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Color Image Segmentation Using Soft Rough Fuzzy-C-Means and Local Binary Pattern

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ABSTRACT

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 (MSVM) classifier for segmentation. Local Binary Pattern is used for extracting the textural features and L*a*b color model is used for obtaining the color features. The MSVM is trained using the samples obtained from a novel soft rough fuzzy c-means (SRFCM) clustering. The 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 is 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 local binary pattern (LBP) used for texture feature extraction has the advantage of being dealt in the spatial domain thereby reducing computational complexity.

KEYWORDS: **Segmentation, Classification, Clustering, Fuzzy Sets, Local Binary Pattern, Multi-Class SVM Rough Sets, Soft Sets, Texture.**

1 INTRODUCTION

COLOR image segmentation (Cheng et al. 2001) is a pre-processing step and used in numerous computer vision, image processing and related applications such as robotic vision, face recognition, content based image retrieval and medical imaging. Segmentation splits an image into distinct regions, such that pixels have a peak value of likeness index in each region and a peak value of disparity index between regions. Image properties such as gray-level, intensity, and texture (Arestah & Hung, 2007) are used to identify similar regions and resemblance of such properties is used to construct groups of regions (Cortes & Vapnik, 1995). Image segmentation algorithms can be categorized into four major groups, i.e., thresholding, clustering, edge based and region based segmentation.

Clustering techniques coupled with soft computing are more explored in recent time for color image segmentation as can be seen in the literature (Krishna & Kumar, 2015; Reddy & Prasad, 2010; Wang & Sun, 2010). Lingras & West (2004) proposed rough k-means (RKM) algorithm for use in clustering of internet users, which was later applied for image segmentation applications. Maji & Pal, 2007 proposed a rough fuzzy c-means (RFCM) algorithm for segmenting magnetic resonance (MR) images. The lower and upper approximation concepts of rough sets effectively overcome the vagueness and incompleteness in MR images. The fuzzy memberships overcome the problem of overlapping of classes.

Mushrif & Ray (2009) proposed color image segmentation using only color features. This work was improved by Morales et al. (2014) by integrating both texture and color features. The information of neighboring pixels is also considered in this method and the number of segments is automatically determined using the histon technique. The histon is a histogram which considers the lower and upper approximation concepts of rough sets. The major advantage of this technique is that the initialization of clusters is not required. The a and b channels of the Lab color space form the color features and a novel standard deviation map is used to extract the texture features.

Freixenet et al. (2004) proposed to integrate the information pertaining to region and boundary for

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color texture based segmentation. Experiments are conducted to obtain the initial seeds from the regions, by considering perceptual color and texture edges. Arasteh and Hung (2007) proposed color and texture segmentation using uniform LBP. Wang et al. (2011) applied the pixel-wise color and texture features to support vector machine (SVM) for classification, using the training samples obtained by preliminary clustering with FCM algorithm.

Nandy et al. (2015) proposed a novel color image segmentation scheme using the cuckoo search algorithm to optimize the cluster centres in the clustering algorithm used for color image segmentation. Euclidean sum of squares error (SSE) is used to evaluate the proposed algorithm against other evolutionary algorithms.

Bhandari et al. (2014) proposed multi-level thresholding algorithm using Otsu (Between Class Variance) and Kapur's method as fitness functions. The segmented images are obtained at 6, 8, 12 and 16 levels of thresholds for satellite images. The above mentioned fitness functions are optimized using Cuckoo search algorithm and then compared with differential evolution (DE), wind driven optimization (WDO) and particle swarm optimization (PSO) for performance analysis. Results are analyzed both qualitatively and quantitatively, based on the fitness values of obtained best solutions and four performance metrics namely PSNR, MSE, SSIM and FSIM indices. The performance of the considered four optimization algorithms, in terms of robustness is evaluated as CS > > DE > WBO (Kapurs Entropy).

In this paper, color image segmentation using SRFCM and LBP is presented. Initially, the color and texture cues of the color image, at pixel level are obtained from CIE L*a*b color model and LBP respectively. These features are then applied to SRFCM clustering algorithm. Later the MSVM classifier is trained by using samples obtained from SRFCM clustering. The image segmentation step is completed with trained MSVM. The color image information at pixel stage, together with classification capacity of classifier is the major strong point of this technique.

