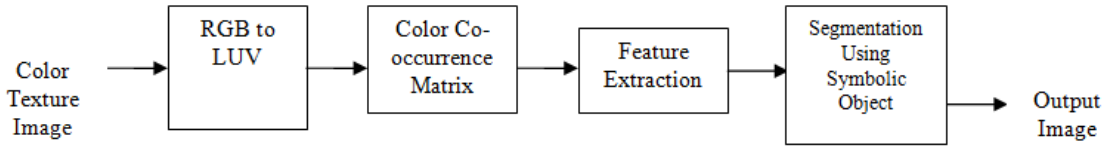


Figure 1. Scheme of Proposed Segmentation Architecture

2.1 Color Conversion

A color model is a color measurement scale or system that numerically specifies the perceived attributes of color. Color model is a method of grouping numeric values by a set of primaries. The purpose of a color model is to facilitate the specification of colors in some generally accepted standard. In essence, a color model is a specification of a Three Dimension (3D) coordinate system and a subspace within that system, where each color is represented by a single point. A pixel can be represented by different color bands that are described by different color models and stored in different data types. To describe a pixel, RGB, HSI, LUV and YC_bC_r color models are used, since some image processing techniques give different results for different color models. The choice of color models actually does not matter because the conversion of a model to another is an easy process. The performance of an image segmentation procedure is known to depend on the choice of color spaces.

According to International Commission on Illumination or CIE, which is the abbreviation for its French name, Commission Internationale de l'éclairage, color spaces are not limited by the rendering capabilities of a particular device or the observers' visual skills. The CIE models form the basis for most quantitative color measurement. LUV, where L stands for luminance, and U and V are chrominance components, is designed to represent additive color systems, including colored lights and emissive phosphor displays. The aim is to have a color space with uniform scales and coordinates, and to have an absolute representation of the object color. However, this is not strictly true, and this system represents a compromise. The LUV is approximately perceptually uniform. Since digital color images are typically stored as RGB values, a conversion between color spaces is necessary. There exists no direct conversion between RGB and LUV color space. LUV color model represents all colors that are visible to the human eye using the following three bands

$$L = R^*.299 + G^*.587 + B^*.114 \quad (1)$$

$$U = R^* - .169 + G^*.332 + B^*.500 + 128 \quad (2)$$

$$V = R^*.500 + G^* - .419 + B^* - .0813 + 128 \quad (3)$$

where, L -represents the luminance

U-represents position of luminance. The negative values of u yield green, where the positive values indicate red

V-represents position of luminance. The negative values of u yield blue, where the positive values indicate yellow

2.2. Color Co - Occurrence Matrix

Gray Level Co-occurrence Matrix was proposed by Haralick [13] and is widely used for texture analysis. It estimates the second order statistics related to image properties by considering the spatial relationship of pixels. GLCM depicts how often different combinations of gray levels co-occur in an image. The GLCM is created by calculating how often a pixel with the intensity value *i* occurs in a specific spatial relationship to a pixel with the value *j*. The spatial relationship can be specified in different ways, the default one is between a pixel and its immediate neighbor to its right. However, specify this relationship

with different offsets and angles. The pixel at position (*i*,*j*) in GLCM is the sum of the number of times the (*i*,*j*) relationship occurs in the image.

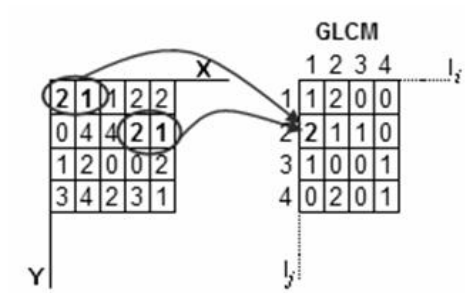


Figure 2. Description of the Gray Level Co-occurrence Matrix

Figure 2 describes how to compute the GLCM. It shows an image and its corresponding co-occurrence matrix using the default pixel's spatial relationship (offset = +1 in x direction). For the pair (2,1) (pixel 2 followed at its right by pixel 1), it is found 2 times in the image, then the GLCM image will have 2 as a value in the position corresponding to *Ii* =1 and *Ij* =2. The GLCM matrix is a 256x256 matrix; *Ii* and *Ij* are the intensity values for an 8 bit image.

135°	90°	45°
180°	X	0°
225°	270°	315°

Figure 3. Directions used for computing isotropic GLCM values for an 8bit image

The GLCM can be computed for the eight directions around the pixel of interest shown in Figure 3. Summing results from different directions lead to the isotropic GLCM and help achieve a rotation invariant GLCM. Extension to color images is straight forward. In color space, the GLCM and its statistical features can be computed for each band. Comparisons can then be done between similar bands from two different images for classification. In this work, the color GLCM are calculated in the LUV color space.

