IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 11 May 2022, accepted 12 July 2022, date of publication 21 July 2022, date of current version 4 August 2022.
Digital Object Identifier 10.1109/ACCESS.2022.3192870

RESEARCH ARTICLE

A Unified Approach for Representing Outdoor Scenes

TILOTTAMA GOSWAMI[1], (Senior Member, IEEE), ARUN AGARWAL[2], (Senior Member, IEEE), AND CHILLARIGE RAGHAVENDRA RAO[2]
[1]Department of Artificial Intelligence, Anurag University, Hyderabad, Telangana 500088, India
[2]School of Computer and Information Sciences, University of Hyderabad, Hyderabad, Telangana 500046, India

Corresponding author: Tilottama Goswami (tilottama.goswami@ieee.org)

This work was supported in part by the University Grants Commission—Basic Scientific Research Fellowship Scheme under Government of India; in part by the Indian National Centre for Ocean Information Services under the Ministry of Earth Sciences, Government of India; and in part by the Basic Boarding and Lodging Scholarship from the University of Hyderabad.

ABSTRACT Generalized image understanding of natural outdoor images is fundamentally a bottom-up approach guided by the data and information received from the digital input images. The importance of intermediate image representation that aids generalized image understanding, inspired the proposed a unified approach for providing a new meaningful and objective representation of a given outdoor scene. The proposed unified framework provides a novel set of string and semantic codes, based on inferential statistical data obtained from segments characterization and blocks characterization of natural outdoor images. The framework acts as an analytical tool that can categorize the input images into four types based on the inferential statistical representation - 1) Object-based image, 2) Heterogeneous color based texture image, 3) Homogeneous color based texture image, 4) Pure toned image. The proposed string and semantic code characterization is also rotation and scale variant. Such a representation is simple, unsupervised, computationally inexpensive and also places minimal demand on the storage. Later for a higher-level image analysis and understanding the proposed unified approach can provide focused interaction between the above intermediate representation and domain scene knowledge for object detection, classification, or recognition.

INDEX TERMS Image segmentation, texture characterization, image analysis, image representation, image blocks, string code.

I. INTRODUCTION

Computer vision and recognition systems need sufficient flexibility for processing the uncertainties coming from any of the low levels of image processing such as image segmentation, and also should be able to retain as much information as possible at each level. An abundance of various automated and semi-automated techniques can be found in literature, that cater to great variety of image analysis and image understanding applications. From the survey, it is evident that in spite of abundance in segmentation algorithms, not a single algorithm can segment all images to a satisfactory level, especially in cases of natural outdoor scenes having large variation in color-texture mix. Till date natural outdoor images is still an open research problem [1]–[8]. Sophisticated/complex algorithms prove to be useful for highly textured images, but at the same time poses to be an overkill for simple tonal/color images. Semantic segmentation or automated image segmentation is performed mostly using modern deep learning techniques based on representation learning [9], [10]. Image representation has been captured as one of main facets in Multi Faceted Image Segmentation Taxonomy [11], in which the authors have also mentioned some of the recent contributions regarding this. Good quality of image representation is good alternative to region detectors as rich metadata. There is a need of a unified approach combining the efforts of low-level segmentation and mid-level characterization process, for compiling rich and quality

The associate editor coordinating the review of this manuscript and approving it for publication was Dost Muhammad Khan.

Paper	Scope	Requirement Specification			Control Specification		Feature		Representation	Segmentation Approach [Image Domain Based Techniques]
		Domain	Source	Precision	Driven By	User Interaction	Type	Space	Transformation and Data Structure	
Jun Yang et.al. (2007), [13]	High Level	Broadcast news video Classification	Outdoor Indoor scenes, TRECVID and PASCAL	Medium	Knowledge Driven (Top Down)	Supervised	Pixel, Visual-Word	Color-Texture	Bag-of-visual-word Dictionary, Keypoint Descriptors, Image Patches	Support Vector Machines (SVM)
P. Arbeláez et. al. (2014), [12]	High Level	General, Object Candidate Generation	Natural images BSD,VOC 2012	Medium	Data Driven (Bottom Up)	Unsupervised	Size and location, Shape, Contours	Brightness, Color, Texture	Ultrametric Contour Map (UCM)	Hierarchical Image Segmentation
Evan Shelhamer et. al. (2017), [10]	High Level	Application Specific, Semantic Categories	Outdoor images, Categorical	Medium	Knowledge Driven (Top Down)	Supervised	Automated Features	Color Location	Fully Convolutional Network	Deep Classification Nets
Fekri-Ershad, Sh., et. al. (2017), [14]	High Level	General Texture Classification	Outex TC_00013, Vistex, KTH-TIPS-2a	High Classification Accuracy	Knowledge Driven (Top Down)	Supervised	Pixel	Color-Texture	Hybrid color local binary patterns	No segmentation used.
Fekri-Ershad, Sh., et. al. (2017), [15]	High Level	General Texture Classification	Outex TC_00013, Vistex, KTH-TIPS-2a	High Classification Accuracy	Knowledge Driven (Top Down)	Supervised	Pixel	Color-Texture	Hybrid color local binary patterns and Kullback-Leiber Divergence	No Segmentation used
Sultan Daud Khan et. al. (2021), [16]	High Level	Application Specific, Land Cover Semantic Segmentation	High-Spatial Resolution Satellite Images	Medium	Knowledge Driven (Top Down)	Supervised	Pixel	Multi scale color texture features	Convolutional Layers	Hybrid Network combining two Deep Learning Models

FIGURE 1. **MFHIST based organization of related research work.**

metadata that can build appropriate knowledge representation about the image for further assisting high level image understanding. By doing so, one can avoid making a crisp bad segmentation at an earlier stage, and rather pass the knowledge gathered, through the higher processing levels. For this purpose, the authors propose to build a unified framework for unsupervised segmentation and characterization for natural outdoor images. A blind clustering based machine learning segmentation approach may lead to meaningless segments, mostly in case of natural outdoor images. A multi-step learning approach is expected to give effective and meaningful segments.

One such unified approach can be generating and compiling useful metadata for images to be segmented. The framework proposes image types as one of the useful metadata, based on statistical analysis of color-texture variations. The paper is arranged in the following manner: Section II discusses the related research work. Section III provides proposed framework and its components. Section IV and Section V focuses on the Segmentation and Block approaches with metadata representations respectively. Section VI demonstrates the texture characterization of segments and blocks generated from the image. Section VII demonstrates the results and observations obtained from the framework. Section VIII summarizes and concludes with future work.

II. RELATED WORK

The proposed methodology is designed keeping various high level characteristics of image - types of image such as textured/tonal, image segmentation and image representation. The proposed framework represents an outdoor scene representation primarily based on color texture segmentation. The approach is generalized using hand crafted features and follows bottom up approach, ie data driven.

The appropriate visual and non-visual image representations still remains an open challenge. The image representations is one of the fundamental building block for image understanding in computer vision applications. Recent trends show a shift from directly using the standard conventional hand featured representations towards learning representations automatically from training data, using Deep convolutional neural networks [10]for high level semantic segmentation. The authors in [10] use Fully Convolutional Networks with supervised pre-training model, which trains on specific categories dataset, require thousands of

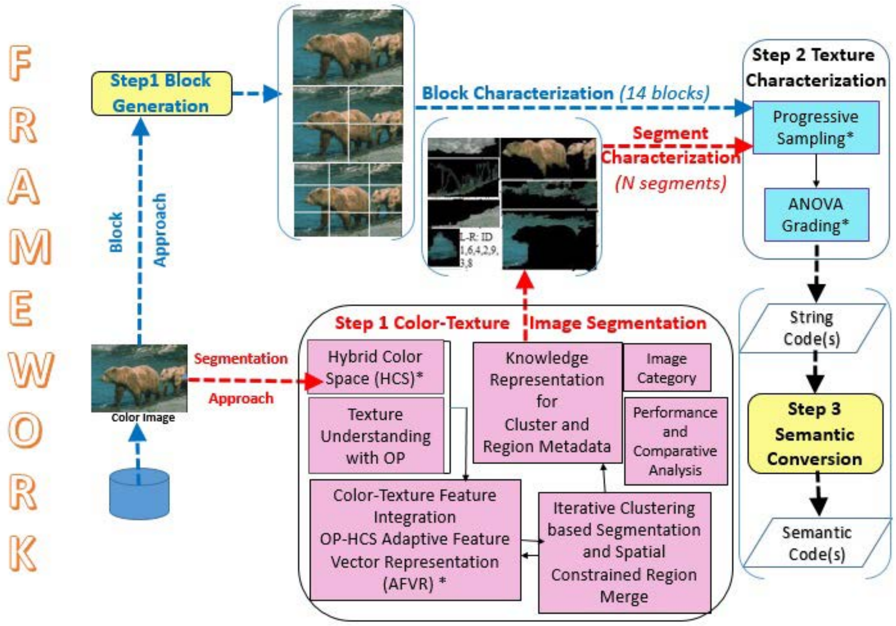


FIGURE 2. **Framework for natural scene representation.**

training images. The model fine tunes and extends classification nets to segmentation task. The representations used in [12] has single-scale and multi-scale configurations for object segmentation and further object recognition. The representation used in this paper is Ultrametric Contour Map (UCM). Bag-of-visual-word representation is in recent use for CBIR and image annotation as mentioned in [13]. The authors in [14] and [15] use joint color texture representation called Hybrid Color Local Binary Patterns (HCLBP) and four supervised machine learning classification algorithms for texture analysis and texture classification. Some of the very recent work in this problem area is [16] based on deep learning.

