International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-5, January 2020

Markov Random Field Based Color Texture Segmentation

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Abstract*: Texture segmentation is one of the popular research domains and researchers across the globe are working on texture segmentation to enhance segmentation performance to address its requirements in many fields. Color texture segmentation has wide spectrum of applications in diverse fields such as segmentation of natural images, medical image analysis, remote sensing, shape extraction and inspection of products etc. This paper presents color texture segmentation algorithm which can satisfy requirements for such applications. Proposed algorithm is based on Markov Random Field (MRF) model eliminating the need of major contributor viz. Gabor filter used in past four decades for feature extraction and use only color as texture feature. Highly crude segmentation results are produced using only color as texture features. Crude segmentation results are enhanced by using Median filter with enlarged window size quantitatively determined by using parameters viz. structural similarity index (SSIM), mean square error (MSE) and peak signal to noise ratio (PSNR). Feature space dimensions are reduced by factor of 11 in proposed approach and this reduced computations by a factor of 11. The experimentation is carried out on 80 multi-class color texture benchmark images from Prague texture segmentation dataset and 4 benchmark images in Vistex dataset. Mean segmentation accuracy achieved for Prague texture dataset is 87.55% and it is higher by 9.82% over the best performing algorithm among 11 state-of-art algorithms suggested in most recent literature. Accuracy achieved for Vistex dataset is 98.21%. Average SSIM for Prague dataset is 0.91403 and Vistex dataset is 0.9405.

Keywords* : Median filter, Markov random Field, Peak signal to noise ratio, Structural Similarity Index, Texture database.

I. INTRODUCTION

Image segmentation is highly demanding as initial step in low vision image understanding and it finds applications in pattern analysis, machine learning, SAR image analysis, medical image analysis and number of other fields. The widely used popular image segmentation methods are edge based, region based, thresholding, watershed segmentation, level set method, parametric methods, clustering based techniques etc. Texture segmentation is one of the important problem domains for research. There are large varieties of textures in nature and universal definition of texture do not exists. This makes texture segmentation a difficult task. Reference [16] defines texture as spatial distribution of intensities in a region observed to be homogeneous by normal human eye throughout the image region.

There is strong correlation between texture and human vision and this has enhanced interests of researchers in various domains viz. texture segmentation and classification, feature extraction of textures, shapes from textures and texture synthesis [22]. Texture has millions of applications in these research domains. It includes applications such as texture synthesis for computer graphics, 3D imaging, animation, synthesis of natural scenes, determination of surface shapes. Texture analysis is used for analysis of sea-ice imagery, image data retrieval and medical image analysis such as performing diagnosis from X-ray images etc. and the list goes on.

This paper improves the approach proposed in [13][17] eliminating need of Gabor filter recommended for texture feature extraction by researchers in past four decades and this reduces dimensionality. This approach yields highest segmentation accuracy among 11 state of art approaches published in recent literature [6]. Related literature is discussed in section 2. Section 3 depicts segmentation task formulation using MRF and proposed approach. Section 4 focuses on experimentation and results. Section 5 discusses conclusion and future scope.

II. RELATED WORK

Texture segmentation using Gabor filter and classic classifiers is proposed in [3][16][17][19][21]. Markov Random Field based texture segmentation, SAR and medical image segmentation is discussed in [11][13][15][17]. Segmentation results in MRF based approaches are obtained by minimizing energy using optimization algorithm. Texture segmentation suggested in [13][17] use both Gabor filter and color as texture features. The dimensionality of feature space in [13][17] is high due to Gabor filter. This is computationally very expensive.

A state of art approach for unsupervised color texture segmentation using Mumford Shah model for 80 multi-class Prague texture segmentation benchmark images is suggested in [6]. They carried out experimentation on two databases viz.

Manuscript published on January 30, 2020.
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Prague texture segmentation database, Histological database. They achieved first rank in 11 state of art approaches with mean segmentation accuracy of 77.73%

based on Hoover's CS (correct segmentation) segmentation metric [20].

Most of the researchers used Gabor filter for feature extraction. The proposed approach uses MRF model based on only colour as texture feature and eliminates the need of Gabor filter. Highly crude segmentation results are obtained using only colour as texture feature. Crude segmentation results are improved by using Median filter with enlarged window size quantitatively determined by segmentation performance parameters viz. structural similarity index (SSIM), mean square error (MSE) and peak signal to noise ratio (PSNR). These quantitative parameters are old [14] but they are used for performance evaluation in most recent literature [1][2][4][5]. Therefore, they are used in proposed approach. The dimensionality of feature space is reduced from 33 to 3 for image size of 512 x 512. The segmentation accuracy achieved is 87.55% using Hoover's segmentation metric correct segmentation (CS) [20] and it is higher by 9.82% than best performing approach in 11 state of art methods published in recent literature [6].