The organization of the paper is as follows. The preliminaries of the proposed novel 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 LBP are discussed in Section 4. In section 5 the proposed color image segmentation using SRFCM clustering and LBP is discussed. 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 (SRFCM) CLUSTERING ALGORITHM

SRFCM has its roots in the k-means algorithm proposed by J Mc Queen. This algorithm assigns objects to the nearest cluster by distance. Later 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 a certain degree of belongingness. RKM was proposed by Lingras & West (2004) by borrowing some of the concepts of the rough set theory (Pawlak, 1991), but not all core concepts. RFCM was proposed by Mitra et al. (2006) and they applied the algorithm to medical image segmentation problem. In this paper, SRFCM is proposed by applying concepts of soft sets to rough fuzzy framework. The major advantage of SRFCM is the computational simplicity in calculating the lower and upper approximation of the rough sets. The computation involves simple AND & OR operations.

2.1 Soft Sets

Let U be a universe of objects and E be the set of parameters $\in$ U. Let $P(U)$ denote the power set of U. A pair (F,E) is called a soft set over U, where F is a mapping given by

$$F : E \to P(U)$$

Table 1. Soft Set Representation of a universe

U/E	e_1	e_2	e_3
o_1	0	1	0
o_2	1	1	0
o_3	0	0	1
o_4	0	1	1
o_5	1	1	1
o_6	1	0	1

Let the universe of six elements $U = \{o_1, o_2, o_3, o_4, o_5, o_6\}$ be a universal set and $E = \{e_1, e_2, e_3\}$ be a set of parameters. If $A = \{e_1, e_3\} \subseteq E$, the soft set represented over U with respect to A is defined as:

$$F_A = \{(e_1, \{o_2, o_5, o_6\}), (e_3, \{o_3, o_4, o_5, o_6\})\} \tag{1}$$

All the entries in Table 1, are either 0 or 1. The Table 1 becomes a fuzzy soft set representation if all the entries of the table are in the unit interval [0, 1] The fuzzy Soft Set (Mushrif et al. 2006) is defined as

$$F(fs)_A = \left\{\left(e_1, \{o_2 / 0.3, o_5 / 0.3, o_6 / 0.3\}\right), \left(e_3, \{o_3 / 0.2, o_4 / 0.4, o_5 / 0.2, o_6 / 0.4\}\right)\right\} \tag{2}$$

2.2 Soft Fuzzy Rough Sets

Let U and W be two finite non-empty universes of discourse and R is a fuzzy relation from U to W. The triple (U,W,R) is called a generalized fuzzy approximation space. For any set $A \in F(W)$, the lower

($\underline{R}(A)$) and upper ($\overline{R}(A)$) approximations of A, with respect to the approximation space *(U,W,R)* are fuzzy sets of U, whose membership functions, for each $x \in U$, are defined, respectively, by

$$\overline{R}(A) = \vee_{y \in W} [R(x,y) \wedge A(y)], x \in U \tag{3}$$

$$\underline{R}(A) = \wedge_{y \in W} [(1 - R(x,y)) \vee A(y)], x \in U \tag{4}$$

The pair $\underline{R}(A)$ and $\overline{R}(A)$ is referred as a generalized fuzzy rough set, and $R: F(W) \to F(U)$ are referred as lower and upper generalized fuzzy rough approximation operators respectively.

2.3 Clustering using Soft Fuzzy Rough Sets

Let us consider that the set of objects $U = \{o_1, o_2, o_3, o_4, o_5, o_6\}$ are to be clustered into two groups. Let $E = \{c_1, c_2\}$ represent the set of randomly chosen cluster centres. Here the sets of objects and cluster centres can be defined as a fuzzy soft set as shown in the Table 2. The entries in the Table 2 represent the membership of the six objects in the two clusters represented by c_1 and c_2.

If the task is to find the objects that are more inclined towards c_1, then a new fuzzy soft subset A belonging to $P(E)$, which is an optimal and ideal case with respect to the given task is to be defined. Such ideal case is a subset of E which has the highest membership in c_1 and least membership in c_2, defined as $A = \{0.9, 0.1\}$.