The Figure 1 depicts the comparison of the above mentioned state of art related works using the Multi-Faceted Hierarchical Image Segmentation Taxonomy (MFHIST) [11]. This will help in proper categorization and comparative study of the algorithms depending on the six facets presented in hierarchical manner - scope, requirement, control, feature, image representation and approach specifications.

The proposed framework is lightweight, generalized, unsupervised computationally inexpensive method of knowledge representation for any given color texture outdoor scene image. While present trend is using deep learning techniques, which may not be apt for image representation of any outdoor scene. Outdoor scenes are heterogeneous and have high variation, this may demand in huge volume of training set. The authors have come up with unified framework of representation of both textured and tonal images. The details of the proposed methodology is put forward in the next section.

III. PROPOSED FRAMEWORK AND ITS COMPONENTS

A framework is often a structure indicating the interrelation between its components. The framework usually supports a specific objective, and serves as a guide to make use of the components as required and applicable from case to case. The authors have developed a conceptual framework, which acts as an analytical tool for color-texture image segmentation and image characterization, which can work with several tonal-texture variations present in natural outdoor images. A schematic diagram of the framework has been presented in Figure 2 for a BSD image - 100075.jpg referred from dataset [17].

The proposed framework makes an attempt to achieve low and mid level image analysis goals under one umbrella having two components:

1 Segmentation approach: Color-Texture Image Segmentation and Segments Characterization. Image Type metadata is also the by-product
2 Block approach: Block Generation and Blocks Characterization

The paper adapts the methodology for the color-texture image segmentation from [18]. The methodology for texture characterization of outdoor natural images has been adapted from [19]. Both the above mentioned methodologies will be discussed in brief in forthcoming sections III and IV respectively for the sake of readers continuity. This paper proposes the two major output of the framework - segment characterization and block characterization as novel intermediate image representation for natural outdoor images. More advanced methodologies can then be applied, for higher level analysis in future.

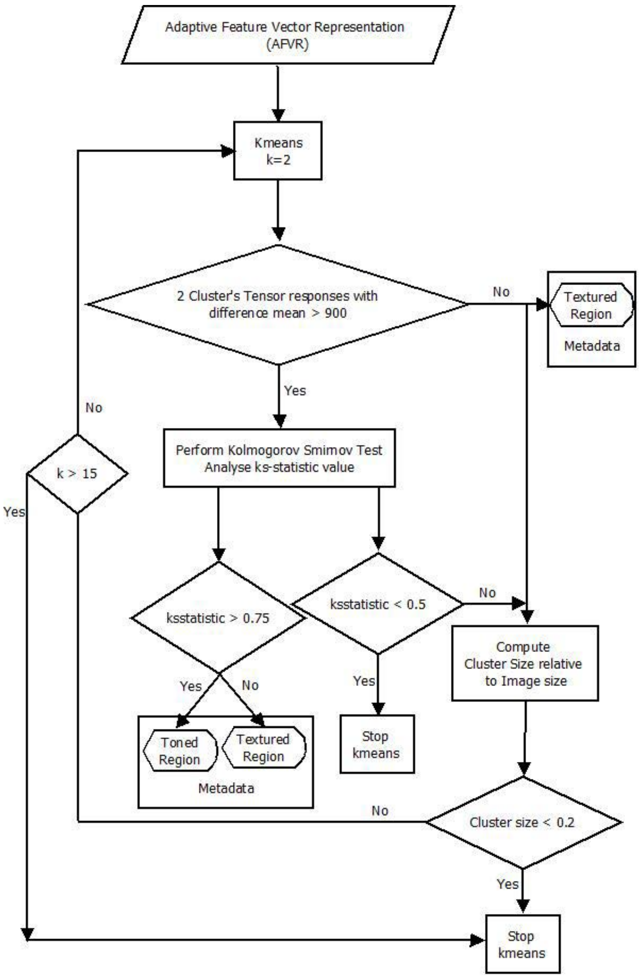
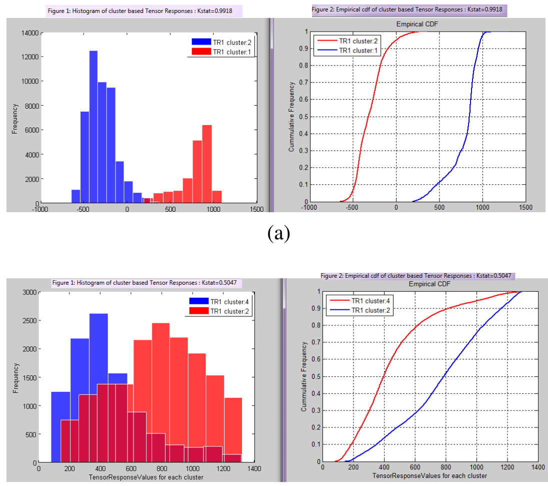


FIGURE 3. Flowchart of OP-HCS iterative segmentation generating metadata.



(a)

(b)

FIGURE 4. Quantitative cluster similarity assessment (Dark Red colored region marks overlap) (a) Non-overlapping supports, KS Statistic = 0.9918 (b) Overlapping supports, KS Statistic = 0.5047.

Segmentation approach has two sub-components in sequence - unsupervised segmentation and generation of texture characterization codes. The block approach will go through block generation and then generation of texture characterization codes. The output of the framework, thus is a collection of string and semantic codes and is referred as the image representation.

IV. SEGMENTATION APPROACH AND METADATA GENERATION

A natural outdoor image when given as an input to the framework, is 1) segmented into objects or regions, which can be further processed for 2) texture characterization. The authors adapt the segmentation methodology proposed in [18], a region based segmentation technique to divide the image into separate regions based on color-texture homogeneity. Figure 3 depicts the flowchart of OP-HCS Iterative Segmentation generating Metadata. The discriminative features of this segmentation include adaptive feature vector representation (AFVR), iterative K-means based on cluster similarity test on histogram and two sample K-S Statistic test is shown in the flowchart. The quantitative cluster similarity assessment between local color-texture distributions is evaluated only for the clusters whose tensor responses have non-overlapping support using the two sample Kolmogorov-Smirnov (KS Test) metric. When the clusters have different feature characteristics, they have non-overlapping support and the test statistic difference is near to one as shown in Figure 4 a), KS Statistic =0.9918. With KS Statistic greater than 75 percent, the region is labelled with toned region. This segmentation associates with metadata generated with each segmented region as toned or textured based on the sequence of K Statistics, stopping criteria used while segmentation process. Textured segments have KS Statistic near or less than 0.5 value as shown in Figure 4 b). It is not considered as a good candidate for further segmentation as they are found similar in color and texture. This condition stops further processing of K-means (max 15 times allowed), which makes the segmentation process adaptive. The iterative clustering is based on Orthogonal Polynomial(of order 3 - OP3 or order 5 - OP5) and Hybrid Color Space feature space (as mentioned in [18]) has been referred in this paper as OP-HCS and is discussed in next paragraph. The flowchart for OP-HCS iterative segmentation generates image region type metadata as textured/tonal. Hybrid Color Space selection is based on multiple color spaces such as L*a*b*, HSV, CMYK. The input image is in RGB color space which does not correspond to human sensor topology as humans do not perceive color as a combination of tri-stimulus values. The motivation behind proposing the hybrid color space has couple of aspects – color purity and color space with highest number of dimensions. The color purity is obtained from chrominance dominant color components of perceptual spaces L*a*b* and HSV. The four chromatic components used are – a*,b*, hue H and saturation S. CMYK, a subtractive color space is the only color space represented in four higher dimensions.

The method considered for conversion from RGB to CMYK is a non-linear process unlike the conventional simpler version of conversion.

Some of the orthogonal polynomial operators resemble edge operators. All possible contrasting filters are adapted through OP. No prior knowledge about number of clusters is known, hence an intelligent stopping criteria is employed based on Kolmogrov-Smirnov Test (KS-Test), region size (less than or equal to 20 percent) and number of clusters (eg 15) as threshold. The experimental setup and parameters for segmentation are taken from the paper [18]. These parameters balances the segmentation under-segmentation and over-segmentation.

The proposed segmentation methodology has been compared to eleven state of art segmentation techniques using four performance metrics - Probability Rand Index(higher the better), Border Displacement Error (BDE), Variation of Information (VoI), Global Consistency Error (GCE) - all three, the lower value the better. The dataset used for comparison is BSD Dataset consisting of 300 outdoor natural scenes [17]. The comparison graph is shown in the following Figure 5. Abbreviations of the methods mentioned in the graph can be elaborated as follows: MDS-Multi-Dimensional Scaling, CTM - Compression based Texture Merging, NTP - Normalized Tree Partitioning, GBIS - Graph Based Image Segmentation, SC - Spectral Clustering, GBMS - Gaussian Blurring Mean Shift, NCuts - Normalized Cuts, JND - Just Noticeable Difference histogram, DCM- Dirichlet Compound Multinomial distribution, HMC - Hierarchical graph-based Markovian Clustering, MIS - Modal Image Segmentation. The proposed OP3-HCS is ranked fifth for PRI and BDE metrics as shown in Figure 5(a) and (b) respectively. OP3-HCS ranked third for VoI and eighth for GCE metric as shown in Figure 5(c) and (d) respectively. For details about each of the above mentioned eleven segmentation methodologies, readers area advised to refer [20]. Metrics are designed to elicit the information of subjective nature. The proposed method has not ranked the best as it has many objectives apart from segmentation, such as identifying the tonal and highly textured images and their representation at a later stage.