III. PROPOSED COLOR TEXTURE SEGMENTATION APPROACH

The visual analysis of 80 multi-class texture benchmark images from Prague texture database [12] indicates that if color is used to discriminate the boundaries of texture segments boundaries can be detected nicely for most of the benchmark images. Therefore, color is used as feature in proposed approach. The determination of color distance in RGB tristimulus color space is complex. If the RGB color space is transformed to CIE-Luv color space, it becomes Euclidean color space with uniform spacing of colour [17].

This CIE-Luv colour space is used to discriminate boundaries between texture segments. The segmentation task is formulated in the form of energy function based on colour features and labelling information as depicted in [15]. The segmentation is performed by minimizing energy using simulated annealing. The segmentation results obtained contains dots and very small islands relative to size 512 by 512 of benchmark image as shown in image located in first row and third column of Fig. 1. It is concluded from exhaustive analysis of crude segmentation results of all benchmark images that segmentation results can be enhanced by applying Median filter of variable window size.

Window size of Median filter is different for every benchmark image due to variation in island size in segmented result. Window size is quantitatively determined by one of the parameters viz. SSIM, MSE and PSNR. Each of these parameters is measure of similarity between ground truth and segmentation result. MSE and PSNR have limitations and they are eliminated by structural similarity index. SSIM is quantitative measure developed based on human visual system [14]. It takes into consideration the structural similarity between ground truth image and segmented image including edge information. Literature recommends window size of 3 x 3, 5 x 5 and 7 x 7 for Median filter to remove impulse noise [1][2][4][5], however Fig. 1 indicates that best results are obtained for window size of 23 x 23 with negligible degradation in boundaries with SSIM = 0.9782, MSE = 0.0314, PSNR = 30.583. Enlarged window size is required for all benchmark images of Prague dataset.

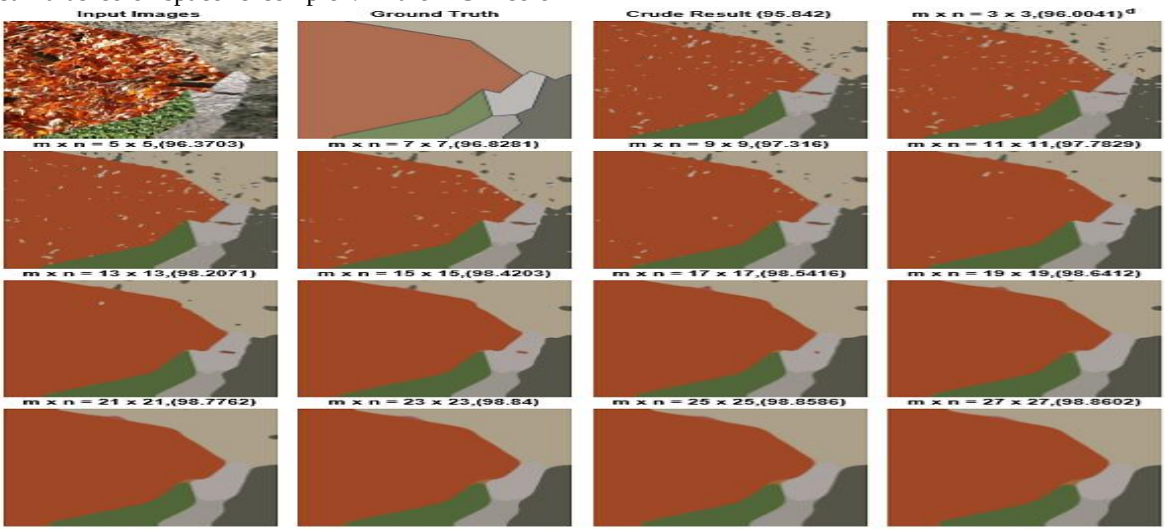

Fig. 1 Segmentation results using Median filter with variable window size quantitatively determined by SSIM, MSE and PSN

Note[d]: Number in parentheses indicate segmentation accuracy and m, n indicate window size of Median filter.

The task performed by Gabor filter in segmentation process in [13][17] is achieved by applying Median filter with enlarged window size. This reduces dimensionality of feature vectors from 33 to 3 for image size of 512 x 512 yielding gain in computations and segmentation accuracy.

