COLOUR IMAGE SEGMENTATION USING SOFT ROUGH FUZZY-C-MEANS AND MULTI CLASS SVM

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ABSTRACT

Color image segmentation algorithms in the literature segment an image on the basis of color, texture, and also as a fusion of both color and texture. In this paper, a color image segmentation algorithm is proposed by extracting both texture and color features and applying them to the One-Against-All Multi Class Support Vector Machine classifier for segmentation. A novel Power Law Descriptor (PLD) is used for extracting the textural features and homogeneity model is used for obtaining the color features. The Multi Class SVM is trained using the samples obtained from Soft Rough Fuzzy-C-Means (SRFCM) clustering. Fuzzy set based membership functions capably handle the problem of overlapping clusters. The lower and upper approximation concepts of rough sets deal well with uncertainty, vagueness, and incompleteness in data. Parameterization tools are not a prerequisite in defining Soft set theory. The goodness aspects of soft sets, rough sets and fuzzy sets are incorporated in the proposed algorithm to achieve improved segmentation performance. The Power Law Descriptor used for texture feature extraction has the advantage of being dealt in the spatial domain thereby reducing computational complexity. The proposed algorithm is comparable and achieved better performance compared with the state of the art algorithms found in the literature.

KEYWORDS

Segmentation , Classification, Clustering, Fuzzy Sets, Homogeneity, Rough Sets, , Soft Sets, Multi Class SVM, Texture, Power Law Descriptor.

1. INTRODUCTION

Color image segmentation [2] is a pre-processing step of prime importance, used in numerous computer vision and image processing, connected applications such as robotic vision, face recognition, content based image retrieval and medical imaging [5]. Image segmentation algorithms can be categorized into four major groups, thresholding, clustering, edge based and region based segmentation.

Clustering techniques are explored in recent times for color image segmentation. Wang et al., in their work [19] applied the pixel wise homogeneity and texture features to SVM by training SVM, using the features obtained by preliminary clustering with Fuzzy C Means (FCM) algorithm. Lingras [9] et al., proposed rough k means algorithm for use in clustering of internet users, which was later applied for image segmentation applications. Pradipta Maji and Sankar Pal proposed RFCM, [12] in which they presented that, crisp lower bound and fuzzy boundary of a

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class, enables efficient selection of cluster prototypes.Freixenet et al., [8] proposed to integrate the information pertaining to region and boundary for colour texture based segmentation. They experimented and obtained the initial seeds from the regions, by considering perceptual colour and texture edges. The authors proposed “Colour Image Segmentation using Soft Rough Fuzzy C Means Clustering and SMO SVM”,[14] in which they explored the parallel processing capability of Sequential Minimal Optimization Support Vector Machine. Deng et al., [6] proposed the well known J-SEGmentation (JSEG) algorithm, which combines both quantization process and clustering techniques for extraction of colour-texture cues in images. Mean Shift clustering in sync with edge information was employed by christoudias et al.,[4] in their work on edge detection and image segmentation (EDISION) system. Colour and texture cues play a predominant rule in segmenting the image. The segmentation algorithms based on clustering are unsupervised and so avoid human intervention.

In this paper, “*Color image segmentation using Soft Rough Fuzzy C Means and Multi Class SVM*” is presented. Initially the color and texture cues of the colour image, at pixel level are obtained through homogeneity and Power Law Descriptor. These features are then applied to Soft Rough Fuzzy C means (SRFCM) clustering algorithm. Later the Multi class SVM classifier is trained by using samples obtained from SRFCM clustering. The image segmentation step is completed with trained Multi Class SVM. The color image information at pixel stage, together with classification capacity of classifier is the major strong point of this technique. Simulated results show that the proposed method achieves better segmentation results. Performance measures compared with state of the art algorithms has been discussed in this paper.

The organization of the paper is as follows. The preliminaries of SRFCM clustering are discussed in Section 2. The basic concepts of Two Class SVM and Multi-Class SVM are discussed in section 3. The fundamentals of Power Law Descriptor are discussed in Section 4.In section 5 the proposed Color image segmentation using SRFCM clustering and Multi class SVM is discussed, followed by justification for using this algorithm. In Section 6 the performance measures used in evaluating the segmentation algorithm are presented. Section 7 shows the pictorial and objective evaluation results of the proposed algorithm. The concluding remarks are given in section 8.