A. REGION DESCRIPTIVE STATISTICAL METADATA

Each region obtained after post processing is also associated with set of statistical metadata. The region information basically consists of descriptive statistics - first order statistics (mean intensity) and second order statistics (GLCM properties). Gray level co-occurrence matrix mentioned by ([22]), is one of the early methods used for global description of textural images. Once GLCM is created, several statistics about the texture of the image is computed such as contrast, homogeneity, energy, correlation, and mean intensity. A window size of 11×11 has been considered on grayscale intensity values of the image for GLCM computation. These measures serve as a metadata for the regions produced after object segmentation and region merge. and is illustrated in Figure 6.

Once GLCM is created, one can derive several statistics about the texture of the image. The statistics considered are listed below. a) Contrast: gives a measure of the intensity difference computed between any pixel and its neighbor considered over the image as a whole or segmented region. Contrast is zero for a tonal image, with constant intensity values. b) Correlation: gives a measure as how a pixel is correlated to its neighbor over the image. Correlation value is 1 or -1 for a fully positively or negatively correlated image and is 'Not a Number' for a tonal image with constant intensity values. c) Energy: gives the sum of squared elements in the GLCM. Energy value is 1 for a single colored image. d) Homogeneity: gives a value that measures the closeness of the distribution of elements in the GLCM to the diagonal GLCM. Homogeneity measures one for a diagonal GLCM.

GLCM has its basic limitation of capturing textural information from only grey-scale images across different orientations. To perform textural knowledge representation for a color image and its regions, the paper proposes 2-way and 3-way Anova to capture the local variability of color information as well. This is taken up in the Section V - color image texture characterization based on simple perceptual variations in row, column or diagonal specific.

This is taken up in the Section V - color image texture characterization based on simple perceptual variations in row, column or diagonal specific.

B. IMAGE TYPES AS METADATA

Let us digress briefly, and discuss difficulty in segmenting natural outdoor images before proceeding further with iterative region splitting procedure. The natural image object segmentation pose to be quite challenging due to the intrinsic characteristics found in the images in terms of various ratio of color and texture mix. The image contains a single object or many different objects which can vary from being tonal to complex color-textured as illustrated in Figure 7. In tonal images, the presence of single object or multiple objects are very prominent due to certain factors such as large object size, the presence of salient contrast in color (as can be seen in Figure 7a)) or color-texture variation (as seen in Figure 7b,c). This makes the object detection demonstrable to certain extent.

The poorly performed segmented images usually consist of homogeneous color based textured images, as camouflage makes it difficult to segment the object in totality as shown in Figure 8(b,e). Segmentation also becomes difficult in case of heterogeneous color based texture as shown in Figure 8(c,f), where perceptual grouping becomes a challenge when segmented, and outputs large number of meaningless regions. A pure toned image also needs to be identified before going for segmentation process. Such type of images is single coloured, which cannot be segmented into objects as shown in Figure 8(a,d).

The BSD dataset is meant for object segmentation in images catering to outdoor natural scenes as mentioned by [22]. The unsupervised algorithm is tested on the BSD

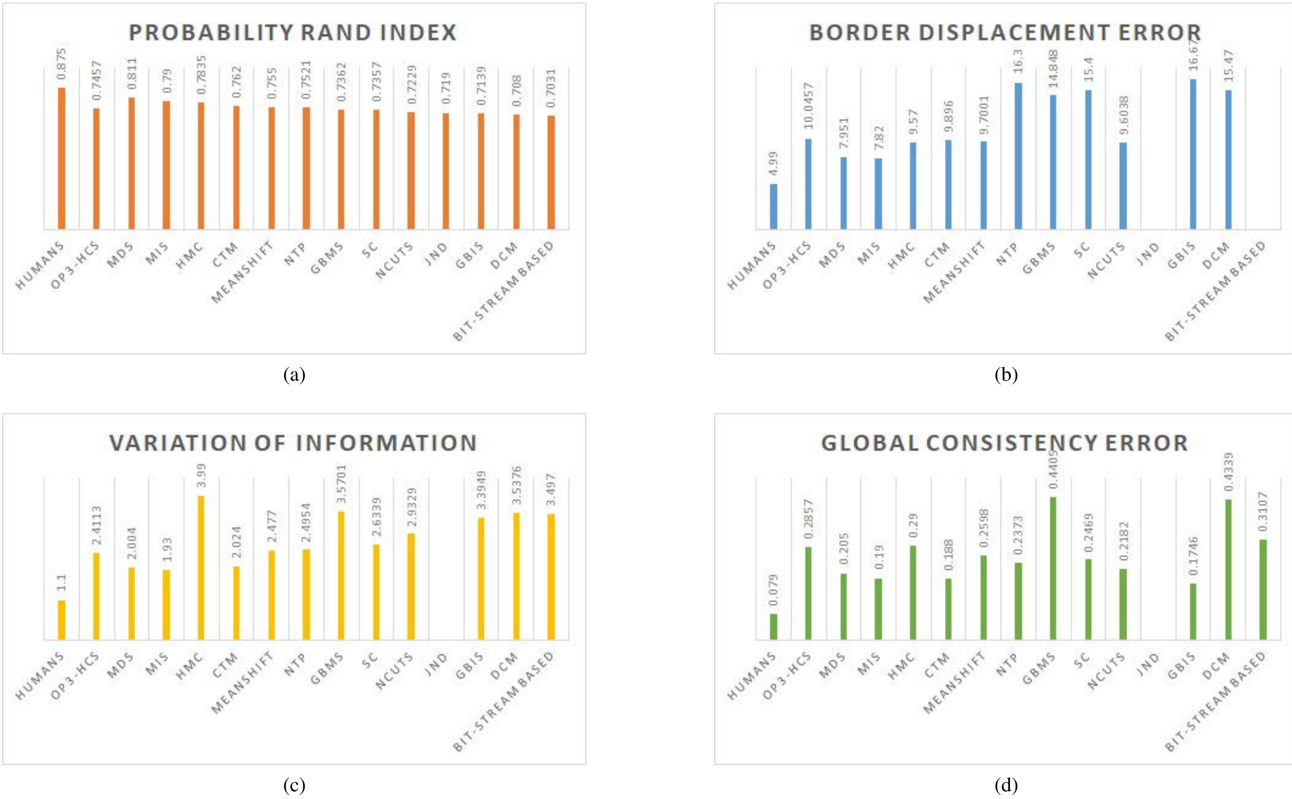


FIGURE 5. Comparative study of proposed OP3-HCS with other methods [20].

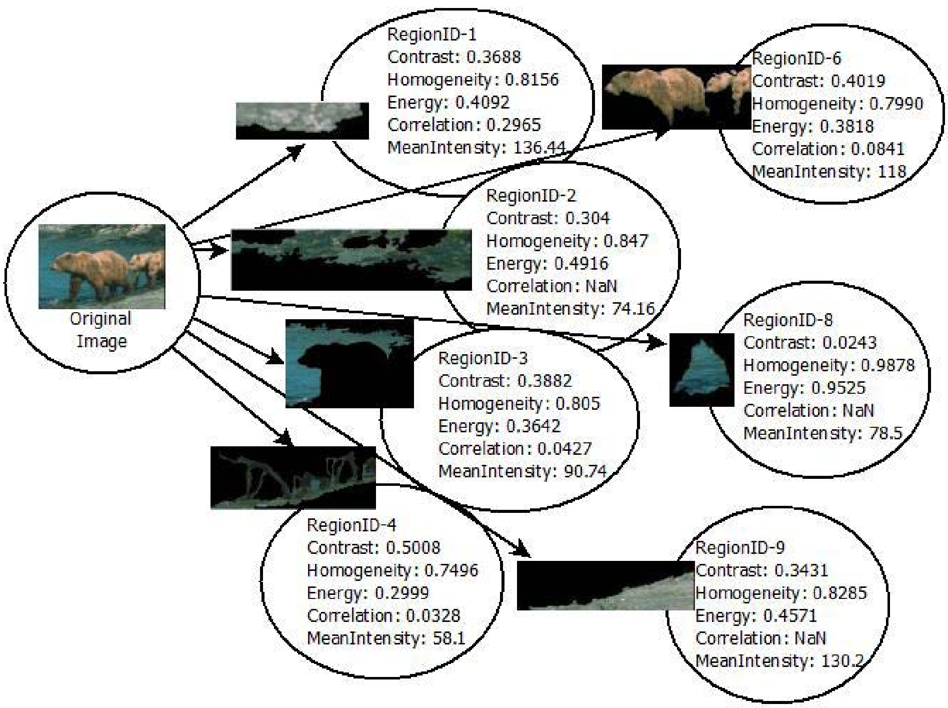


FIGURE 6. Region metadata based on descriptive statistics: First order statistics - Mean of gray scale intensity, second order statistics - 4 GLCM measures for 11 × 11 sub-region.

for quantitative evaluation and comparisons. The authors do not want to limit the work to only BSD, and aim to cater to an overall variations of color-texture present in the nature irrespective of whether an object is present or not. Hence this paper has considered various other datasets such as Vistex textured images, Corel categorical (food, building) images,

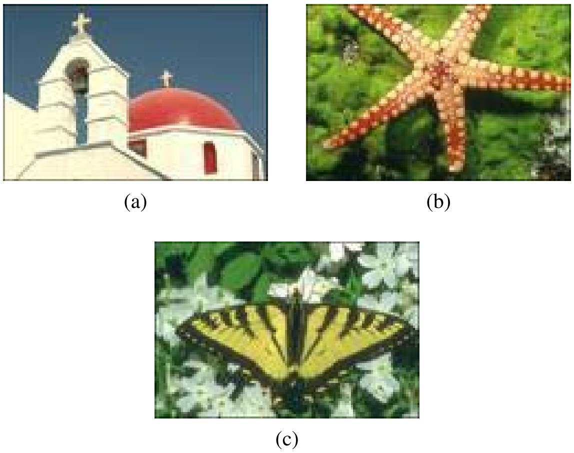


FIGURE 7. Natural images for object segmentation.