To make the algorithmic steps comprehensive we denote number of rows of Median filter by m and columns by n and provide relevant comment for a step if required. The proposed segmentation approach consists of four steps.

1. Perform RGB to CIE-Luv color space transformation.
   Comment: Refer [17] for more details.

2. Initialize the segmentation output based on Luv color features
3. Apply Simulated annealing to minimize energy to get crude segmentation results.
   Comment: Refer [18][24] for more details
4. Apply Median filter with variable window size on segmentation output obtained in step 3 to get refined segmentation output.

Window size of Median filter is determined based on segmentation performance parameters viz. SSIM, MSE and PSNR. The steps of algorithm used for determining window size of Median filter are given below.

Table- I: Segmentation performance with quantitative parameters viz. SSIM, MSE and PSNR

Window size	SSIM	MSE	PSNR	Segmentation Accuracy
3 x 3	0.903023	0.148975	23.831897	96.004105
5 x 5	0.914411	0.129571	24.437958	96.370316
7 x 7	0.930936	0.104946	25.353361	96.828079
9 x 9	0.946329	0.079501	26.559277	97.315979
11 x 11	0.957780	0.061957	27.642154	97.782898
13 x 13	0.968398	0.044415	29.087715	98.207092
15 x 15	0.972789	0.038123	29.751118	98.420334
17 x 17	0.974865	0.034652	30.165691	98.541641
19 x 19	0.975761	0.032603	30.430447	98.641205
21 x 21	0.977498	0.031782	30.541257	98.776245
23 x 23	**0.978223**	**0.031474**	**30.583551**	**98.839951**
25 x 25	0.977937	0.034003	30.247791	98.858643
27 x 27	0.977013	0.036724	29.913476	98.860168
Optimum quantitative performance parameters				
Window size	SSIM	MSE	PSNR	Maximum Accuracy
23 x 23	0.978223	0.031474	30.583551	**98.839951**

1. Initialize window size of Median filter to m = 3 and n = 3.
   Comment: Odd window size is used for better performance.
2. Refine crude segmented image by applying Median filter on it with current window size.
   Comment: Every pixel in crude image is visited in this step for Median filtering
3. Estimate SSIM, MSE and PSNR for current window size for whole image. Comment: These parameters are estimated using ground truth image and crude segmented image.
4. If segmentation performance parameters in step 3 improve, save improved parameters and increase window size by 2 *i.e. m = m + 2 and n = n + 2.*
5. Go to step 2 and continue execution of step 2 through step 4 until performance parameters specified in step 3 ceases to improve.

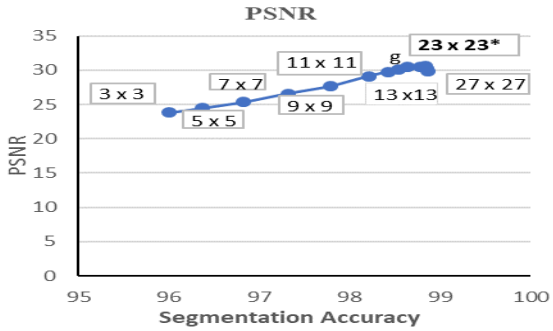

Fig. 2(a) Graph of structural similarity index (SSIM) against segmentation accuracy with varying window size

Note[e]: Window size of Median filter is not shown for few values of SSIM due to space constraint

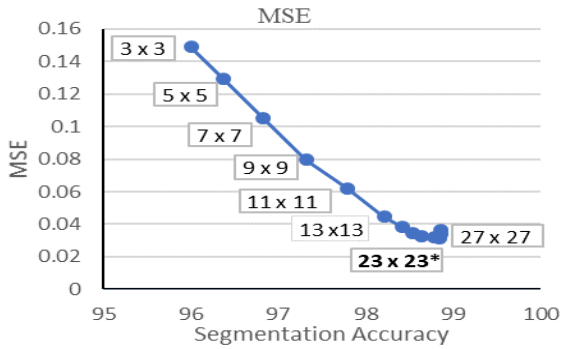

Fig. 2(b) Graph of Mean Square Error (MSE) against segmentation accuracy with varying window size

Note[f]: Window size of Median filter is not shown for few values of MSE due to space constraint

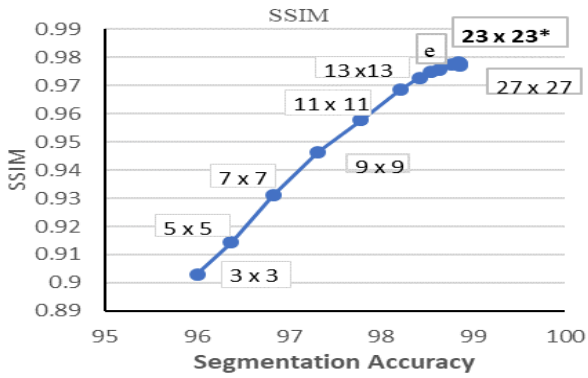

Fig. 2(c) Graph of Peak Signal to Noise Ratio (PSNR) against segmentation accuracy with varying window size