Table 2. Soft rough fuzzy set representation of universe

U/E	c_1	c_2	$\underline{R}(A)$	$\overline{R}(A)$	choice value (σ_i)
o_1	0.8	0.2	0.8	0.8	1.6
o_2	0.3	0.7	0.3	0.3	0.6
o_3	0.6	0.4	0.6	0.6	1.2
o_4	0.3	0.7	0.3	0.3	0.6
o_5	0.4	0.6	0.4	0.1	0.5
o_6	0.1	0.9	0.1	0.1	0.2
A	0.9	0.1	-	-	-

The lower and upper approximation operators defined in equations (4) and (5) applied on o_1 w.r.t A is defined as

$$\overline{R}(A)(o_1) = \vee_{y \in E} [R(x,y) \wedge A(y)] \tag{5}$$

$$\underline{R}(A)(o_1) = \wedge_{y \in E} [(1 - R(x,y)) \vee A(y)] \tag{6}$$

For example the lower and upper approximation of object o_1 w.r.t. A are calculated using AND and OR operations

$$\overline{R}(A)(o_1) = 0.8$$
$$\underline{R}(A)(o_1) = 0.8$$

The rough lower approximation and upper approximation are two most close to the approximated set of the universe. Hence the choice value of each object is the sum of the lower and upper approximation operators.

$$\sigma_i = \underline{R}(A)(o_i) + \overline{R}(A)(o_i) \quad o_i \in U \tag{7}$$

A threshold of 0.8 on the choice value can be chosen for allocating the members to the first cluster. It can be observed that o_1 and o_3 in the above example have choice values greater than 0.8 and are assigned to the cluster c_1

If the task otherwise is to find the objects that are more inclined towards c_2, then a new fuzzy soft subset A belonging to $P(E)$, which is an optimal and ideal case with respect to the given task is to be defined. Such ideal case is a subset of E which has the highest membership in c_2 and least membership in c_1, defined as $A = \{0.1, 0.9\}$.

2.4 Algorithm for Soft Rough Fuzzy C Means Clustering

1. Assume k random initial cluster prototypes denoted by c_j , $j = 1$ to k.
2. Find the initial membership u_{ij} , $i=1 \ldots m, j=1 \ldots k$ between m data points and k clusters.
3. For each cluster, numbered 1 to k perform the following steps
   i. Find the best or maximum membership of objects in the desired cluster j, and the worst or minimum memberships of objects in each of the remaining $(k-1)$ clusters.
   ii. Denote the resulting k length vector A as the ideal or optimum normal decision object for finding the members of desired cluster j.
   iii. Compute the soft fuzzy rough lower and upper approximation of A using the equations
   $$\overline{R}(A)(x) = \vee_{y \in E} [R(x,y) \wedge A(y)], x \in U$$
   $$\underline{R}(A)(x) = \wedge_{y \in E} [(1 - R(x,y)) \vee A(y)], x \in U$$
   iv. The score corresponding to each object is calculated as the sum of lower and upper approximation.

$$\sigma_i = \underline{R}(A)(o_i) + \overline{R}(A)\,(o_i) \quad o_i \in U$$

v. Identify all the objects having a score higher than a pre-defined threshold, which upon experimentation is found to be 0.8. The set of all points with a score higher than 0.8 are considered as belonging to the positive region of the desired cluster j, $POS(c_j)$.

vi. Find the cluster centroid of the desired cluster j using the formula

$$M_j = \frac{\sum_{o_k \in POS(Cj)} u_{ik}^m o_k}{\sum_{o_k \in POS(Cj)} u_{ik}^m}$$

vii. Repeat steps (i) to (vi) for all the clusters and update the cluster centroids or prototypes of all the clusters.

Iterate and run the steps (1) - (3) until there is no considerable difference between the present and previous cluster centroids.

3 MULTI CLASS SUPPORT VECTOR MACHINE

3.1 Two Class SVM

SUPPORT Vector Machine (SVM) (Wang, 2005) is generally 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 the smallest distance between any two groups as depicted in Figure 1.