Palm [14] derived Color Co-occurrence Matrix (CCM) similar to GLCM, which measures both the color distribution in an image and considers the spatial interaction between pixels. These matrices are defined for each color space denoted by (C_1, C_2, C_3). Let C_k and $C_{k`}$, be two of the three color components of this space (k, k` ε {1, 2, 3}) and $CCM_{k,k'}$, the color co-occurrence matrix which measures the spatial interaction between the components C_k and $C_{k`}$ of the pixels in the image I. The cell $CCM_{k,k'}$ (i,j) of this matrix contains the number of times that any pixel P whose k^{th} color component value is equal to i, and k'^{th} color component value is equal to j,

$$CCM_{k,k'}(i,j) = \sum_{\Delta x}\sum_{\Delta y}\begin{cases} 1, & if\ \ k(x+\Delta x, y+\Delta y) = i\ \& \\ & \quad k'(x+\Delta x, y+\Delta y) = j \\ 0, & \text{otherwise} \end{cases} \qquad (4)$$

Each color image I characterized by the six color co-occurrence matrices for LUV color planes are $CCM_{L,L}$, $CCM_{L,U}$, $CCM_{L,V}$, $CCM_{U,U}$, $CCM_{U,V}$, and $CCM_{V,V.}$. Texture can be perceived at different scales. Each scale, however, requires a different window size. This is true for both human perception and computer-based texture recognition.

2.3 Feature Extraction

In pattern recognition and image processing, feature extraction is a special form of dimensionality reduction. In statistics, dimensionality reduction is the process of reducing the number of random variables under consideration, and can be divided into feature selection and feature extraction. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information), then the input data will be transformed into a reduced representation set of features. Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen, it is expected that the feature set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. Features often contain information relative to gray scale, texture, shape or context. Most of the researchers used Gabor filter[15][16], Wavelet[17-19], Local Binary Pattern (LBP)[20], Fractals [21][22] and Haralick's features for their work. Here Haralick's features are used for the proposed work.

2.3.1 Haralick's Features

Color and texture are usually considered separately, and most texture extraction algorithms work on gray level images only. The interest for integrating color and texture stems from the observation that considering texture as purely an intensity-based structure disregards, for instance, colored texture primitives with constant intensity.

Texture is modeled for certain image blocks. The block size should be appropriate for the computation of the texture features. Concerning blocks of increased size, however, the probability of regions containing a mixture of textures is increased. This can bias the comparison, since the reference textures contain only features of individual patterns. On the other hand, if the block size is too small, it is impossible to calculate a texture measure. Within this constraint, it is impossible to define an optimum size for segmenting the entire image. Therefore, segmenting regions of a fixed block size is inappropriate.

Haralick's features are considered for extracting the properties from texture images. Haralick [13] introduced 14 texture features denoted as I1 to I14 extracted from co-occurrence matrices. These features are statistical measures on the co-occurrence matrices of an image which allow reducing the information quantity of each matrix. For example, Palm used eight of these fourteen Haralick's features, namely homogeneity, contrast, correlation, variance, inverse difference moment, entropy, correlation 1 and 2 [14].

For each image coded in a color space, 3 color co-occurrence matrices are calculated and so $N_f = 3\times14$ Haralick's features are extracted from these matrices.

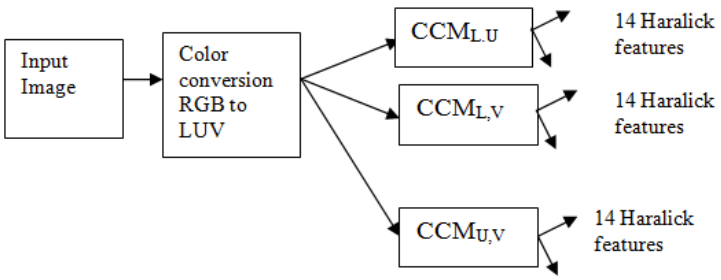


Figure 4. Color Texture Features

Since the total number (N_f) of candidate color texture features is very high, it is interesting to select the ones in order to reduce the size of the feature space. In this work, five features, namely Contrast, Correlation, Inverse Difference Moment (IDM), Variance and Angular Second Moment (ASM) are used from the fourteen Haralick's features.