Prague (mosaic textured images) and found the difficult segmentation scenarios. Some border cases have also been tested such as pure toned colors. Researchers deploying segmentation techniques mostly assume the image to have objects. Sometimes meaningless pseudo segments are obtained when the technique fails in perceptual grouping. One can overcome, such type of failures by setting some informative flags to the image as metadata, whether to subject it to segmentation or not. For this purpose, the authors have developed a schematic methodology to categorize the images into types, which serves the purpose of image metadata as well. In all, the paper has identified four types of images. The OP-HCS segmentation algorithm implements in identifying such images which are as follows.

1) Type-1: Object-based Image: Image can be segmented into meaningful objects with prominent color-texture variations.
2) Type-2: Heterogeneous color based texture Image: Image can be segmented into large number of small regions, where perceptual grouping is a challenge.
3) Type-3: Homogeneous color based texture Image: Image is not having many color variations. If there is any object present, it poses a camouflage problem with the similar shaded background.
4) Type-4: Pure toned Image: Single coloured image, which cannot be segmented into objects.

Out of the four image types listed above, segmentation is not possible for three image types except the *objects-based image* type. OP-HCS segmentation methodology is able to find the object (snake) from similar shaded homogeneous color based texture image 196073.jpg (Figure 8(b)). Once it is able to extract a prominent region, it labels the image as object-based image. But in case of Vistex grass image (Figure 8(e)), the category is correctly identified as homogeneous color based texture. The paper further aims to build some knowledge about these images using block approach as mentioned in the next section. The block approach provides an added advantage by providing block level metadata to appropriate higher order complex algorithms for image understanding. Hence, such images once identified needs to be characterized using texture characterization for pattern recognition, which will be discussed in the Section V. In case the segments are obtained from the *objects-based image* type; the segmented regions can also be further processed for texture characterization based on statistical learning as mentioned in Section V.

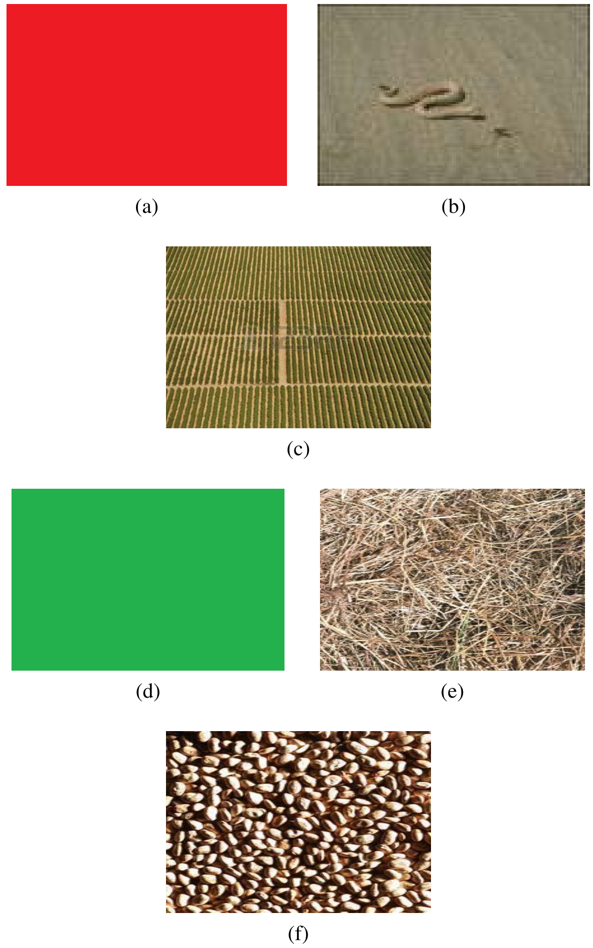


FIGURE 8. (a,d) Pure toned images, (b,e) Homogeneous color based texture, (c,f) Heterogeneous color based texture.

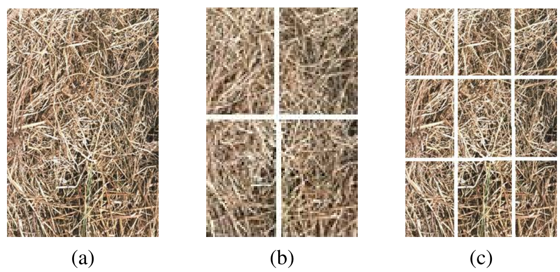


FIGURE 9. Vistex dataset - Grass image a) Block-1 b) Block-4 c) Block-9.

V. BLOCK APPROACH

Block approach, a systematic way of texture analysis is also implemented in addition to segmentation approach. This has been adapted from [19] for its two benefits - 1) capturing

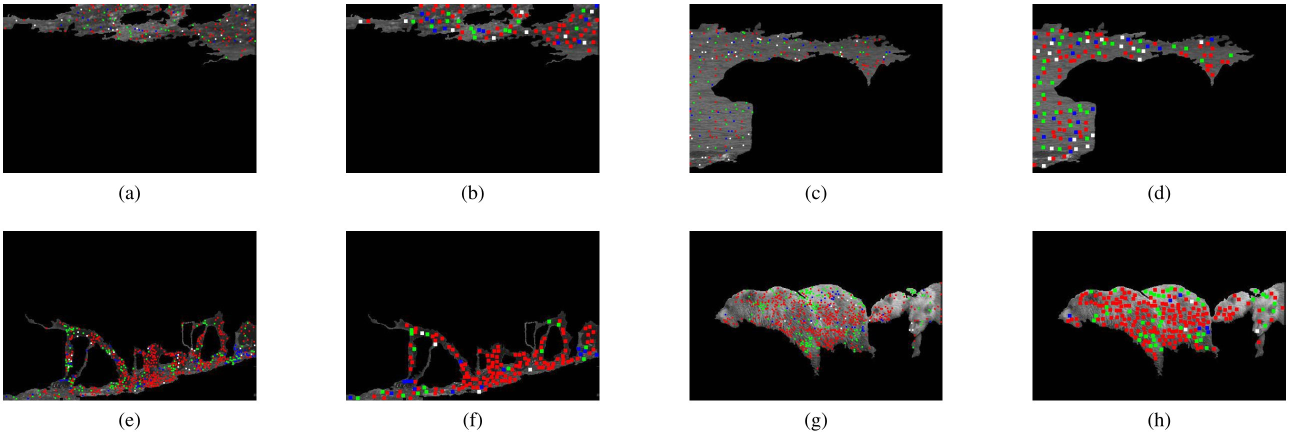


FIGURE 10. Each set of images contain sampling of segmented region with window size 3 and 7. Each image is of size 321 × 481.

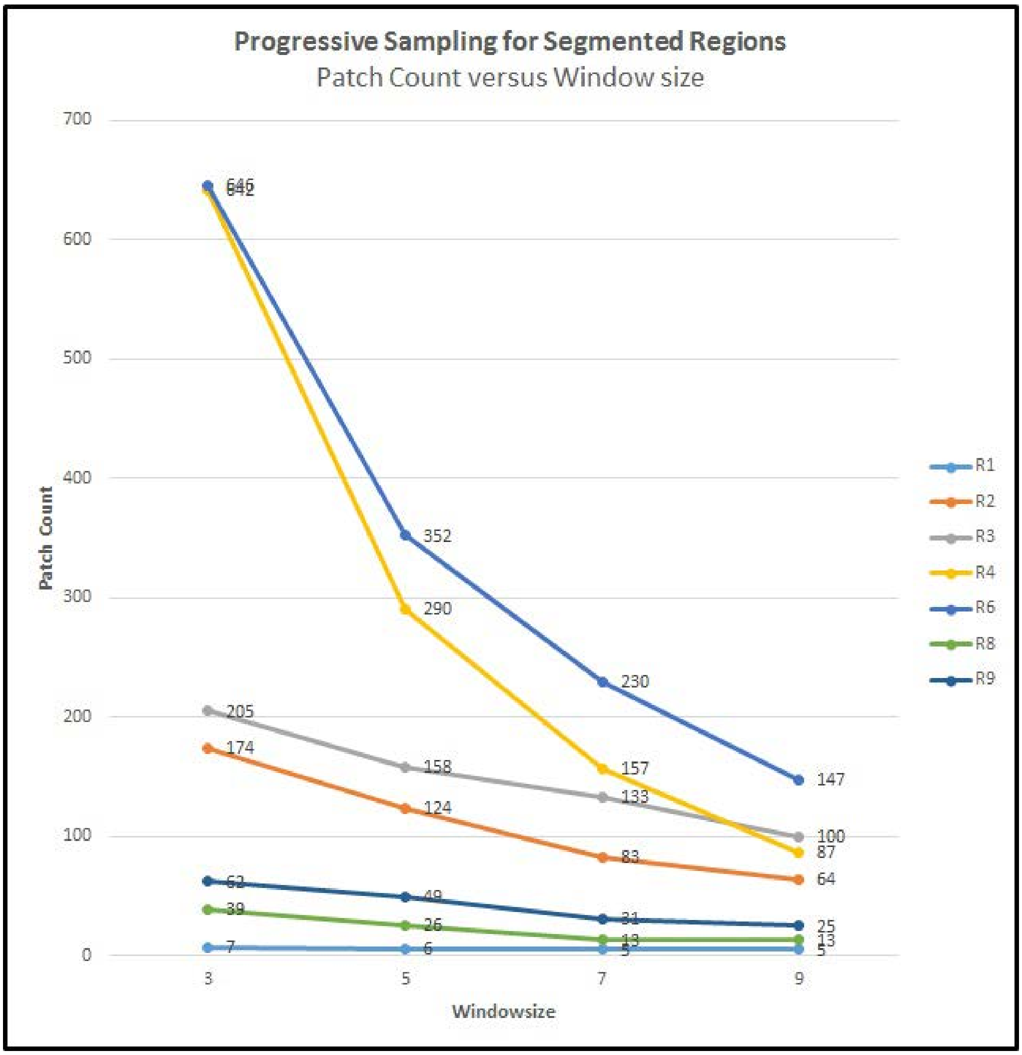


FIGURE 11. Progressive sampling for segmented regions: Patch count decreases with increase in window size.

hierarchical texture characterization and 2) capturing repetitive patterns in highly textured images. At first level, the whole image is considered as one block. Further, the block approach partitions an image into two block sets - collection of 4 and 9. This can also be extended further to smaller blocks if required.