Note[g]: Window size of Median filter is not shown for few values of PSNR due to space constraint

Refined segmentation result is best for window size associated with optimal value of performance parameter. Performance parameters are estimated from ground truth and segmented image. Table-I indicates that optimum performance is achieved for window size of 23 x 23 with optimum values of SSIM, MSE and PSNR. Fig. 2(a) and Table-I indicates that SSIM reach very close to unity (0.978223) for window size of 23 x 23 indicating that segmentation result is close to ground truth.

As indicated by Fig. 2(b) and Table-I MSE reduces to minimum value of 0.031474 (close to zero) for window size of 23 x 23 and Fig. 2c and Table-I indicates that PSNR reach to maximum value of 30.583551 dB for window size of 23 x 23. The very small value of MSE and large value of PSNR associated with window size of 23 x 23 indicate that segmentation result approach very close to ground truth yielding highest accuracy of 98.889542%.

A.Formulation of Texture Segmentation Problem

The segmentation problem is formulated in the form of energy function using MRF model developed based on Bayesian frame work and Gibbs distribution [13][15][17] [18]. Total energy is sum of feature energy and label energy [15]. Total energy is denoted by $U(y_s, x_{st})$ in this paper. Total feature energy U_f is sum of U_{f1} and U_{f2} . The expressions for U_{f1} and U_{f2} are given in (2) and (3). Label energy U_l is given by (4). Hence expression for total energy is

$$U(y_s, x_{st}) = U_f + U_l \quad (1)$$

$$U_{f1} = \sum_{s \in S} \left\{ ln\left(\sqrt{(2\pi)^K \, |\Sigma_m|}\right) \right\} \quad (2)$$

$$U_{f2} = \sum_{s \in S} \left[\frac{1}{2} \, (y_s^k - u_m^k) \, \Sigma_m^{-1} (y_s^k - u_m^k)^T \right] \quad (3)$$

$$U_l = \left[\beta \sum_{t \in N_s} \delta \, (x_s, x_t) \right] \quad (4)$$

$$\delta(x_s, x_t) = 1 \quad \text{if} \quad x_s \neq x_t$$

$$\delta(x_s, x_t) = -1 \quad \text{if} \quad x_s = x_t$$

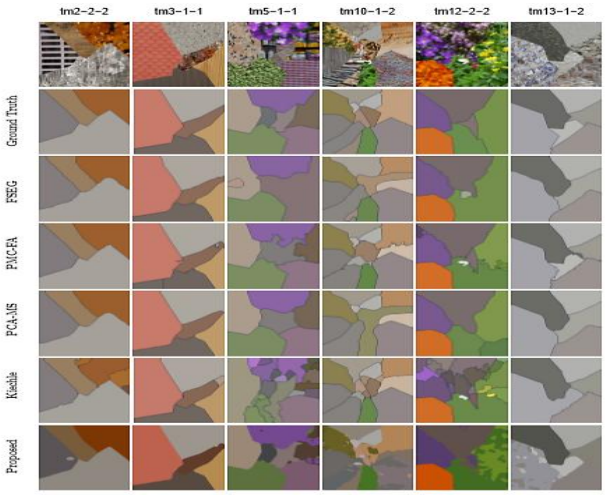

Fig. 3 Comparison of proposed algorithm with 4 top performing algorithms on six benchmark images[h]. Note:[h] tm2-2-2, tm3-1-1, tm5-1-1, tm10-1-2, tm12-2-2 and tm13-1-2 are names of images in Prague texture benchmark dataset.

Here δ is delta Kronecker function. K is length of feature vectors. K = 3 in this paper. y_s^k is feature vector associated with pixel s and k = 1,2,…,K, u_m^k is vector of means associated with texture segment m and k = 1,2,,….,K. x_s and x_t are labels of pixel s and t. N_s is neighborhood of pixel s in the image lattice S. Σ_m is covariance matrix of class m. β is constant set priori.

The energy $U(y_s, x_{st})$ of whole image is minimized using simulated annealing with Gibbs sampler to get crude segmentation result. The MRF parameter viz. covariance matrix and mean for a region are estimated from input images by cropping a section of texture segment.