2. SOFT ROUGH FUZZY C-MEANS ALGORITHM (SRFCM)

SRFCM has its roots in the k-means algorithm proposed by J Mc Queen. Fuzzy C-Means (FCM) Algorithm was proposed by Bezdek. In FCM, objects are not confined to belong to a single cluster. Each object belongs to all clusters with certain degree of belongingness. Rough k-means (RKM) was proposed by Lingras and West [9] by borrowing some of the concepts of rough set theory [13]. Rough Fuzzy c-means algorithm was proposed by Mitra et al., [11] . In this paper SRFCM is proposed by applying similarity concepts of soft sets to Rough Fuzzy Frame work.
Many authors were intrigued, and mined the issue of similarity measurement between sets. Majumdar and Samanta [10] presented the theory of similarity measurement of soft sets as follows.

Let $U = \{o_1, o_2, ... o_m\}$ be the set of objects and

$P = \{p_1, p_2, .. p_n\}$ be the set of parameters.

$\hat{Q} = \{F(o_i), i = 1,2,.... m\}$ and

$\hat{R} = \{G(p_i), i = 1,2,..... n\}$ be two groups of fuzzy soft sets.

The similarity between $\hat{Q}$ and $\hat{R}$ is denoted by S $(\hat{Q},\hat{R})$ and is defined as follows
$S(\hat{Q},\hat{R}) = \max S_i(\hat{Q},\hat{R})$ where

$$S_i(\hat{Q}, \hat{R}) = 1 - \frac{\sum_{j=1}^{n} \left| \hat{Q}_{ij} - \hat{R}_{ij} \right|}{\sum_{j=1}^{n} \left| \hat{Q}_{ij} + \hat{R}_{ij} \right|} \tag{1}$$

The fuzzy soft set based similarity technique is applied to compute the similarity of objects in images. The soft set similarity proposed by Majumdar and Samanta is adapted to the Rough Fuzzy C-Means algorithm by considering that $\hat{Q}$ is the soft set representing the samples and $\hat{R}$ is the soft set representing cluster centroids.

The fundamental steps of SRFCM are as follows.

1. Assume m random initial cluster prototypes denoted by c_i.
2. Find membership u_{ik} between m cluster centers and k data points.
3. Allocate each data point o_k to the lower approximation ($\underline{A}U_i$) or upper approximation ($\overline{A}U_i$ and $\overline{A}U_j$) by calculating $u_{ik} - u_{jk}$, where u_{ik} be maximum and u_{jk} be second maximum membership of a data point o_k among all the clusters. A data point can belong to at most one lower approximation, and may belong to two or more than two upper approximations.
4. If the difference between the highest and next highest membership of a data point in all the clusters i.e ($u_{ik} - u_{jk}$) is below some pre-defined threshold value, then $o_k \in \overline{A}U_i$ and $0_k \in \overline{A}U_j$.. It also implies that o_k cannot be a member of any lower approximation. On the other hand if ($u_{ik} - u_{jk}$) is above the threshold value then $o_k \in \underline{A}U_i$ which implies that membership value $u_{ik}$is highest among all the clusters.
5. Compute similarity of sample points soft set to the cluster centre soft set by using the given formula.

$$S_i(\hat{O}, \hat{V}) = 1 - \frac{\sum_{j=1}^{n} \left| \hat{O}_{ij} - \hat{V}_{ij} \right|}{\sum_{j=1}^{n} \left| \hat{O}_{ij} + \hat{V}_{ij} \right|} \tag{2}$$

Calculate the maximum similarity and assign a pixel to a cluster to which it has maximum similarity after fuzzification.