- Contrast: Measure of the amount of local variation in the texture patch. It is high when the local region has dissimilarity. It is the opposite of Homogeneity.

$$f_1(CCM) = \sum_{k=0}^{Nc-1} k^2 \left\{ \sum_{|i-j|=k} p(i,j) \right\} \tag{5}$$

- Correlation: Measures the linear dependency of neighboring image pixels.

$$f_2(CCM) = \frac{\sum_{i=1}^{Nc} \sum_{j=1}^{Nc} (ij)\, p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{6}$$

- Angular second moment: Inverse of Entropy

$$f_3(CCM) = \sum_{i=1}^{Nc} \sum_{j=1}^{Nc} p(i,j)^2 \tag{7}$$

- Inverse difference moment: Direct measure of the local homogeneity of a digital image

$$f_4(CCM) = \sum_{i=1}^{Nc} \sum_{j=1}^{Nc} \frac{p(i,j)}{1+|i-j|^2} \tag{8}$$

- Variance: Measure of the dispersion of the values around the mean.

$$f_5(CCM) = \sum_{i=1}^{Nc} \sum_{j=1}^{Nc} \left(P(i,j) - \mu \right)^2 p(i,j) \tag{9}$$

2.4 Segmentation

Unsupervised segmentation techniques propose the advantage of automatic clustering of any given dataset without the need of *a priori* class information. In unsupervised mechanisms, the segmentation is performed by computing a similarity / dissimilarity measure across the pixels in the image by a given distance metric.

2.4.1 Similarity

Similarity approach is the method by which the distance measures are calculated for all the prototypes, and the sample is assigned to the type that has the maximum value. When similarity is viewed as a decision rule for segmentation of a set of texture images, the determination of "resemblance or closeness or similarity" becomes an important role and a

fundamental step. Thus, similarity become indispensable, when segmentation is carried out on the group of images.

Symbolic objects are extension of classical data types. In conventional data sets, the objects are "individualized", whereas in symbolic data sets, they are more "unified" by means of relationships.

New similarity and dissimilarity measures for symbolic objects defined by Gowda and Diday [11] are obtained by taking into consideration the components due to "position", "span" and "content" of the symbolic objects. The efficacies of these measures are brought out by successfully using them for texture segmentation. Manimegalai[12] proposed similarity measure due to position, span and position for texture classification.

Distance Measures

The three distance measures used in the symbolic classifier are due to

i. Position
ii. Span
iii. Content

i) Position

Position reveals how close the end points of the prototype and the input image are. This closeness can be obtained through Gowda's (1991) similarity and dissimilarity measures.

ii) Span

Span indicates how close the prototype and the sample are in their lengths. This is nothing but finding the union between two images' feature values in case of qualitative data.

iii) Content

Content exhibits the common interval in the case of quantitative data or the intersection in the case of qualitative data. This plays a vital role, if both similarity and dissimilarity are combined for segmentation.

The segmentation phase starts with the calculation of similarity values for the Distance measures, Position, Span and Content. Once the similarity values have been obtained for each of the distance measures separately, all the three are combined together to get the net similarity value for that feature. This value calculation has to be repeated for all the features, and color components of the images and the total similarity values are determined.

2.5 Segmentation Algorithm Using Similarity Approach

1. While entire image is being processed,
2. Extract two texture patches (A, B) of size m x m.

   a) Extract k^{th} feature from two texture patches as A_k and B_k.

      i) Find out similarity due to position

$$S_p(A_k, B_k) = 1-(a_l-b_l)/ |U_k|$$

ii) Find out similarity due to span

$$S_s\,(A_k, B_k) = (l_a + l_b)\,/(2 \times l_s)$$

iii) Find out similarity due to content

$$S_c\,(A_k, B_k) = \textit{inters}\,/\,l_s$$

iv) Find out the Net similarity between A_k and B_k as

$$S(A_k, B_k) = S_p(A_k, B_k) + S_s(A_k, B_k) + S_c(A_k, B_k)$$

b) Find out total similarity between A and B for all features as

$$S(A,B) = S(A_1, B_1) + S(A_2, B_2) + \ldots\ldots + S(A_k, B_k)$$

c) Group the color textures for which the total similarity is high.

where, U_k = Length of the maximum interval

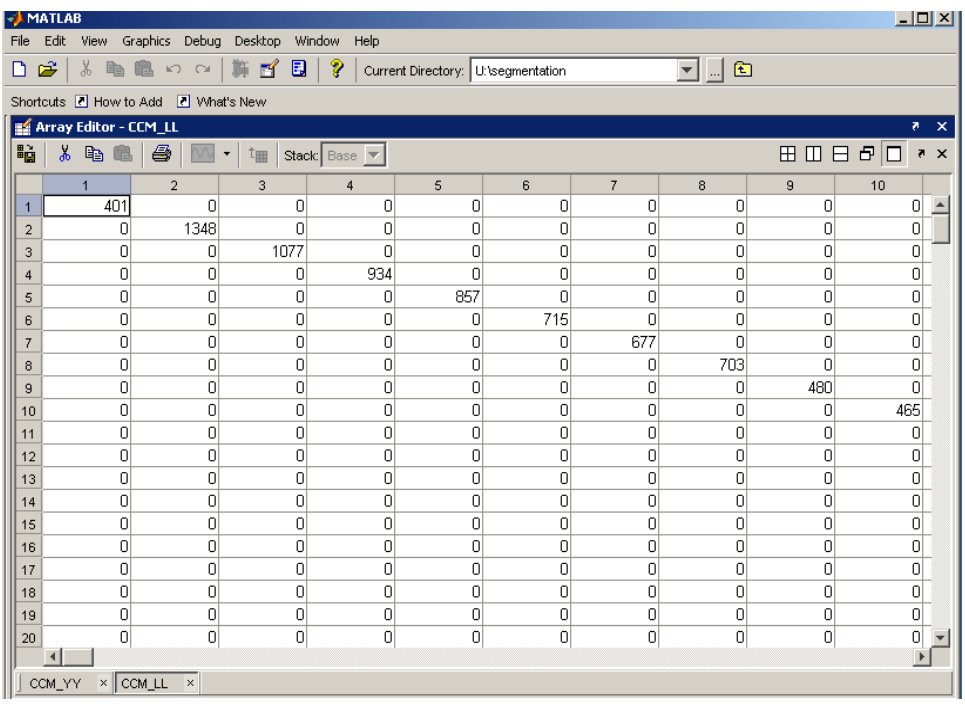
inters = length of the intersection of A_k and B_k