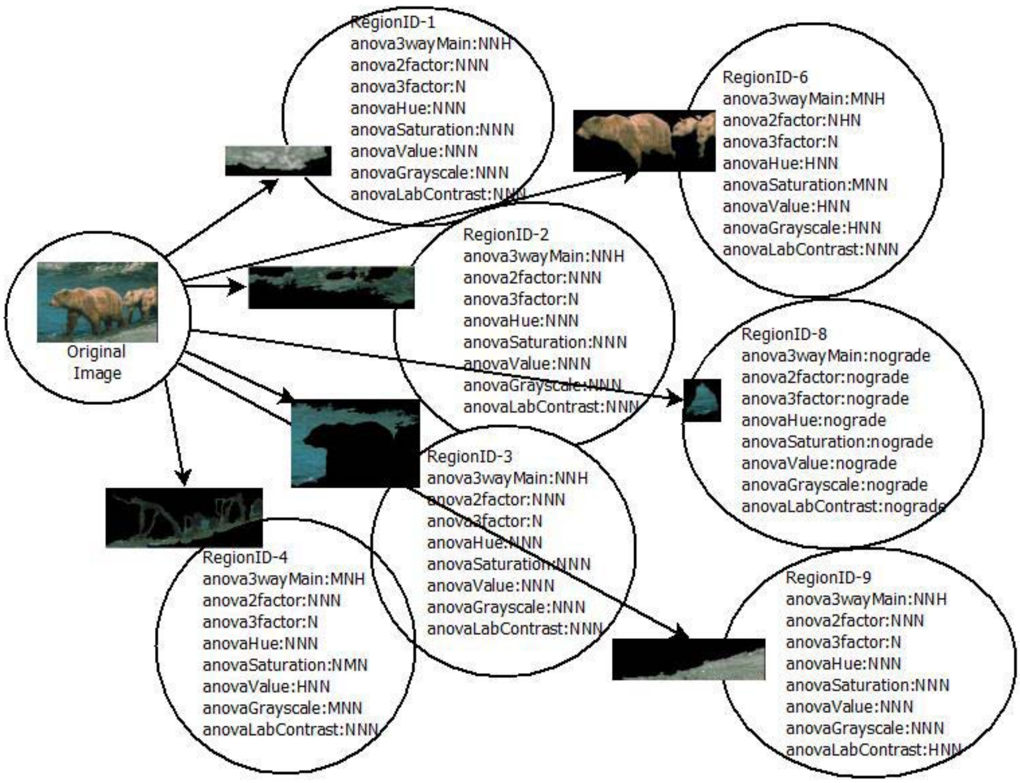


FIGURE 12. Region metadata based on ANOVA-inferential statistics of 100075.jpg.

Figure 9 shows a Vistex grass image (referred in two papers by [23] and [24])The proposed block illustrations are as follows:

1) Whole image considered as 1 block
2) Image partitioned into 4 blocks
3) Image partitioned into 9 blocks

Usually when an image is highly textured, or when it is difficult to segment meaningful object, the global image characterization helps in capturing some idea about its inherent orientation. The image taken from Vistex categorical texture dataset of grassland is highly textured and no meaningful segments are produced, only characterization from block approach results are obtained from the framework.

TABLE 1. Region Metadata for Region 6 of 100075.jpg.

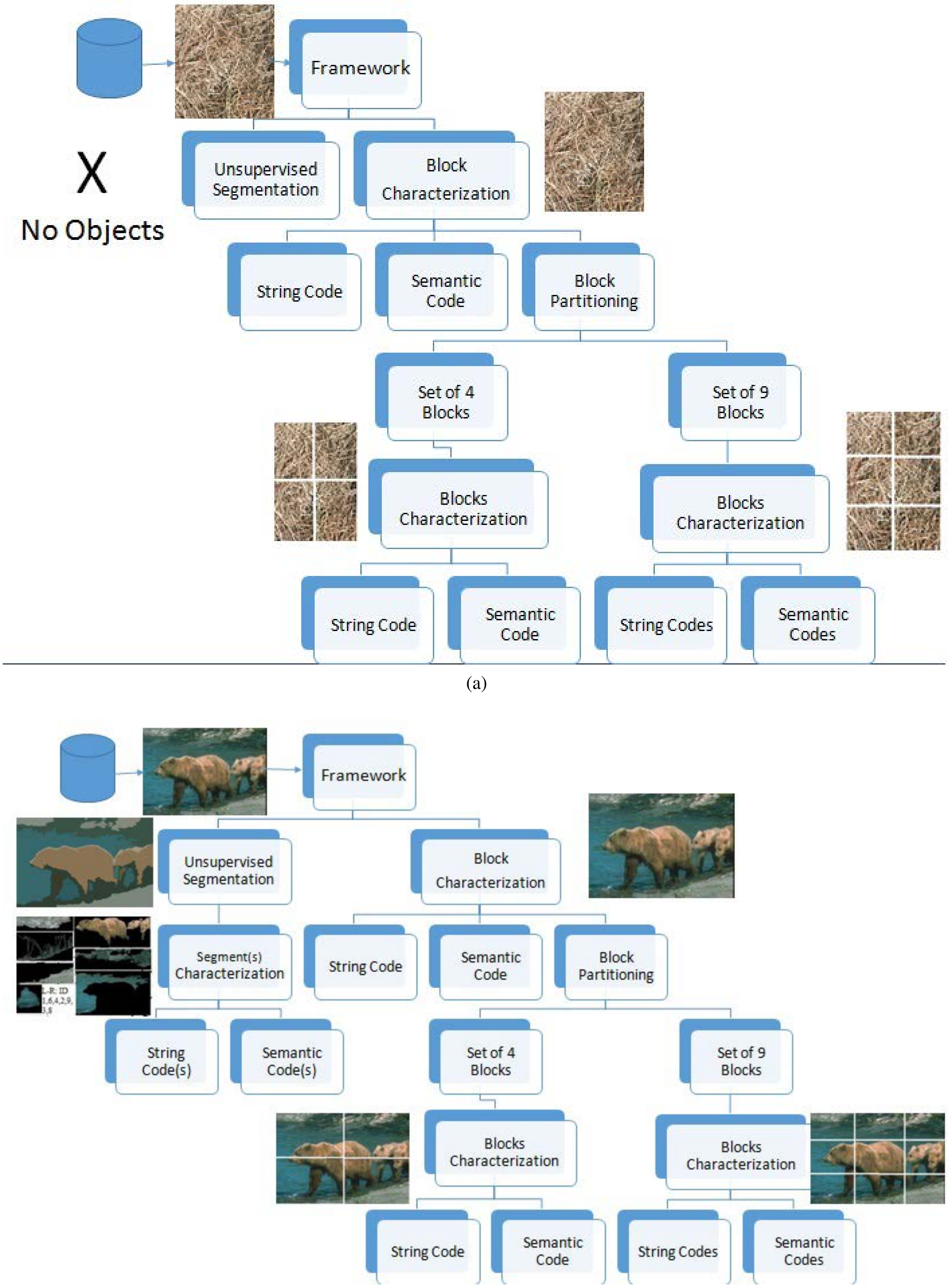
Region-6	Metadata	Value
1	Contrast	0.4019
2	Homogeneity	0.7990
3	Energy	0.3818
4	Correlation	0.0841
5	Mean Intensity	118
6	Anova3wayMain	MNH
7	Anova2factor	NHN
8	Anova3factor	N
9	AnovaHue	HNN
10	AnovaSaturation	MNN
11	AnovaValue	HNN
12	AnovaGrayscale	HNN
13	AnovaLabContrast	NNN
14	Semantic code	ROW

VI. TEXTURE CHARACTERIZATION OF REGION SEGMENTS AND BLOCKS

Outdoor natural images consist of random patterns based on its visual characteristics, which is a mixture of tonal-texture variations. For automatic texture characterization, the intrinsic property of the object surface has to be modelled or mathematically defined. Texture is a measure of variability aspect, which is sometimes very difficult to model due to its subjective and irregular nature. Natural images have multi-textural components which in most of the cases have non-regular and non-periodic variations in surfaces. The authors have implemented the methodology referred in [19] to capture the local variability in visual appearance in terms of orientation specific using Analysis Of Variance, an inferential statistical technique. The details of the 2-way and 3-way ANOVA with replication modelling, progressive sampling can be found in details in the paper [19].

The characterization is represented by string code representation based on ANOVA grading. The semantic meaning can be extracted from the string code using polling method. Experiments have been conducted for Vistex natural textures [25] and Prague mosaic textures [26]. The approach is totally unsupervised.

The knowledge representation of the segments, after texture characterization becomes more informative with additional inferential statistical ANOVA grading, to the already available descriptive statistics metadata computed during segmentation stage.



(a)

(b)

FIGURE 13. Framework workflow a) Vistex - Grass b) BSD 100075.