6. Compute updated cluster prototype for each cluster U_i, as in (3).

$$v_i = \begin{cases} M_1, & \text{if } \underline{A}U_i \neq \Phi \ \wedge \overline{A}U_i - \underline{A}U_i \neq \Phi, \\ M_2, & \text{if } \underline{A}U_i = \Phi \ \wedge \overline{A}U_i - \underline{A}U_i \neq \Phi, \\ M_3 & \textit{otherwise} \end{cases}$$

$$M_1 = w_{low} \times \frac{\sum_{o_k \in \underline{A}U_i} u_{ik}^m o_k}{\sum_{o_k \in \underline{B}U_i} u_{ik}^m} + w_{up} \times \frac{\sum_{o_k \in \overline{A}U_i - \underline{A}U_i} u_{ik}^m o_k}{\sum_{o_k \in \overline{A}U_i - \underline{A}U_i} u_{ik}^m} \qquad M_2 = \frac{\sum_{o_k \in \overline{A}U_i - \underline{A}U_i} u_{ik}^m o_k}{\sum_{o_k \in \overline{A}U_i - \underline{A}U_i} u_{ik}^m} \qquad M_3 = \frac{\sum_{o_k \in \underline{A}U_i} u_{ik}^m o_k}{\sum_{o_k \in \underline{A}U_i} u_{ik}^m} \tag{3}$$

7.Iterate and run steps 2–6 until there are no further changes in cluster centroids. The weights (w_{up}, w_{low})are chosen to be values between 0 and 1.Further ($w_{up}+w_{low}$) = 1; (1/2 < w_{low}<1), 0 < T <0.5.

3. MULTI CLASS SUPPORT VECTOR MACHINE

3.1 Two Class SVM

Support vector machine (SVM) [5] in general is used to solve classification problems encountered in pattern recognition. Two class SVM is used to divide data into two sets of classes, by estimating the location of a slicing plane that optimizes (increases) the smallest distance between any two groups. Different hyper planes separate the data, but the hyper plane that optimizes the distance 2/w between the classes has to be found. SVM require training data which are manually annotated. The training data is used as reference for automatic classification of unclassified data. Let the training data be (x_i, y_i) and the corresponding output be $y_i \in(-1,+1)$. SVM is modelled as

$$y = w^T x + b \tag{4}$$

where b is bias and w is weighted vector with dimensions akin to that of feature space.

SVM is formulated by assuming that given data can be linearly separated as given below.

$$\begin{aligned} w^T x_i + b &\geq +1 (y_i = +1) \\ w^T x_i + b &\geq -1 (y_i = -1) \end{aligned} \tag{5}$$

The margin m is thus

$$m = \frac{1}{\|\overline{w}\|^2} \tag{6}$$

Maximum margin implies minimum w, and the problem is solved as follows

$\min\limits_{w,b} \frac{1}{2} \|\overline{w}\|^2$ with the constraint

$$y_i (\overline{w} . \overline{x} - b) \geq 1 \qquad \forall\, i \tag{7}$$

where x_i is the i^{th} training data point and y_i is the expected response of the SVM for i^{th} training data point. The value of y_i is +1 for the excitations from group 1 and -1 for excitations from group 2.

3.2 Multi-Class Support Vector Machine Using One-Against-All Approach

This method is also called one-against-rest classification[5].To solve a classification problem in which a given set of data points is to be categorized into N classes, N SVM binary classifiers are created, where each individual classifier discriminates , each class from the remaining (N-1) classes. To elaborate, the first binary classifier is trained to distinguish class-1 data points and the data points belonging to the other classes. Data points are classified by maximizing the location of the data point from the periphery of the linear slicing hyper plane. The final output class is the one that corresponds to the SVM with the largest peripheral distance. Nevertheless, if the responses of two or more classes are indistinguishable, those points are marked as unclassified, and are arbitrarily resolved. The multiclass method discussed is advantageous in the sense that the number of binary classifiers constructed is of the order of the number of classes. The hitch, however is that, in the training phase, the memory necessity is very high and is of the order of square of the selected training samples.

4. POWER LAW DESCRIPTOR:

The proposed texture descriptor is an extension to the Weber Local Descriptor proposed by Chen et al.,[3].

Ernst Weber observed that the ratio of incremental threshold to the background intensity is a constant [1]. This relation known since as weber's law can be expressed as:

$$\frac{\Delta I}{I} = k \tag{8}$$

0	0	0
0	1	0
0	0	0

1	1	1
1	-8	1
1	1	1

x_o	x_1	x_2
x_7	x_c	x_3
x_6	x_5	x_4

where ΔI represents the increment threshold (just noticeable difference for discrimination); I represents the initial stimulus intensity and k signifies that the proportion on left side of the equation remains constant despite variations in the I term. The fraction $\Delta I / I$ is known as the Weber fraction. Weber's law more simply stated says that the size of a just noticeable difference is a constant proportion of the original stimulus value. So, for example, in a noisy environment one must shout to be heard while a whisper works in a quiet room.