l_s, l_a, l_b = span length of A_k and B_k , length of A_k, and B_k

a_l, b_l = lower limit of interval for A_k and B_k respectively

3. Results Obtained by Similarity Measure

This approach can handle a variety of textures in different categories of images. Figures 5 to 10 show the CCM values for LL, UU, VV, LU, LV and UV color planes.



	1	2	3	4	5	6	7	8	9	10
1	401	0	0	0	0	0	0	0	0	0
2	0	1348	0	0	0	0	0	0	0	0
3	0	0	1077	0	0	0	0	0	0	0
4	0	0	0	934	0	0	0	0	0	0
5	0	0	0	0	857	0	0	0	0	0
6	0	0	0	0	0	715	0	0	0	0
7	0	0	0	0	0	0	677	0	0	0
8	0	0	0	0	0	0	0	703	0	0
9	0	0	0	0	0	0	0	0	480	0
10	0	0	0	0	0	0	0	0	0	465
11	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0

Figure 5. CCM Values for LL Color Plane

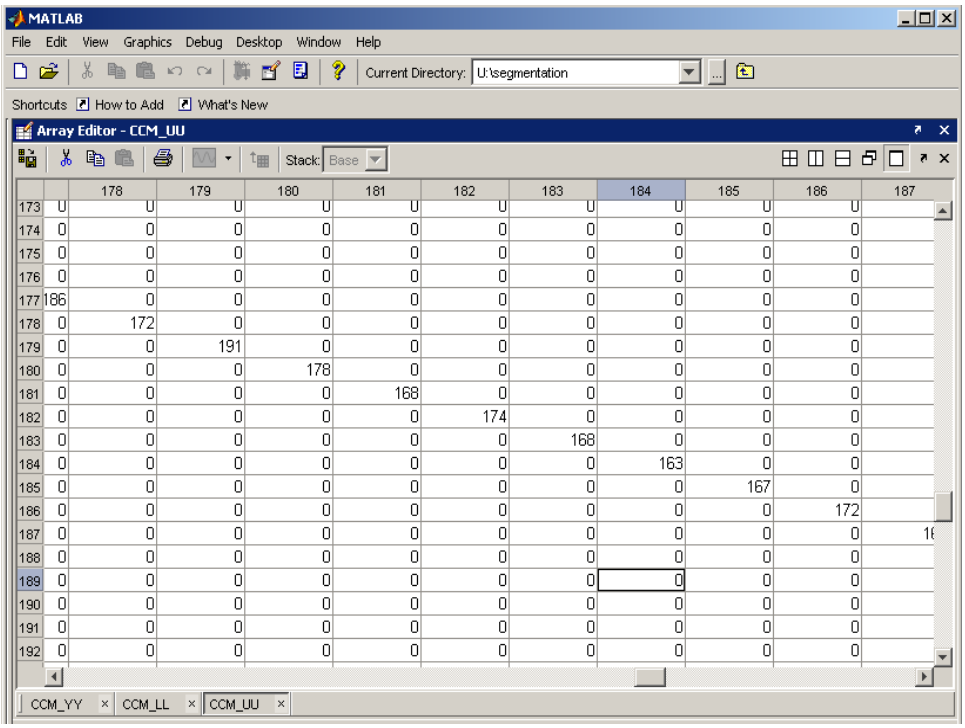


Figure 6. CCM Values for UU Color Plane

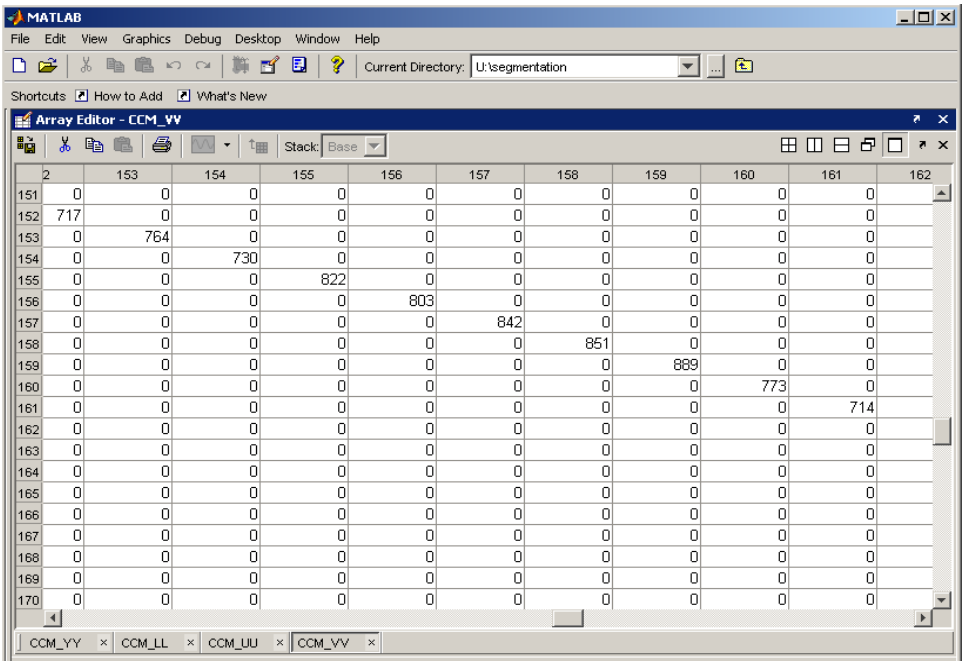
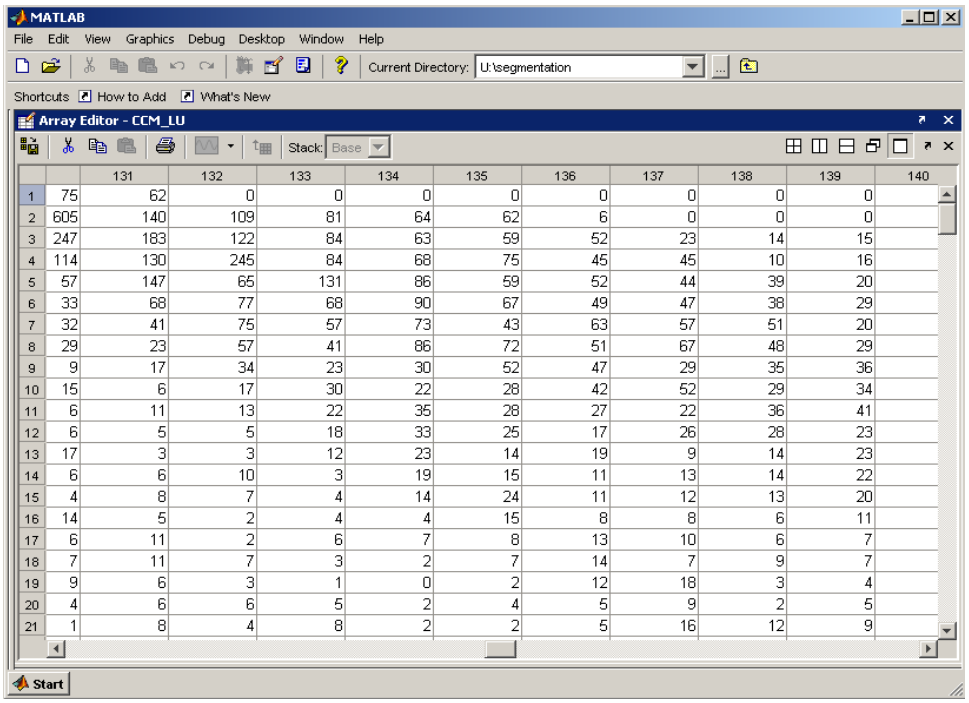
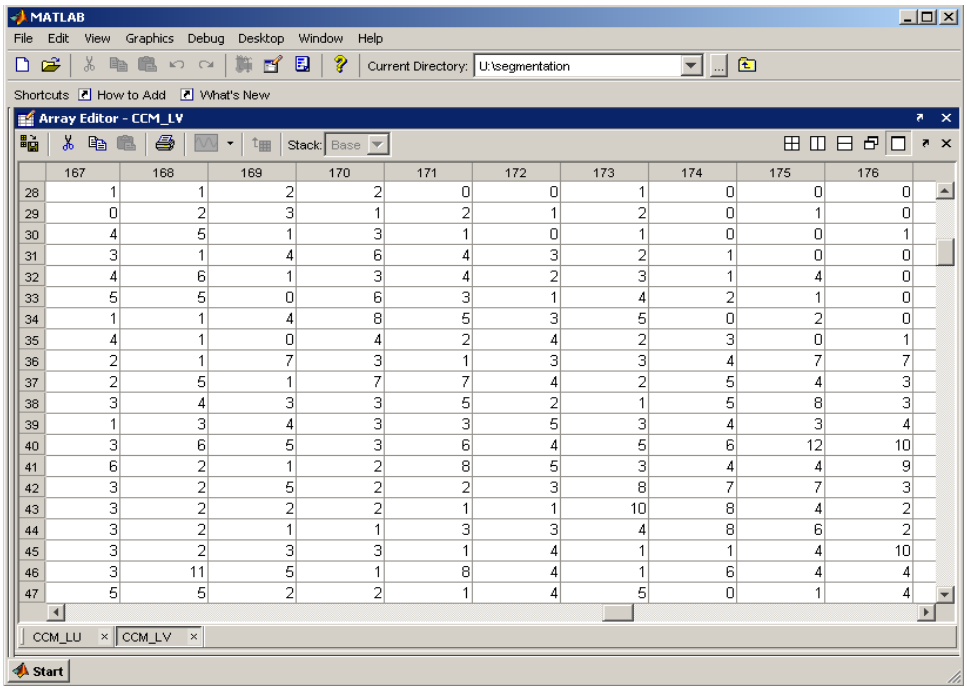