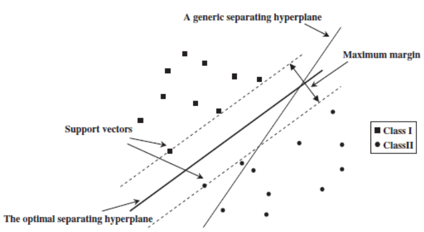


Figure 1. SVM classification (linear)

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

This method is also called one-against-rest classification (Cortes & Vapnik, 1995; Vapnik, 1998). To solve a classification problem in which a given set of data points is to be categorized into N classes, N number of binary SVM classifiers are created, where the 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. The 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. If the responses of two or more classes are indistinguishable, those points are marked as unclassified and are arbitrarily resolved. The multiclass method is advantageous in the sense that the number of binary classifiers constructed is only for the number of classes. But the limitation for this method is in the training phase, the memory necessity is very high and is proportional to the number of training samples.

4 LOCAL BINARY PATTERN

LBPs, proposed by Ojala et al. (1996) for texture description, belong to the class of non-parametric texture analysis, describing, the local texture of any image by thresholding each pixel in the image against its neighbors (Freixenet et al. 2004 ; Nanni et al. 2012). In contrast to other texture descriptors like Gabor filters and wavelets, which are transformation based, LBP is spatial based texture descriptor and is robust to illumination changes and computationally feasible.

$$\mathrm{LBP}_{\mathrm{P,R}} = \sum_{i=1}^{P} 2^{(i-1)} g(p(g_i) - p(g_c)) \qquad (8)$$

$$g(x) = \begin{cases} 1 & x \geq 0 \\ 0 & else \end{cases} \qquad (9)$$

where $p(g_c)$ denotes the gray value of the centre pixel, $p(g_i)$ denotes the gray value of its neighbors. P indicates the number of neighbors and R indicates the radius of the neighborhood.

3	6	4	10	2
7	18	30	2	6
3	6	10	19	3
4	18	4	3	10
2	3	4	3	2

(a)

1	1	0
0		1
1	0	0

(b)

	45	

(c)

Figure 2. (a) Gray Level values (b) Threshold values (c) Local Binary Pattern

5 IMAGE SEGMENTATION USING SRFCM AND LBP (PROPOSED METHOD)

IN this work the color image segmentation is performed on natural color images using the advantages of SRFCM and LBP.

5.1 Algorithm Steps

1) Color and texture cues are extracted from the image. Lab color model is used to extract color features and LBP for texture features respectively. The Color feature is a three length vector and the texture feature is a vector of length 28. Hence the integrated feature is a vector of length 31.
2) The number of clusters in the image is determined by using homogeneity histogram.
3) SRFCM based clustering is applied on the feature space. Post Clustering, one-third of the samples from each cluster are selected as training samples and remaining are test samples.
4) Multi Class SVM training

   The One-Against-All Multi Class SVM classifier is trained using samples obtained from preceding step.
5) Multi Class 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.

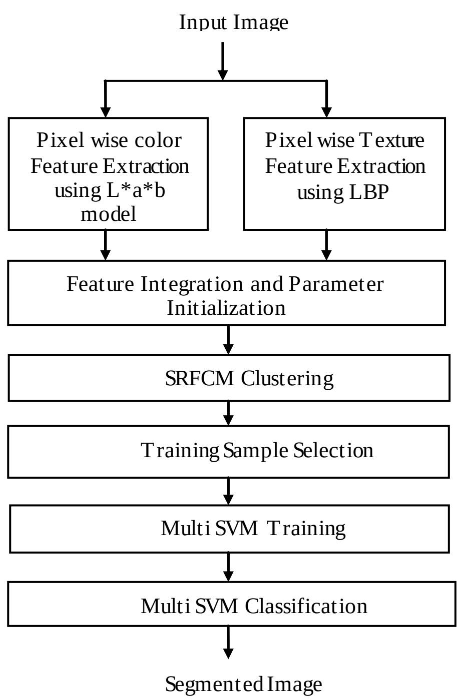


Figure 3. Flow chart of the proposed method

5.2 Color Feature Calculation

All the pixels in the image are marked as homogenous region pertaining to an object. 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 color model, corresponding to a pixel at the point (i,j) in an image. The color feature at the k^{th} pixel in the image is given by

$$C_{ij}^k = [C_{ij}^L, C_{ij}^a, C_{ij}^b] \tag{10}$$

where L* is lightness, a* and b* are the green–red and blue–yellow color components.

5.3 Texture Feature Extraction by LBP

The LBP [Huang et al. 2011] is a robust local texture descriptor which resists the illumination changes in the image.