Few big segments have been illustrated for segment sampling in Figure 10. Illustrations show sampling for each of the four big segments with window size 3×3 in Figure 10(a,c,e,g) and with window size 7×7 as seen in Figure 10(b,d,f,h).

In the experiments, the window size as 3×3 is not considered, as it gives 9 data points, which are not enough for analysis. Just for the sake of illustration, window sizes 3×3 and 7×7 have been considered. The color code of the samples in each image, changes to depict the progressive sampling.

Each segment obtained from image segmentation, is considered separately for segment characterization. Experimentally it has been observed that the window size has an

TABLE 2. Knowledge representation for Vistex-Grass image.

Region	String Code	Semantic Code
Block-1	NNHNHHHNNNMHMNNNNNNNNHH	INTERACTION SPECIFIC
Block4-1	NNHNHNNNHNNNNNHNHNNNHN	ROW AND COLUMN
Block4-2	NNHNNNNNNNNNNNNNNNNNNM	INTERACTION SPECIFIC
Block4-3	NNHNHHNNNNNHNNNNNNNNHN	ROW AND COLUMN
Block4-4	NNHNHNNNNNHNNNNNNHNNHN	ROW AND COLUMN
Block9-1	NNHNHMNNMNNNNNMNNNNNHH	INTERACTION SPECIFIC
Block9-2	NNHNNHNNNNNHNNNNMNNHNN	ROW AND COLUMN
Block9-3	NNHNNNNNHNNNNNHNNNNNHN	COLUMN SPECIFIC
Block9-4	NNHNNNNNHNNNNNHNNNNNNN	COLUMN SPECIFIC
Block9-5	NNHNHNNNNNNNNNNNNHNNNN	ROW AND COLUMN
Block9-6	NNHNNHNNHNNMNNHNHHNNHN	ROW AND COLUMN
Block9-7	NNHNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Block9-8	NNHNNHNNNNNNNNNNMNNHNN	ROW AND COLUMN
Block9-9	NNHNHNNNNNHNNNNNNNNNNN	ROW SPECIFIC

Region	String Code	Semantic Code
Block-1	NNHNHNNNNNNNNNNNHNNHNN	ROW SPECIFIC
Block4-1	NNHNNNNNNNNNNNNNNNNHNN	ROW SPECIFIC
Block4-2	NNHNNNNNNNNNNNNNHNNNNN	ROW SPECIFIC
Block4-3	NNHNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Block4-4	NNHNNNNNNNNNNNNNHNNHMN	ROW AND COLUMN
Block9-1	NNHNNNNNNNNNNNNNNNNNMN	COLUMN SPECIFIC
Block9-2	NNHNNNNNNNNNNNNNHNNNMN	ROW AND COLUMN
Block9-3	MNHNNNNNNNNNNNNNHNNNNN	ROW SPECIFIC
Block9-4	NNHNNNNNNNNNNNNNNMNNNN	COLUMN SPECIFIC
Block9-5	NNHNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Block9-6	NNHNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Block9-7	NNHNNNNNNNNNNNNNNNNNHN	COLUMN SPECIFIC
Block9-8	NNHNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Block9-9	NNHNNNNNNNNNNNNNNNNMNN	ROW SPECIFIC
Segment1-ID1	NNHNHNNNNNNNNNNNHNNHNN	ROW SPECIFIC
Segment2-ID2	NNHNHNNMNNNNNMNNHNNNMN	ROW AND COLUMN
Segment3-ID3	NNHNNHNNNNNHNNNNNHNNHN	COLUMN SPECIFIC
Segment4-ID4	NNHNNNNNNNNNNNNNNNNHNN	ROW SPECIFIC
Segment5-ID6	NNHNHNNMNNNNNMNNHNNNMN	ROW AND COLUMN
Segment6-ID8	NNHNNNNNNNNNNNNNNNNHNN	ROW SPECIFIC
Segment7-ID10	NNHNNNNNNNNNNNNNNNNNNN	COLOR SHADE

FIGURE 14. Knowledge representation for BSD 100075.jpg.

impact on the characterization code. Patch or sample count, decreases significantly on increasing the window size as shown in Figure 11. Each color code represents a segment, in the figure. For every case, it can be seen that, the patch count decreases, for increasing window size.

The framework not only characterizes image segments, but also whole image and image blocks, depending upon the input image, as will be discussed in the next section. Hence to have a one time parameter setting for each and every case, window size of 5×5 has been found to be appropriate for progressive sampling in both the cases of block and segment characterization.

The knowledge representation of the segments become more informative with additional inferential statistical data on color planes as mentioned in Figure 12 as compared to only descriptive statistics on grayscale as shown earlier in Figure 6. The codes obtained from ANOVA grading considers feature sets such as hue plane, saturation plane, value plane, grayscale, L*a*b* color contrast; are plugged onto the region metadata (descriptive statistics) already computed initially during segmentation process as discussed in Section 3. The *nograde* is assigned for very small regions as enough sampling is not obtained. The metadata for Region-6 is shown in Table 1. In case, no segments are produced after segmentation, still the framework generates metadata for the input image using block approach as discussed in Section IV.

There is an impact of image size in ANOVA grading. If number of blocks for partitioning the image, is further increased, the patch count would be very less and the texture characterization won't be robust and effective. However one can do extensive experimentation for different sizes, and carry out application and domain specific computational intelligence methods, for fixing the block size for each image size.

Thus the approach is very flexible and can prove to be an suitable mid-level image analysis component, irrespective of the nature of texture. The progressive guided sampling replicates will be minimal, for producing robust statistical analysis. The next section demonstrates the results obtained from the framework.

VII. FRAMEWORK RESULTS FOR NATURAL SCENES

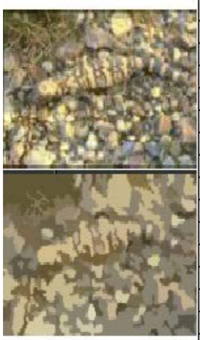
This section provides the framework results in terms of output, obtained from segmentation approach and block approach. The experimental setup is referred in Section VI A. The demonstration of framework workflow for an outdoor natural image has been depicted discussed in Section VI B. The texture characterization metadata collected at the segment level and block level, collectively represent the

Region	String Code	Semantic Code
Block-1	NNHNNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Block4-1	NNHNNNNNNNNNNNNNNNNNHNN	ROW SPECIFIC
Block4-2	NNHNNNNNNNNNNNNNNNNNNMN	COLUMN SPECIFIC
Block4-3	NNHNNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Block4-4	NNHNNHNNNNNHNNNNNNHNNNN	COLUMN SPECIFIC
Block9-1	NNHNNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Block9-2	NNHNNNNNNNNNNNNNNNNNNMN	COLUMN SPECIFIC
Block9-3	NNHNMNNNNNNNNNNNNNNNNNN	ROW SPECIFIC
Block9-4	NNHNHNNNNNHNNNNNNNNNNNN	ROW SPECIFIC
Block9-5	NNHNNNNNNNNNNNNNNNNNHNN	ROW SPECIFIC
Block9-6	NNHNHNNNNNMNNNNNNNNNHNN	ROW SPECIFIC
Block9-7	NNHNNHNNNNNHNNNNNNNNNHN	COLUMN SPECIFIC
Block9-8	NNHNNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Block9-9	NNHNNNNNNNNNNNNNNNNNMNN	ROW SPECIFIC
Segment1-ID1	NNHNNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Segment2-ID3	NNHNNHNNNNNHNNNNNNHNNHN	COLUMN SPECIFIC
Segment3-ID5	NNHNHNNNNNHNNNNNNHNNHNN	ROW SPECIFIC
Segment4-ID7	NNHNNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Segment5-ID11	NNHNNHNNNNNHNNNNNNMNMNN	ROW AND COLUMN
Segment6-ID15	NNHNNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Segment7-ID17	NNHNNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Segment8-ID33	NNHNNNNNNNNNNNNNNNNNHNN	ROW SPECIFIC
Segment9-ID37	NNHNNNNNNHNNNNNNNNNNNNN	ROW SPECIFIC
Segment10-ID45	NNHNNHNNNNNNNNNNNNHNNHN	COLUMN SPECIFIC

(a)

Region	String Code	Semantic Code
Block-1	NNHNHNNMNNHNNMNNHNNNNN	ROW SPECIFIC
Block4-1	NNHNHNNNNNHNNNNNHNNHNN	ROW SPECIFIC
Block4-2	NNHNNNNNNNNNNNNNMNNNNN	ROW SPECIFIC
Block4-3	NNHNNNNNNNNNNNNNNNNHNN	ROW SPECIFIC
Block4-4	NNHNNNNNNNNNNNNNNNNNHN	COLUMN SPECIFIC
Block9-1	NNHNHMNNNNMNNNNNNNNNNN	ROW AND COLUMN
Block9-2	NNHNNNNNNNNNNNNNNNNHNN	ROW SPECIFIC
Block9-3	NNHNNHNNNNNHNNNNHNNNNN	ROW AND COLUMN
Block9-4	NNHNNNNNNNNNNNNNNNNNHN	COLUMN SPECIFIC
Block9-5	NNHNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Block9-6	NNHNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Block9-7	NNHNNNNNNNNNNNNNMNNNNN	ROW SPECIFIC
Block9-8	NNHNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Block9-9	NNHNHMNNNNHNNNNNNNNNNN	ROW AND COLUMN
Segment1-ID1	NNHNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Segment2-ID5	NNHNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Segment3-ID7	HNHNHNNHNNHNNHNNHNNHNN	ROW SPECIFIC
Segment4-ID8	NNHNNNNNNNNNNNNNNNNHNN	ROW SPECIFIC
Segment5-ID9	NNHNHNNNNNHNNNNNHNNNNN	ROW SPECIFIC
Segment6-ID10	NNHNHNNHNNHNNHNNNNNNNN	ROW SPECIFIC
Segment7-ID11	NNHNNNNHNNNNNHNNNNNNNN	ROW SPECIFIC