Figure 7. CCM Values for VV Color Plane



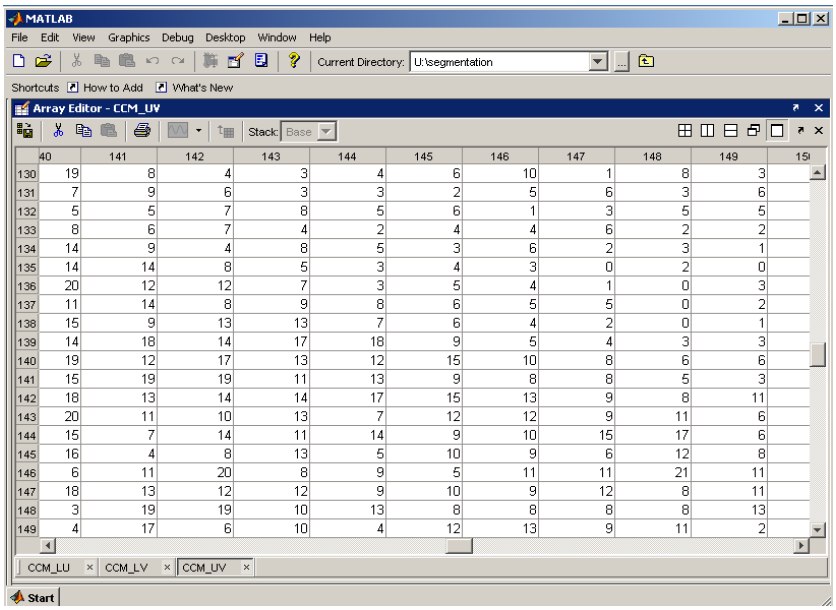
	131	132	133	134	135	136	137	138	139	140
1	75	62	0	0	0	0	0	0	0	0
2	605	140	109	81	64	62	6	0	0	0
3	247	183	122	84	63	59	52	23	14	15
4	114	130	245	84	68	75	45	45	10	16
5	57	147	65	131	86	59	52	44	39	20
6	33	68	77	68	90	67	49	47	38	29
7	32	41	75	57	73	43	63	57	51	20
8	29	23	57	41	86	72	51	67	48	29
9	9	17	34	23	30	52	47	29	35	36
10	15	6	17	30	22	28	42	52	29	34
11	6	11	13	22	35	28	27	22	36	41
12	6	5	5	18	33	25	17	26	28	23
13	17	3	3	12	23	14	19	9	14	23
14	6	6	10	3	19	15	11	13	14	22
15	4	8	7	4	14	24	11	12	13	20
16	14	5	2	4	4	15	8	8	6	11
17	6	11	2	6	7	8	13	10	6	7
18	7	11	7	3	2	7	14	7	9	7
19	9	6	3	1	0	2	12	18	3	4
20	4	6	6	5	2	4	5	9	2	5
21	1	8	4	8	2	2	5	16	12	9

Figure 8. CCM Values for LU Color Plane



	167	168	169	170	171	172	173	174	175	176
28	1	1	2	2	0	0	1	0	0	0
29	0	2	3	1	2	1	2	0	1	0
30	4	5	1	3	1	0	1	0	0	1
31	3	1	4	6	4	3	2	1	0	0
32	4	6	1	3	4	2	3	1	4	0
33	5	5	0	6	3	1	4	2	1	0
34	1	1	4	8	5	3	5	0	2	0
35	4	1	0	4	2	4	2	3	0	1
36	2	1	7	3	1	3	3	4	7	7
37	2	5	1	7	7	4	2	5	4	3
38	3	4	3	3	5	2	1	5	8	3
39	1	3	4	3	3	5	3	4	3	4
40	3	6	5	3	6	4	5	6	12	10
41	6	2	1	2	8	5	3	4	4	9
42	3	2	5	2	2	3	8	7	7	3
43	3	2	2	2	1	1	10	8	4	2
44	3	2	1	1	3	3	4	8	6	2
45	3	2	3	3	1	4	1	1	4	10
46	3	11	5	1	8	4	1	6	4	4
47	5	5	2	2	1	4	5	0	1	4