The following steps are used for texture feature extraction using LBP

1) Convert the original images into a gray scale images.
2) Calculate the LBP values of the gray scale image (pixel wise) and the LBP image.
3) Identify the unique values in the gray LBP image.
4) Sort the unique LBP values in the decreasing order of magnitude.
5) Retain only the top 28 values of the sorted LBP, since these are the only frequently occurring LBP values.
6) Find the histogram of LBP values at each pixel location in a 5x5 neighbourhood.
7) The resulting histogram at pixel location (i,j) forms the texture feature $TF_{i,j}$ for SRFCM clustering algorithm. The texture feature is a vector of length 28.

5.4 Determination of cardinality of clusters using Homogeneity histogram

Color feature extraction through Lab model and texture feature extraction through LBP are thoroughly discussed in the previous section. The feature extraction step is followed by clustering step using SRFCM Clustering algorithm.

Clustering is an unsupervised method where the user is oblivious to the number of clusters present in the image. Wide of the mark selection of the number of clusters, results in erroneous cluster results. Cluster validation is an important step in the feature clustering process.

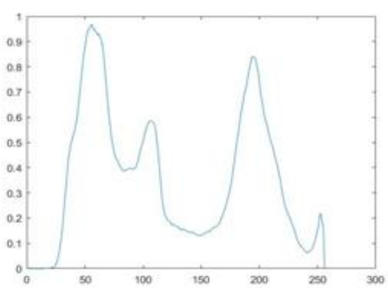
Cluster validity is to verify the clustering results using many defined cluster validation measures like Rand index, Jaccard coefficient, Dunn index, and Davies-bouldin index.

To obtain better and successful clustering results through the above mentioned validity measures, the user should have knowledge of the number of clusters in the image. This knowledge is obtained using homogeneity histogram,

The fundamental steps involved to obtain the homogeneity histogram are given as.

1) Convert the image from RGB to gray scale image.
2) Calculate the homogeneity value at each pixel location.
3) The homogeneity value lie between 0 and 1, where 0 indicates that corresponding pixel is an isolated point and 1 indicates that the neighbouring values similar to the corresponding pixel.
4) Add the homogeneity values associated with each gray level values
5) Plot the histogram between gray level and normalized homogeneity values
6) Find the significant peaks in the homogeneity histogram
7) The number of significant peaks is considered as the number of clusters as shown in Figure 4.

(a)



(b)

Figure 4. ClusterValidity (a)Original Image (b) Homogeneity histogram

6 PERFORMANCE MEASURES

THERE exists many segmentation evaluation measures in the literature viz sensitivity, specificity, Precision, Recall, ROC, F-measure, Local consistency Error, Global consistency Error etc (Dana & Paul, 2011). The Performance measures proposed by (Unni Krishnan et al. 2007; Maji & Pal, 2007) which are Rand Index (RI), Variation of Information (VOI), Global Consistency Error (GCE), Boundary Displacement Error (BDE) and Euclidian Sum of Squares Error (SSE) are used in evaluating and comparing our segmentation results with benchmark algorithms. The Rand Index indicates the segmentation accuracy and a higher value close to 1 is preferable for good segmentation. The remaining four performance measures indicate the error between segmentation and ground Truth. A low value of error is preferable for good segmentation

7 RESULTS AND DISCUSSION

THE experimental results show the performance comparison of the proposed algorithm, with state of the art algorithms JSEG algorithm (Deng & Manjunath, 2001), EDISON (Christoudias et al. 2002) and Cuckoo based segmentation (Nandy et al. 2015).

Deng and Manjunath (2001) proposed the well known J-SEGmentation (JSEG) algorithm, which combines both quantization process and clustering techniques for extraction of color-texture cues in images. The implementation is made available online by the authors(http://vision.ece.ucsb.edu/segmentation/jseg/software/).

Mean Shift clustering in sync with edge information was employed by Christoudias et al. (2002) in the work on edge detection and image segmentation (EDISON) system. The implementation of this algorithm is developed by Robust Image Understanding Laboratory at Rutgers University and available in the weblink. http://coew.rutgers.edu/riul/research/code/EDISON/doc overview.html).