IV. EXPERIMENTATION AND RESULTS

The proposed algorithm is evaluated on Prague texture segmentation benchmark images [12]. This benchmark set consists of 80 multi-class color texture images. Minimum number of texture classes in this benchmark set are 3 and maximum number of texture segments are 12 with arbitrary boundaries. The size of each image is 512 by 512. These images are generated from 10 categories of 114 textures in Prague Segmentation database. Performance of this algorithm is compared with 11 most recent algorithms in [6]. These algorithms include Martin Kiechle's algorithm, Priority Multi-Class Algorithm (PMCFA), Variational Multi-Phase Segmentation (PCA-MS), Factorization based Segmentation (FSEG), Texture Fragmentation and Regression (TFR), 3D Auto Regressive Model (AR3D), Regression based segmentation (RS), Gaussian MRF with Expectation Maximization (GMRF+EM), Texture Segmentation by Weighted Aggregation (SWA) and Texel based Segmentation (TS). The TS algorithm is evaluated on 10 texture images in the benchmark set and SWA, AR3D and GMRF+EM algorithms are evaluated on 20 images. The remaining all algorithms are evaluated on all 80 benchmark images.

Each value in Table-II indicates the mean of segmentation accuracy of eleven state of art algorithms [6] along with proposed algorithm and it indicates that proposed algorithm achieves first rank among all algorithms with mean accuracy of 87.55% for 80 multi-class texture images in Prague benchmark set. The segmentation accuracy is computed using Hoover's segmentation metric viz. CS (correct segmentation) [20]. The experimentation is carried out on Vision texture database 4 multi-class benchmark images in [13][17]. Each image is 128 x 128 size. Accuracy achieved is 98.21% with CS segmentation metric on these images.

Fig. 3 shows results obtained with proposed approach and other 4 top performing algorithms viz. Martin Kiechle's algorithm, PMA-FA, PCA-MS and FSEG on six benchmark images. Performance of proposed algorithm is superb compared to four top performing algorithms. The names of benchmark images are mentioned at the top of all six images in Fig. 3. SSIM is measure of similarity between ground truth and segmented result. Mean value of SSIM for each dataset is given in Table-II. The images for which segmentation results are not good, detailed justification is provided in next part of this section.

A. Result Analysis and Discussion

The algorithm presented in this paper uses color as feature (CIE-Luv color space) for discriminating the different texture segments. As indicated in Fig. 3 there is intra-class color variation in some of the images viz. tm5-1-1, tm12-2-2 and tm13-1-2 due to which clear discrimination is not achieved. For example, in tm5-1-1 image right top texture segment

Table-II: Quantitative segmentation results on benchmark texture images

Results Comparisons with eleven state of art algorithms on Prague texture database												
Metric	Proposed	Kiechle	PMCFA	PCA-MS	FSEG	RS	TFR	TFR+	AR3D	GMRF	SWA	TS
CS	87.55	77.73	75.32	72.27	69.02	46.02	46.13	51.25	37.24	31.93	27.04	59.1
SSIM	0.91403	Not provided										
Results comparison with Benchmark images of Vision texture database in [13, 17]												
Metric	Proposed	Four benchmark images in [13, 17]										
CS	98.21	98.22										
SSIM	0.9405	Not provided										

contains yellow, faint blue and violet color patches. Similarly, in tm12-2-2 image bottom right texture segment is dark green and right top segment is relatively faint green along with yellow flowers scattered in it. This has degraded segmentation performance. The two texture segments at the center of image tm10-1-2 has intra-class color variation and segmentation performance is degraded for them. Performance of the approach proposed here is very excellent for image containing uniform colored texture segments. It also works for highly complex textures.

V. CONCLUSION AND FUTURE SCOPE

Median filter with enlarged window size eliminates the need for Gabor filter used by researchers in past four decades for texture segmentation. This reduces the dimensionality of feature space effectively reducing computations in optimization process. Optimum window size is determined based on segmentation performance parameters viz. SSIM, MSE and PSNR. Proposed approach achieves higher segmentation accuracy over best performing approach by 9.82 % over best performing approach among 11 state-of-the-art algorithms published in recent research literature [6]. Segmentation accuracy achieved on Vision texture database is 98.21%. SSIM is measure of similarity between ground truth and segmented image and its value is very close to unity for both databases. This approach is simple alternative to replace Gabor filter with Median filter with enlarged window size for MRF based segmentation task. The nature inspired optimization algorithm [23] such as flower pollination algorithm, bat algorithm, fire-fly algorithm, cuckoo search algorithm can be used instead of simulated annealing for optimization as future scope.

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