Figure 9. CCM Values for LV Color Plane



	40	141	142	143	144	145	146	147	148	149
130	19	8	4	3	4	6	10	1	8	3
131	7	9	6	3	3	2	5	6	3	6
132	5	5	7	8	5	6	1	3	5	5
133	8	6	7	4	2	4	4	6	2	2
134	14	9	4	8	5	3	6	2	3	1
135	14	14	8	5	3	4	3	0	2	0
136	20	12	12	7	3	5	4	1	0	3
137	11	14	8	9	8	6	5	5	0	2
138	15	9	13	13	7	6	4	2	0	1
139	14	18	14	17	18	9	5	4	3	3
140	19	12	17	13	12	15	10	8	6	6
141	15	19	19	11	13	9	8	8	5	3
142	18	13	14	14	17	15	13	9	8	11
143	20	11	10	13	7	12	12	9	11	6
144	15	7	14	11	14	9	10	15	17	6
145	16	4	8	13	5	10	9	6	12	8
146	6	11	20	8	9	5	11	11	21	11
147	18	13	12	12	9	10	9	12	8	11
148	3	19	19	10	13	8	8	8	8	13
149	4	17	6	10	4	12	13	9	11	2

Figure 10. CCM Values for UV Color Plane

CCM values for LL, UU and VV are diagonal values. CCM values for LU, LV and UV are contributing more

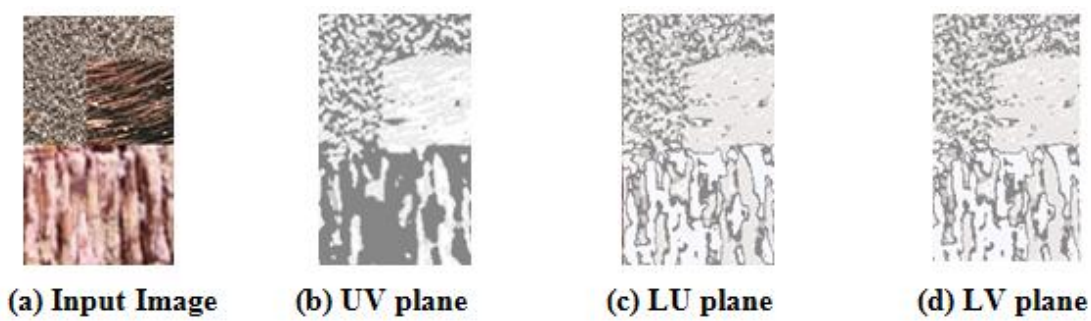


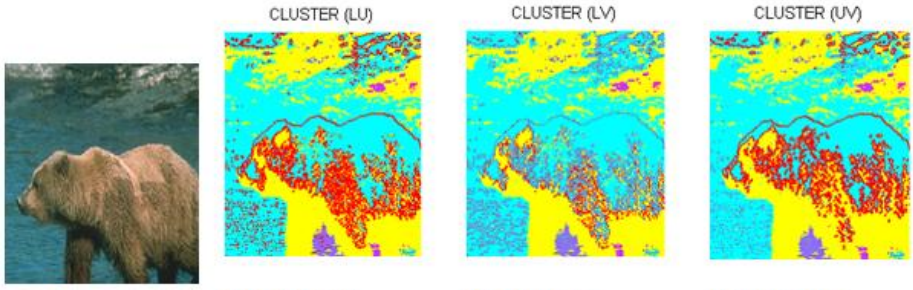
Figure 11. Results using Similarity Approach in LUV Color Space

The experiment has been repeated for a number of textured images having many textured regions, and the results are found to be good and encouraging.

4. Comparative Analysis

In this comparative analysis, LUV color space is used. The experiments have been conducted on a number of images. But a few sample results are shown for discussion. Experiments were also repeated for different sets of images.

In the first set of experiment, it is attempted to evaluate the efficiency of the proposed approach to segment the natural color texture images.