Nandy et al.(2015) proposed a novel color image segmentation scheme using the cuckoo search algorithm to optimize the cluster centres in the clustering algorithm used for color image segmentation. Euclidean SSE is used to measure the accuracy of the proposed algorithm in comparison with other evolutionary algorithms.

Experiments are conducted on 300 natural color texture images from Berkeley segmentation Database. The obtained average performance measures for 300 images are tabulated in Table 4, which indicate that the proposed algorithm obtained the highest RI value of 0.73 and least values of GCE (0.16), VOI (2.16) , BDE (11.47) and SSE (5315.95). For visual inspection 5 randomly selected images from the database are selected and the segmentation results of JSEG (Deng & Manjunath, 2001), EDISON (Christoudias et al. 2002), Cuckoo based segmentation (Nandy et al. 2015) and the proposed algorithm are shown for comparison in Table 3.

It can be observed that in image 5 (Tiger), JSEG algorithm could not identify the bush on the bottom right portion, and the tail is partially segmented. The image segmentation by EDISON scheme for the same image is over segmented. The results of the proposed

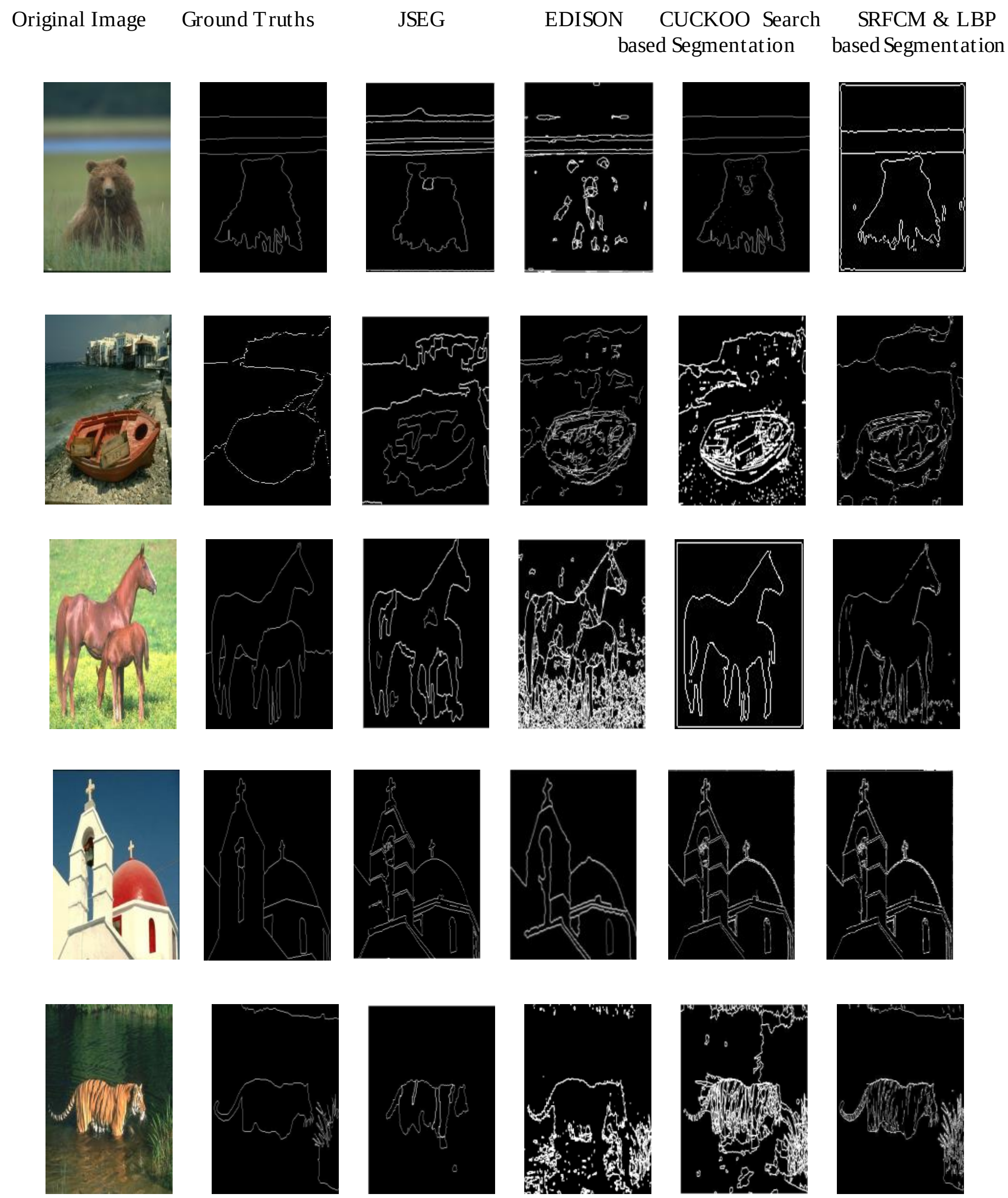


Figure 5. **Comparison of segmentation results obtained by the proposed algorithm SRFCM & LBP with state of the art algorithms**

Figure 6. **Segmentation labels obtained from the proposed method**

7.1 Tabular Representation

Table 3. Comparative analysis between SRFCM & LBP and state of the art algorithms, on five images selected from Berkeley segmentation database

Image	Method	RI	GCE	VOI	BDE	SSE
Image 1	JSEG	0.61	0.19	2.09	6.12	9871.54
	EDISON	0.68	0.19	2.55	6.00	8457.60
	Cuckoo Based	0.69	0.13	1.54	5.12	2457.71
	SRFCM & MSVM	**0.70**	**0.12**	**1.70**	**4.88**	**1504.12**
Image 2	JSEG	0.45	0.32	3.64	4.22	9948.48
	EDISON	0.46	0.31	5.61	3.45	8659.25
	Cuckoo Based	0.48	0.31	4.80	3.23	2257.48
	SRFCM & MSVM	**0.65**	**0.30**	**3.62**	**3.43**	**2014.45**
Image 3	JSEG	0.48	0.21	3.03	10.24	9874.14
	EDISON	0.67	0.19	3.06	8.74	9012.12
	Cuckoo Based	0.73	0.20	2.56	5.86	2104.79