(b)



Region	String Code	Semantic Code
Block-1	HHHNHHNNNNHHNNNNNHHMNHN	INTERACTION SPECIFIC
Block4-1	NNHNHHNNNNHNNNNNHHNNHN	ROW AND COLUMN
Block4-2	NNHNNNNNNNNNNNNNHNNNNN	ROW SPECIFIC
Block4-3	NNHNNNNNNNNNNNNNHHNNMN	ROW AND COLUMN
Block4-4	NNHNHNNNNNMNNNNNHNNNNN	ROW SPECIFIC
Block9-1	NNHNNNNNNNNNNNNNNNNNNN	COLOR SHADE
Block9-2	NNHNHNNNNNHNNNNNHNNNNN	ROW SPECIFIC
Block9-3	NNHNHNNNNNMNNNNNHNNMNN	ROW SPECIFIC
Block9-4	NNHNNNNNNNNNNNNNNHNHMN	ROW AND COLUMN
Block9-5	NNHNHNNNNNHNNNNNNNNNHN	ROW AND COLUMN
Block9-6	NNHNHNNNNNMNNNNNHNNNNN	ROW SPECIFIC
Block9-7	NNHNHNNNNNNNNNNNHNNNNN	ROW AND COLUMN
Block9-8	NNHNNNNNNNNNNNNNHNNNNN	ROW SPECIFIC
Block9-9	NNHNHNNNNNMNNNNNHNNNNN	ROW SPECIFIC
Segment1-ID1	NNHNNNNNNNNNNNNNNNNHNN	ROW SPECIFIC
Segment2-ID2	NNHNNHNNNNNNNNNNNHNNNN	COLUMN SPECIFIC
Segment3-ID19	NHHNNNNNHNNNNNHNNNNNNN	COLUMN SPECIFIC
Segment4-ID28	NNHNNMNNNNNNNNNNNMNNNN	COLUMN SPECIFIC
Segment5-ID33	NNHNNNNNNNHNNNNNNNNNNN	ROW SPECIFIC

(c)

FIGURE 15. **Knowledge representation a) 175032.jpg b) 148026.jpg c) 87065.jpg.**

knowledge representation of a given image, which has been discussed here. In Section VI C highly textured image knowledge representation has been demonstrated and the importance of block code representation has been justified.

A. EXPERIMENTAL SETUP

The experimental setup consists of images, taken from various sources of benchmark color-texture image datasets, such as - Berkeley [17], Vistex [25], Prague [26] and Corel [27]. One time initialization is done for all the parameters required for segmentation approach and block approach as discussed in their respective sections.

Time complexity for characterization of each image - segments and blocks took an average of 40 seconds. The hardware environmental setup for the experiments consists of P600 Intel Pentium CPU, clock speed 2.00 GHz with RAM 2.00 GB. The software used is Matlab, Image Processing Toolbox.

B. DEMONSTRATION OF FRAMEWORK WORKFLOW

The workflow as discussed earlier in Section II consists of two components - Segmentation Approach and Block Approach. The workflow has been visually represented as in Figure 13 for two images Vistex-grass and BSD 100075, taken from two different datasets.

The framework workflow at various stages generates two types of codes as metadata - Semantic Code and String Code as mentioned in Section V. The framework workflow is shown in Figure 13 a). For the grass image from Vistex, no meaningful segments can be realized from segmentation approach (marked as X). The workflow in Figure 13 b) represents for BSD image 100075.jpg. This image on the contrary when segmented, could separate out the tonal-texture portions in bear, water and the land segmented areas.

C. DEMONSTRATION OF IMAGE KNOWLEDGE REPRESENTATION

The knowledge representation of an image obtained from the unified approach based on the proposed framework, includes the segmentation metadata and block-level metadata in terms of ANOVA grading - a collection of string codes and semantic codes. The texture orientation captured using ANOVA factors are given a confidence level based on hypothesis testing. The ANOVA grading system uses standard level of significance with p-value=0.05. There are 3 grades assigned depending on the value of p-value obtained - 1) H as highly significant for p-value < 0.05, 2) M as medium significant for p-value in 0.05 and 0.1, both inclusive and 3) N as not significant for p-value > 0.1. The factors in 2-way ANOVA are row and column. Depending on the significance of main and interaction effects, semantic code is generated accordingly as ROW SPECIFIC, COLUMN SPECIFIC, ROW AND COLUMN and INTERACTION SPECIFIC. The strength of color contrast in the image is studied using 3-way Anova, where now 3 factors are considered - row, column and color specific (as an additional one). The knowledge representation for Vistex grass image generated by the framework, constitutes of the collection of both fourteen string codes and semantic codes only for the blocks as shown in Table 2. The knowledge representation of 100075 image is illustrated in Figure 14 constitutes of 22 character string code and semantic codes for both blocks and segments. In case of BSD image 100075.jpg, out of fourteen segmented regions, seven regions (Region IDs-1,2,3,4,6,8,10) could be graded, as the region sizes are large enough for progressive sampling and variation analysis.

The BSD image 175032.jpg when segmented, produced 54 regions out of which 44 were not meaningful, had small region size and ANOVA fails to grade them. Only ten segments could be graded. The knowledge representation of this image obtained from the framework is shown in Figure 15 a). The BSD image 148026.jpg when segmented, produced 36 regions out of which 29 were not meaningful and no grade could be assigned. In this case too only seven segments could be graded. The knowledge representation of this image obtained from the framework is shown in Figure 15 b). The image 87065.jpg when segmented produced 60 segmented regions, out of which only a handful of 5 could be graded as shown in 15 c). Thus it may be observed that, for highly textured images, texture characterization using block approach is more appropriate, gives compact knowledge representation and may facilitate higher level image processing in future.

VIII. SUMMARY AND CONCLUSION

The image representation of natural outdoor images is very crucial for semantic segmentation, and remains a challenging and one of the open areas of research. The authors have proposed a framework for generating novel intermediate image representation which provides rich region metadata for natural outdoor images of varying complexity from simple pure toned to complex heterogeneous color-textured. The framework serves the dual purpose of image segmentation and texture characterization of the outdoor natural images. Segment characterization adds inferential statistical data in the form of *string code* and its corresponding *semantic code* to the region metadata, which has been initially populated during unsupervised segmentation. The framework can also identify the type of input image as object based, pure toned, homogeneous or heterogeneous color-textured. This makes the representation even more informative for future use. In case where not even a single distinct object can be extracted from the image by segmentation; the framework processes the texture characterization using block approach, to know the basic orientation embedded in the image as whole and the blocks. The knowledge representation requires minimal storage and gives comprehensive hierarchical viewpoint of any given image in an unsupervised manner.

The characterization code is rotation and scale variant. Computationally intensive high order algorithms for image understanding can be appropriately applied at subsequent stages based on the metadata generated by the framework in future.

The authors recommend this unified approach based on the proposed framework as a mid-level image analysis component which generates valuable metadata, stage by stage in both segmentation and block approaches which can be further used for vision tasks.

The proposed framework is expected to be useful in the field of computer vision for cases where prior knowledge about the scene is unknown. The framework for color-texture segmentation and characterization of natural outdoor images can be further extended, as a guide towards image content characterization for domain specific applications.

ACKNOWLEDGMENT

This work was supported in part by the University Grants Commission-Basic Scientific Research Fellowship Scheme under Government of India; in part by the Indian National Centre for Ocean Information Services under the Ministry of Earth Sciences, Government of India; and in part by the Basic Boarding and Lodging Scholarship from the University of Hyderabad. The authors would like to thank the anonymous reviewers for their valuable suggestions which helped them to improve the content and quality of this paper.

REFERENCES

[1] A. Agarwal, "A framework for distributed machine perception in understanding static natural scenes," Ph.D. dissertation, Dept. Comput. Sci. Eng., IIT Delhi, New Delhi, India, 1989.

[2] J. Batlle, A. Casals, J. Freixenet, and J. Martí, "A review on strategies for recognizing natural objects in colour images of outdoor scenes," *Image Vis. Comput.*, vol. 18, nos. 6–7, pp. 515–530, May 2000.

[3] J. Li, "Semantic image understanding: From the web, in large scale, with real-world challenging data," Ph.D. dissertation, Dept. Comput. Sci., Stanford Univ., Stanford, CA, USA, 2011.

[4] T. Dhariwal, A. Agarwal, and C. R. Rao, "A soft approach for feature selection and recognition of outdoor natural images," in *Proc. IEEE Int. Conf. Fuzzy Syst. (FUZZ-IEEE)*, Jul. 2013, pp. 1–8.

[5] N. Satrawala, "Strategic plan generation for realizing high-level vision," Ph.D. dissertation, School Comput. Inf. Sci., Univ. Hyderabad, Hyderabad, India, 2017.

[6] H. Riaz, A. Terra, K. Raizer, R. Inam, and A. Hata, "Scene understanding for safety analysis in human-robot collaborative operations," in *Proc. 6th Int. Conf. Control, Autom. Robot. (ICCAR)*, Apr. 2020, pp. 722–731.

[7] P.-Y. Chen, A. H. Liu, Y.-C. Liu, and Y.-C.-F. Wang, "Towards scene understanding: Unsupervised monocular depth estimation with semantic-aware representation," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2019, pp. 2619–2627.

[8] M. Leordeanu, M. Pirvu, D. Costea, A. Marcu, E. Slusanschi, and R. Sukthankar, "Semi-supervised learning for multi-task scene understanding by neural graph consensus," in *Proc. 35th AAAI Conf. Artif. Intell.*, 2020, pp. 1882–1892.