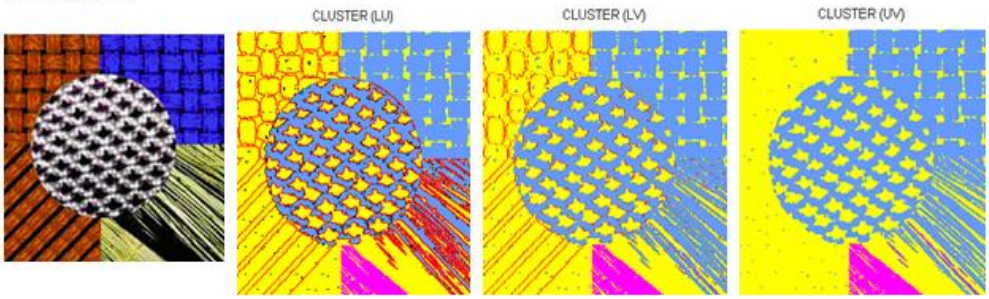
(a) Input image (b) LU space (c) LV space (d) UV space

No. of Clusters	12	13	15

Figure 12. Results using Similarity Approach in LUV Space for Natural Image

In the second set of experiment, the combination of texture images is used.

Input Image



(a) LU space (b) LV space (c) UV space

No. of Clusters	18	17	12

Figure 13. Results using Similarity Approach in LUV Space for Combination of Textures Image

For natural images, it is observed that LU and LV color planes give better results compared to UV color plane.

The third set of experiment is intended to provide a comparative analysis and study of the proposed approach with the existing works. Dana Elena Ilea's [23] Self initializing Expectation-Maximization (EM) algorithm, Junqing Chen's [24] Adaptive Clustering Algorithm (ACA) and Comaniciu and Meer's [25] CM algorithm are considered for comparison to determine the dominant effect of the proposed symbolic object approach towards unsupervised color texture segmentation. Here, images that are used and reported in [24][25] are used for testing. From these images shown in Figure 14, one can notice that the proposed algorithm shown in Figure 14 (d) outperforms the self initializing EM algorithm which is shown in Figure 14 (c). Their performances are comparable, but it is useful to notice that the results returned by the self initializing EM algorithm contain more colors than the proposed algorithms. An important advantage over the Comaniciu-Meer algorithm is the fact that the color segmented output is relatively insensitive to changes in the input parameters, whereas the segmentation result returned by the Comaniciu-Meer algorithm is very sensitive to changes in input parameters which are shown in Figure 14 (b). The experimental data

indicates that the devised algorithm offers reproducible and accurate color segmentation results, and its performance is comparable with the performance offered by other established color segmentation techniques. The developed algorithm has been applied to a large number of images including synthetic and natural images.

Figure 14 Segmentation results a) original image b) Comaniciu-Meer Algorithm c) self initializing EM algorithm d) our proposed method.

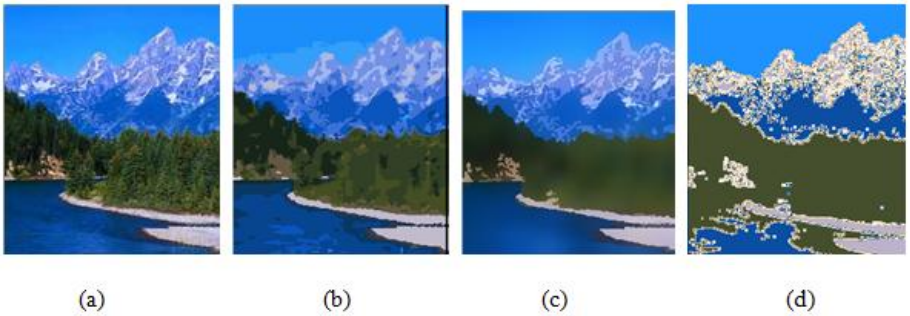


Figure 15 Segmentation results a) original image b) Comaniciu-Meer Algorithm c) Adaptive Clustering Algorithm d) our proposed method.

The Comaniciu-Meer algorithm which is shown in Figure 15 (b) has produced the false contours in the water and the sky. Also, while there are color variations in the forest region, the segment boundaries do not appear to correspond to any true color boundaries. The Adaptive Clustering Algorithm (ACA) which is shown in Figure 15 (c) smooth over the water, sky and forest regions, while capturing the dominant edges of the scene is limited to images of objects with smooth surfaces only. But the proposed method which is shown in Figure 15 (d) is developed for space invariant texture segmentation and eliminated false contours. Also, most importantly the number of segments is automatically and adaptively derived from local characteristics of the given image.

5. Conclusion

In this paper we have proposed fuzzified distance metric for color texture image segmentation. The proposed method has been compared with the existing methods. It is found that the computation complexity has been compared with existing methods. It is found that the computation complexity has been reduced in our method since we use only $CCM_{L,U}$, $CCM_{L,V}$, and $CCM_{U,V}$ matrices. The experiments conducted with various combinations have revealed that the best approach and technique to be used in segmentation of textures is Symbolic object based approach. The similarity measure due to position, span and content together give better segmentation result compared to other methods. Also it is found that our method is highly adaptive to synthetic and natural color texture images.

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