Chen et al., [3] proposed Weber Local Descriptor, as a texture descriptor, by considering the concepts of weber's law. But Guilford observed that empirical data such as an image does not always fit well into weber's law. He suggested a modification to weber's law as follows and hence called as Guilford power law[1].

$$\frac{\Delta I}{I^{\alpha}} = k \tag{9}$$

where α is an exponent slightly less than 1.The perceived brightness of the human eye is proportional to the logarithm of actual pixel value, rather than the pixel value itself. The power law is also scale invariant. Hence the proposed power law descriptor models the perception of human beings better than weber local descriptor

The Power law descriptor consists of two components differential excitation (ξ) and orientation (θ)

Differential excitation finds the salient variations within an image to simulate the pattern perception of human beings. It is defined as the ratio between two terms V_s^{00} and $[V_s^{01}]^{\alpha}$.

$$\xi(x_c) = \arctan\left[\frac{v_s^{00}}{[v_s^{01}]^{\alpha}}\right] \tag{10}$$

where V_s^{00} at any pixel is the sum of the differences between the neighbors and the current pixel, whereas V_s^{01} is the value of the current pixel to a power of α

$$V_s^{00} = \sum_{i=0}^{p-1}(\Delta x_i) = \sum_{i=0}^{p-1}(x_i - x_c) \tag{11}$$

These values are obtained by convolving the image with the following filters.

Filter used to realize V_s^{00} Filter used to realize V_s^{01} Template

The orientation component is the gradient orientation which is computed as

$$\theta(x_c) = \gamma_s^1 = \arctan\left[\frac{v_s^{11}}{v_s^{10}}\right] \tag{12}$$

$V_s^{10} = x_5 - x_1$ and $V_s^{11} = x_7 - x_3$

0	-1	0
0	0	0
0	1	0

0	0	0
1	0	-1
0	0	0

where V_s^{11} and V_s^{10} are obtained using the following filters

Filter used to realize V_s^{10} Filter used to realize V_s^{11}

Both the orientation and excitation values range in the interval
$[-\pi/2, \pi/2]$

Finally the two dimensional histogram of the differential excitation and orientation component is the texture descriptor used in the segmentation process.

The Texture feature is expressed as

$$TF_{ij}^{k} = 2D\ Histogram\ [\xi(x_c), \theta(x_c)]_{ij} \quad k = L, a, b \tag{13}$$

5. IMAGE SEGMENTATION USING SRFCM AND MULTI CLASS SVM (PROPOSED METHOD)

5.1 Algorithm Steps

1. Color, texture and spatial feature cues are extracted from the image. Homogeneity model is used to extract color features and Local Binary Pattern for texture features. Additionally the spatial information is embedded in the feature vector to nullify the effect of noise and outliers.
2. SRFCM based clustering is applied on the feature space for selecting the training samples which are to be applied to the Multi class SVM classifier in next stage of segmentation.
3. Multi Class SVM training
The One-Against-All Multi Class SVM classifier is trained using samples obtained from preceding step. For image pixels in j^{th} cluster some pixels are chosen as training samples remaining are used as test samples.
4. Multi SVM pixel classification
Apply the test set to SVM for classifying new data. Combine test set and training set to obtain the final segmentation result.

5.2 Colour Feature Calculation

All the pixels in the image are marked as homogenous region pertaining to an object. The image segmentation task is now a classification problem and the process of segmentation is aimed at assigning a label to each individual pixel or an entire region based on homogeneity. Color features are extracted from the Lab color model, because color difference can be measured conveniently in *LAB* color space.

Let $C_{ij} = (C_{ij}^L, C_{ij}^a, C_{ij}^b)$ be the representation of color components in Lab colour model, corresponding to a pixel at the point (i,j) in an image. The colour feature CF_{ij}^k , k=L, a, b is derived from the color component C_{ij}^k , k=L, a, b as follows.