[9] W. Wang, Q. Lai, H. Fu, J. Shen, H. Ling, and R. Yang, "Salient object detection in the deep learning era: An in-depth survey," 2019, *arXiv:1904.09146*.

[10] E. Shelhamer, J. Long, and T. Darrell, "Fully convolutional networks for semantic segmentation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 4, pp. 640–651, Apr. 2017.

[11] T. Goswami, A. Agarwal, and R. R. Chillarige, "Multi-faceted hierarchical image segmentation taxonomy (MFHIST)," *IEEE Access*, vol. 9, pp. 33543–33556, 2021.

[12] P. Arbelaez, J. Pont-Tuset, J. Barron, F. Marques, and J. Malik, "Multiscale combinatorial grouping," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2014, pp. 328–335.

[13] J. Yang, Y.-G. Jiang, A. G. Hauptmann, and C.-W. Ngo, "Evaluating bag-of-visual-words representations in scene classification," in *Proc. Int. Workshop Workshop Multimedia Inf. Retr. (MIR)*, 2007, pp. 197–206.

[14] S. Fekriershad and F. Tajeripour, "Color texture classification based on proposed impulse-noise resistant color local binary patterns and significant points selection algorithm," *Sensor Rev.*, vol. 37, no. 1, pp. 33–42, 2017.

[15] S. Fekri-Ershad and F. Tajeripour, "Impulse-noise resistant color-texture classification approach using hybrid color local binary patterns and Kullback–Leibler divergence," *Comput. J.*, vol. 60, no. 11, pp. 1633–1648, Nov. 2017.

[16] S. Khan, L. Alarabi, and S. Basalamah, "Deep hybrid network for land cover semantic segmentation in high-spatial resolution satellite images," *Information*, vol. 12, no. 6, pp. 33–42, 2021.

[17] D. Martin, C. Fowlkes, D. Tal, and J. Malik, "A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics," in *Proc. 8th IEEE Int. Conf. Comput. Vis. (ICCV)*, vol. 2, Jun. 2001, pp. 416–423.

[18] T. Goswami, A. Agarwal, and C. R. Rao, "Hybrid region and edge based unsupervised color-texture segmentation for natural images," *Int. J. Inf. Process.*, vol. 9, no. 1, pp. 77–92, 2015.

[19] T. Goswami, A. Agarwal, and C. R. Rao, "Statistical learning for texture characterization," in *Proc. Indian Conf. Comput. Vis. Graph. Image Process.*, Dec. 2014, pp. 1–8.

[20] T. Goswami, A. Agarwal, and C. R. Rao, "Color texture features integration for unsupervised image segmentation based on orthogonal polynomial operators and hybrid color space," in *Proc. 8th Int. Conf. Image Signal Process., (ICISP)*, 2014, pp. 52–59.

[21] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-3, no. 6, pp. 610–621, Nov. 1973.

[22] S. Todorovic and N. Ahuja, "Texel-based texture segmentation," in *Proc. IEEE 12th Int. Conf. Comput. Vis.*, Sep. 2009, pp. 841–848.

[23] A. Sanda, E. Ezin, P. Gouton, and J. Tossa, "Clifford algebra and Gabor filter for color image texture characterization," in *Proc. Int. Conf. Signal-Image Technol. Internet-Based Syst.*, Dec. 2013, pp. 212–216.

[24] G. Van de Wouwer, P. Scheunders, S. Livens, and D. Van Dyck, "Wavelet correlation signatures for color texture characterization," *Pattern Recognit.*, vol. 32, no. 3, pp. 443–451, Mar. 1999.

[25] MITMediaLab. (2005). *Mitmedialab, Vision Texture-Vistex Database*. [Online]. Available: http://aiweb.techfak.uni-bielefeld.de/content/bworld-robot-contro%l-software/

[26] M. Haindl and S. Mikes. (2014). *Prague Texture Segmentation Benchmark Dataset*. [Online]. Available: http://mosaic.utia.cas.cz/

[27] D. Tao. (2009). *The Corel Database for Content Based Image Retrieval*. [Online]. Available: https://sites.google.com/site/dctresearch/Home/content-based-imag%e-retrieval/

TILOTTAMA GOSWAMI (Senior Member, IEEE) was born in Bhilai, Chhattisgarh, India, in 1972. She received the B.E. degree (Hons.) in computer science and engineering from the National Institute of Technology (N.I.T) Durgapur, Durgapur, in 1995, the master's degree (Hons.) in computer science from Rivier University, Nashua, NH, USA, in 2000, and the Ph.D. degree in computer science from the University of Hyderabad, in 2016.

She is currently a Professor with the Department of Artificial Intelligence, Anurag University, Hyderabad, Telangana, India. She has overall 22 years of experience in academia, research, and industry. During her doctoral studies, she has worked as a Software Engineer to assist in the project leadership for a funded project by INCOIS (under the Ministry of Earth Sciences, Goverment of India) during 2012–2013. Her M.S. program was funded by Kronos Inc., MA, USA, through tuition reimbursement scheme based on her excellent performance (awarded High Distinction) during her work period with the company, in 2000. Her research interests include computer vision, machine learning, and image processing.

Dr. Goswami has been a Senior Member of IEEE CIS/GRSS Chapter Hyderabad Section, since 2018. She was a recipient of the Steel Authority of India Ltd. (Bhilai Steel Plant) Scholarship during her tenure of undergraduate studies, from 1991 to 1995. She has been awarded the Star Team Award for developing efficient software for GeoMedia (GIS), leading to complete customer satisfaction at Hexagon (Intergraph), Hyderabad, in 2001. She was a recipient of the University Grants Commission—Basic Scientific Research (UGC-BSR) Fellowship (under Government of India) during 2014–2015. She was a recipient of the Women Researcher Award, awarded by REST Society for Research International, Tamil Nadu, India, in June 2020. She has been serving as the Chair for Hyderabad Deccan ACM Chapter, since 2021, and served as the ACM-W Chair, from 2020 to 2021. She is an Active Researcher and contributes to society and chapters by delivering workshops and guest lectures, participating on the technical program committee, the tutorial chair, and a reviewer in international conferences and journals.

ARUN AGARWAL (Senior Member, IEEE) was born in Balrampur, Uttar Pradesh, India, in 1957. He received the B.Tech. degree in electrical engineering and the Ph.D. degree in computer science from the Indian Institute of Technology (IIT) Delhi, India, in 1979 and 1989, respectively.

He started his career as a Senior Research Assistant at IIT Delhi (1979–1981) and then joined the University of Hyderabad, Telangana, India, in 1984. He is a member of GARUDA Project, an Indian National Initiative on Grid Computing, and a member of DST-LHC Task Force. He was a Visiting Scientist at The Robotics Institute, Carnegie Mellon University, USA, in 1986; and a Research Associate at the Sloan School of Management, Massachusetts Institute of Technology, USA, in 1993. He has visited many other universities and institutes, like Monash University, Australia; Melbourne University, Australia; the National Center for High Performance Computing, Hsinchu, Taiwan; the Chinese Academy of Sciences, Beijing, China; the San Diego Supercomputer Center, USA; Mahasarakham University, Thailand; NECTEC, Thailand; and KISTI, South Korea. He is currently a Senior Professor of computer and information sciences of the University of Hyderabad, where he also served as the Dean (2015–2018) and the Pro Vice Chancellor (2018–2021). He has guided 17 Ph.D. theses and more than 125 post-graduate dissertations. He has published more than 100 papers. He has several projects and consultancy in hand with several industry/research laboratories. His research interests include computer vision, image processing, neural networks, grid, and cloud computing.

Dr. Agarwal was an Elected Fellow of IETE, in 2003, and an Elected Fellow of Telangana Akademi of Sciences, in 2011. He was also a Founding Member of the Steering Committee of PRAGMA, International Committee (2004 onwards), USA; MIWAI, Mahasarakham University (since 2010); and BigData, India (since 2017). He was a recipient of the IEEE Region 10 Outstanding Volunteer Award, in 2009, in recognition to his dedications and contributions. He was awarded the Outstanding Reviewer Status for *Pattern Recognition* (Elsevier), in November 2015. He was felicitated by the Indian Society for Rough Sets in recognition of academic excellence and promotion of Rough Set Activities 2017. He was the Chairperson of IEEE Hyderabad Section for the years 2001 and 2002. He has served on the technical program committee for numerous conferences in the area of pattern recognition and artificial intelligence.

CHILLARIGE RAGHAVENDRA RAO was born in Guntur, Andhra Pradesh, India, in 1958. He received the B.Sc. degree from Andhra University, in 1978, the M.Sc. and Ph.D. degrees in statistics from the College of Science, Osmania University, in 1980 and 1986, respectively, and the M.Tech. degree in computer science and engineering from the College of Engineering, Osmania University, in 1999.

He started his career as a Lecturer in statistics at Osmania University, in 1984. Since 1986, he has been working at the School of Mathematics and Computer/Information Sciences, University of Hyderabad. He is currently a Senior Professor with the School of Computer and Information Sciences, University of Hyderabad. One of his recent books published is *Coefficient of Variation and Machine Learning Applications* (CRC Press, 2019). His research interests include simulation and modeling, rough sets, and knowledge discovery.

Dr. Rao is a member of the International Rough Set Society, Indian Society for Rough Sets, Operational Research Society of India, Indian Mathematical Society, the International Association of Engineers, Society for Development of Statistics, Andhra Pradesh Society for Mathematical Sciences, Indian Society for Probability and Statistics, and Society for High Energy Materials. He is a fellow of The Institution of Electronics and Telecommunication Engineers, Society for Science, and Andhra Pradesh Akademi of Sciences.