	SRFCM & MSVM	**0.74**	**0.18**	**2.30**	**3.84**	**1514.21**
Image 4	JSEG	0.51	0.25	3.34	7.29	9435.21
	EDISON	0.46	0.24	5.33	5.86	8712.12
	Cuckoo Based	0.62	0.25	4.37	4.75	2012.91
	SRFCM & MSVM	**0.62**	**0.24**	**3.33**	**3.06**	**1912.13**
Image 5	JSEG	0.47	0.20	2.63	13.05	9012.31
	EDISON	0.54	0.19	4.15	9.49	7145.34
	Cuckoo Based	0.85	0.14	3.87	6.87	2015.41
	SRFCM & MSVM	**0.87**	**0.15**	**2.48**	**4.42**	**1812.24**

algorithm are more similar to the Ground Truth images in all cases which proves the efficacy of the proposed algorithm. The algorithms have been implemented in Matlab 2014a using P-IV processor system with 8GB RAM. It is observed from Table 4 that SRFCM & LBP produces better accuracy as compared to the other available methods in terms of Rand index for the presented images.

8 CONCLUSION

In this paper an improved method is proposed using the advantages of three soft computing techniques i.e., rough sets, soft sets and fuzzy sets. The results obtained from this hybridization have been applied to the well known machine learning tool, MSVM for segmentation. Extensive experimentation has been done on 300 images from Berkeley segmentation database which consists of 300 natural color texture images along with their ground truths. The effectiveness of the proposed algorithm has been demonstrated along with the comparison with other state of the art algorithms. The results shows that in SRFCM clustering & LBP with MSVM, inter cluster distance has been maximized and intra clustering distance has been minimized. The proposed algorithm can also be extended to evolutionary algorithms which increases the clustering accuracy.

9 DISCLOSURE STATEMENT

NO potential conflict of interest was reported by the authors.

Table 4. Average performance evaluation of the segmentation algorithms for 300 images from Berkeley segmentation database.

	Method	RI	GCE	VOI	BDE	SSE
300 Images (Berkeley Dataset)	JSEG	0.66	0.21	2.49	16.65	9018.42
	EDISON	0.65	0.27	2.54	13.73	11045.18
	Cuckoo Based	0.70	0.19	2.37	10.43	6740.81
	Proposed Algorithm (SRFCM & LBP)	**0.73**	**0.16**	**2.12**	**11.47**	**5315.95**

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