1.Prepare a window of size 3×3 for construction of pixel-level color feature.
2.Calculate pixel wise color feature CF_{ij}^k related to the color component C_{ij}^k, using pixel homogeneity, extracted from image, so that it reflects the uniformity of an image object. Pixel variance in terms of standard deviation and discontinuity in terms of edge detection, of color component C_{ij}^k are calculated. The product of normalized standard deviation and normalized edge discontinuity information is deducted from unity to obtain pixel homogeneity of the objects in the image.

Standard deviation and mean are defined as shown below. They are defined for each color feature C_{ij}^k(k=L,a,b) at location (i,j).

$$v_{ij}^k = \sqrt{\frac{1}{d^2} \sum_{m=i-\left(\frac{d-1}{2}\right)}^{i+\left(\frac{d-1}{2}\right)} \sum_{n=j-\left(\frac{d-1}{2}\right)}^{j+\left(\frac{d-1}{2}\right)} \left(c_{mn}^k - \mu_{ij}^k\right)^2} \quad (14)$$

and

$$\mu_{ij}^{k} = \frac{1}{d^{2}} \sum_{m=i-\left(\frac{d-1}{2}\right)}^{i+\left(\frac{d-1}{2}\right)} \sum_{n=j-\left(\frac{d-1}{2}\right)}^{j+\left(\frac{d-1}{2}\right)} c_{mn}^{k} \tag{15}$$

where μ_{ij}^{k} is mean of color component $c_{ij}^{k} (k = L, a, b)$

The edge variations are calculated in terms of the absolute value of first order derivative.

Let e_{ij}^{k} , k=L,a,b represent the gradient operator at a point (i,j) in the image. Gradient operator indicates the rate of change at any point in the image.

$$e_{ij}^{k} = \sqrt{\left(G_{x}^{k}\right)^{2} + \left(G_{y}^{k}\right)^{2}} \tag{16}$$

$\left(G_{x}^{k}\right)$ *and* $\left(G_{y}^{k}\right)$ are composed of gradient components in x and y dimensions .

$$V_{ij}^{k} = \frac{v_{ij}^{k}}{v_{\max}^{k}}, \quad E_{ij}^{k} = \frac{e_{ij}^{k}}{e_{\max}^{k}} \tag{17}$$

$$where \quad v_{\max}^{k} = \max\{ v_{ij}^{k} \}, \; e_{\max}^{k} = \max\{ e_{ij}^{k} \}, \; (0 \le i \le M-1, 0 \le j \le N-1), k = L, a, b$$

The colour feature is expressed as

$$CF_{ij}^{k} = H_{ij}^{k} = 1 - E_{ij}^{k} \times V_{ij}^{k}, \; (0 \le i \le M-1, 0 \le j \le N-1), \; k = L, a, b \tag{18}$$

5.3 Texture Feature Extraction by Power Law Descriptor

The proposed power law Descriptor is a robust local texture descriptor which is resistant to illumination changes.

The procedural steps for texture feature extraction is as follows

1) Convert the given image into a gray scale image.
2) Calculate the Differential excitation values of the gray scale image and obtain the Differential excitation image.
3) Calculate the orientation values of the gray scale image and obtain the orientation component at each pixel location.
4) Find the 2-D histogram of Differential excitation and orientation values at each pixel location in a 3X3 neighbourhood.
5) The resulting histogram at pixel location (i,j) forms the texture feature $TF_{i,j}$for SRFCM clustering algorithm.

6. PERFORMANCE MEASURES

The Performance measures proposed by Unni Krishnan et al., [16] which are Rand Index (RI), Variation of Information (VOI), Global Consistency Error (GCE), and Boundary Displacement

Error (BDE) are used in evaluating and comparing our segmentation results with benchmark algorithms.

6.1 Rand Index

The Rand index indicates the proportion of pixels which are in agreement between the Computed Segmentation (CS) and the Ground Truth (GT). [16].

The rand index ranges between 0 and 1, where 0 confirms that CS and GT do not have common attributes and 1 confirms that CS and GT are indistinguishable.

6.2Variation of Information

The variation of information (VOI) is a measure that specifies the variation between computed segmentation and ground Truth .The lower is the value of VOI, the better is the segmentation result.

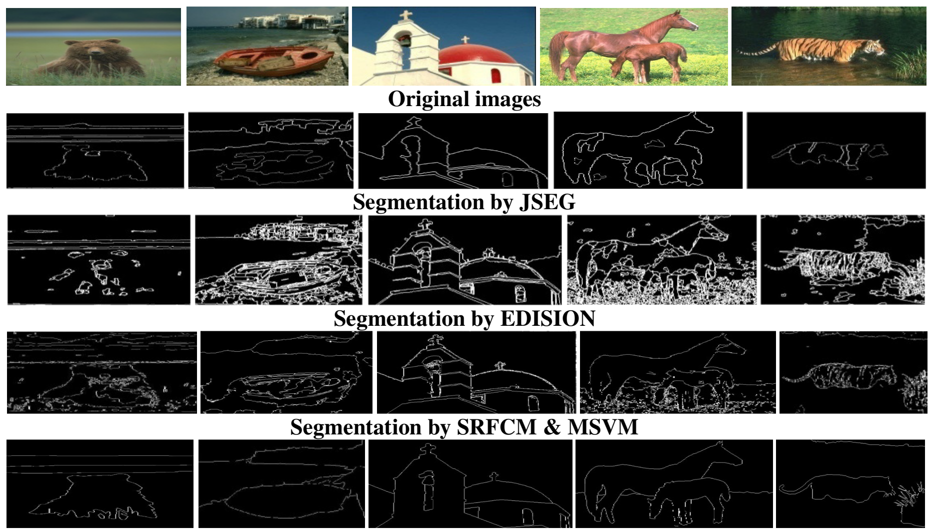
6.3 Global Consistency Error

Global consistency error is a measure of the limits to which the computed segmentation can be seen as transformation of Ground Truth towards Computed Segmentation. If one segment is proper subset of the other, then the pixel lies in an area of refinement, and the error should be zero. If there is no subset relationship, then the two regions overlap.GCE ranges between 0 and 1, where 0 signifies no error . Lower the value of GCE better is the segmentation result.

6.4 Boundary Displacement Error

The Boundary Displacement Error is a measure of the displacement error averaged between boundary pixels in computed segmentation and the nearest boundary pixels in the ground truth. BDE should be low for good segmentation.

7. RESULTS AND DISCUSSION



Human Labelled Segmentations (Ground Truths)

TABLE 1: RI& VOI

Image	RI			VOI		
	MSVM	JSEG	EDI	MSVM	JSEG	EDI
Bear	0.68	0.61	0.68	3.42	2.09	2.55
Boat	0.54	0.45	0.46	3.63	3.64	5.61
Church	0.72	0.45	0.67	2.70	3.03	3.06
Horse	0.60	0.45	0.46	3.30	3.34	5.33
Tiger	0.63	0.47	0.54	2.60	2.63	4.15

TABLE 2: GCE & BDE

Image	GCE			BDE		
	MSVM	JSEG	EDI	MSVM	JSEG	EDI
Bear	0.16	0.19	0.19	5.73	6.12	6.00
Boat	0.34	0.32	0.31	3.43	4.22	3.45
Church	0.18	0.21	0.19	6.87	10.24	8.74
Horse	0.24	0.25	0.24	5.32	7.29	5.86
Tiger	0.18	0.20	0.19	10.63	13.05	9.49

The experimental results show the performance comparison of the proposed algorithm, with state of the art JSEG algorithm [4] and EDISION [6] scheme. Five images with colour and texture variance from Berkeley Segmentation database are used for comparison. It can be observed that the JSEG algorithm could not identify the bush on the bottom right of the tiger image , and also the difference in colour between water and bush texture on the top portion of the image, where as the proposed algorithm could identify both, which claims the superiority of the proposed algorithm. The image segmentation by EDISION scheme for the same image is over segmented as can be seen in the results, further displaying the superiority of the proposed algorithm. The algorithms have been implemented in Matlab 2014a using P-IV processor system with 4GB RAM. The observations in the table shows that SRFCM & MSVM out performs the algorithms in [4] and [6] in terms of rand index for the presented images. It can be observed that the proposed algorithm exhibits better performance results for most of the images in terms of RI, VOI, GCE and BDE.

8. CONCLUSION

The developed approach is a robust technique which integrates the strengths of three soft computing techniques which viz., rough sets, soft sets and fuzzy sets. The results obtained from this hybridization are later applied to the well-known machine learning tool, Multi Class Support Vector Machine for segmentation. Extensive Experimentation has been done on a lot of images from Berkeley segmentation database which consists of 500 natural color images along with their Ground Truths. The effectiveness of proposed algorithm is demonstrated along with the comparison with other state of the art algorithms. The results shows that in soft rough fuzzy c-means clustering with Multi Class Support Vector Machine, inter cluster distance has been maximized and intra clustering distance has been minimized. Various performance metrics have been compared and the proposed algorithm shows better results compared with other existing benchmark algorithms. The proposed algorithm can also be extended to evolutionary algorithms which increases the clustering accuracy. The proposed algorithm can also be used with noisy color images.

REFERENCES

[1] Augustin, Thomas. "The problem of meaningfulness: Weber's law, Guilford's power law, and the near-miss-to-Weber's law." Mathematical Social Sciences57.1 (2009): 117-130.

[2] Cheng H.D, Jiang X.H, Sun Y, and Wang. J, "Colour Image Segmentation: Advances and prospects" *The Journal of Pattern Recognition Society* (2001)2259-2281.

[3] Chen, Jie, et al. "A robust descriptor based on weber's law." Computer Vision and Pattern Recognition, 2008. CVPR 2008. IEEE Conference on. IEEE, 2008.

[4] Christoudias.C.M, Georgescu. B., andMeer. P. "Synergism in low-level vision" in 16^{th} I.E.E.E conference, *Pattern Recognition*,vol.4,pp 150-155,IEEE,New York City,New York

[5] C. Cortes and V. Vapnik, "Support vector networks," *Mach. Learn.*,vol. 20, no. 3, pp.273–297, 1995.

[6] Deng.Y, Manjunath. B.S, "Unsupervised Segmentation of colour-Texture regions in Images and Video" IEEE Transactions on Pattern Analysis and Machine Intelligence VOL.23, NO.8, 2001.

[7] Dana E.I.Paul F.W,"Image Segmentation based on the integration of colour texture descriptors-A review" Elsevier,PatternRecognition,44 (2011) pp2479-2501.

[8] Freixenet. J, Munoz, Marti. J, Llado, Colour texture Segmentation by region boundary cooperation, Proceedings of the European Conference on Computer Vision 2(2004),250-261.

[9] Lingras P, and West C, "Interval set clustering of web users with rough k-means" Journal of intelligent information systems.Springer-2004.

[10] Majumdar. P, Samantha S.K , "On similarity measures of fuzzy soft sets" International journal of advanced soft computing applications 2011.

[11] Mitra. S, Banka. H, and Pedrycz, "Rough Fuzzy Collaborative clustering" IEEE Transactions on systems, MAN AND CYBERNETICS-VOL.36 NO.4 2006.

[12] Pradipta Maji, Sankar.K.Pal ,"A Hybrid Clustering Algorithm Using Rough and Fuzzy Sets",Fundamental Informaticae80(2007),475-496.

[13] Pawalak. Z, "Rough sets, Theoretical aspects of Reasoning about data". Dordrecht, The Netherlands: Kluwer, 1991.

[14] R.V.V.Krishna,S.Srinivas Kumar "Color Image Segmentation Using Soft Rough Fuzzy-C-Means Clustering and SMO Support Vector Machine" SIPIJ, AIRCCSE, Vol 6, No 5
[15] Rocio A. L-Morales, Raul E. S-Yanez,Victor A-R, and Fernando E. C, "Integration of color and texture cues in a rough set based segmentation method" SPIE Journal of Electronic Imaging 23(2).
[16] UnniKrishnan, pantofaru. C. and Hebert. M.," Towards objective evaluation of Image Segmentation Algorithms."IEEE Transactions on Pattern Analysis and Machine Intelligence" Vol 29,no 6,pp 929-944,June 2007..
[17] Wang X, Sun Y,"Colour- and texture-based image segmentation Algorithm", Machine Graphics & Vision 19 (1)-2010 3-18.
[18] Wang. L, "Support vector machines: theory and applications" Springer, Berlin 2005.
[19] Wang. X.Y, Wang. T, Juan B" Colour Image Segmentation using pixel wise support vector machine", Pattern Recognition 44 (2011) 777–787

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