https://doi.org/10.26438/ijcse/v6si1.2631

JCSE International Journal of Computer Sciences and Engineering Open Access

Research Paper Volume-6, Special Issue-1, Feb 2018 E-ISSN: 2347-2693

Outdoor Natural Scene Object Classification Using Probabilistic Neural Network

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Abstract— Region labeling for outdoor scenes to identify sky, green land, water, snow etc. facilitates content-based image retrieval systems. This paper presents use of multiple features to classify various objects of the outdoor natural scene image. Proposed system aims to classify images of the sky, water and green land. As all these nature components are irregular in shape, they can be classified using color and texture features. Color features of the object are extracted by using segmentation in La*b* color space. In the process of texture feature calculation, the image is initially divided into smaller grids. Global GLCM based statistical texture features are calculated using statistical features of these local grids. Results show that color and statistical texture features are not sufficient to differentiate sky and water body. To achieve discrimination between these two objects, a new edge-based horizontal line texture feature is proposed. The proposed feature is used to differentiate between sky and water objects based on the density of horizontal lines. All these features are used together to train probabilistic neural network for classification. The system has achieved improvement of 5% to 8% in F-measure, when all these features are used together for classification of natural scene objects.

Keywords—Color feature, Statistical texture features,Horizontal line texture feature, Image classification, PNN

I. INTRODUCTION

It is observed that as technology grows, the size and resolution of images to be considered for processing the image data grow rapidly. Hence, more efficient processes for searching, retrieving, interpreting and understanding of image data are needed for image based applications. Content Based Image Retrieval (CBIR) systems have been developed to analyze the content of image and to use this information for classification of images [1] [2]. Natural scene images contains complex components of real life scenes. Classification of natural scene images plays important role in many applications of robotics, web search for image, IoT etc. Content based natural scene image classification is one of the big challenges in computer vision field because of complex and overlapping arrangements in real life components in a scene.

Image understanding involves detection and recognition of objects in a scene. Arrangements of these objects in a specific manner in a scene are useful to understand the scene. Natural outdoor scenes generally include objects like sky, grass, water, snow, sand, rock etc. Specific arrangement of these objects gives meaning to a scene image. For example, if an image includes objects like sky, sand and open water then we can understand that image scene as a beach image. Various high level features like semantic cues, Bag of Visual Words (BoVW), region based features are generated using these objects and used to understand and classify the images [16][17][18].

This study contributes toward the classification of outdoor natural scene objects like sky, water and green land which can be further used to understand the image. To classify the images of objects into sky, water and green land, a system has been proposed in this paper using three different features; namely color, statistical texture feature and horizontal line texture feature. These features are used together to train a probabilistic neural network.

For this study, daylight images of outdoor natural scenes have been considered along with blue color sky having white clouds, water body with still water having little waves on it and green forest or green lawn which representing green land body.

Rest of the paper is organized as follows. Section II discusses related work of Natural scene classification. Section III explains proposed system that includes architecture of system, various feature extraction methods and description of probabilistic neural network. Section IV discusses the results achieved by proposed system and Section V provides conclusions.

II. RELATED WORK

The problem of scene classification has been well handled by various researchers to classify scenes like disaster damage images, real estate images, road detection, vehicle detection, sports images etc. [4][5][6][7][9]. To classify such scene images, different types of low level (color, texture etc.) and high level (region based, semantic based etc.) features have been used. Outdoor scenes generally have uniform color distribution; such as sky is on top and blue in color. So, color based features are important to classify the objects like sky, water, sand, rock, grass etc. [11]. These objects can be further used by relating with each other to classify the images of specific category [6][8][9][10][15]. Color based features are individually not sufficient to differentiate the objects which are nearly similar in color. For such objects color features can be used along with texture features. Use of both features together improve the indoor/outdoor scene, classification [12][13][14].

III. FEATURE EXTRACTION AND IMAGE CLASSIFICATION USING PROBABILISTIC NEURAL NETWORK

The components of outdoor natural scene image; sky, water and green land are irregular in shape, so, shape feature cannot be used to recognize them. Sky and water, both objects are blue in color and smooth in texture whereas green land is having rough texture. Green land can be differentiated from sky and water objects by using color and statistical texture features. To differentiate sky and water from each other is very difficult by using both color and texture features. Humans can differentiate these two objects due to presence of little horizontal ripples on water. The same concept is used to distinguish water and sky objects from each other. To achieve the desired result, a new edge based horizontal line texture feature is designed. Based on the characteristics of sky, water and green land, the proposed system uses color, statistical texture and horizontal lines texture features together to distinguish between sky, water and green land using Probabilistic Neural Network.

A. Color Feature Extraction:

Various color space models like RGB, La*b*, HSV etc. can be used to extract color features of an image. Color features can be measured using attributes like brightness, hue, colorfulness, chromaticity, lightness, saturation etc. RGB color space represents the color as percentage of red, green and blue hue mixed together. La*b* color space model represent color in terms of luminance (L) i.e. lightness and other two color channels which represent chromaticity. The color channel a* indicates color along red-green axis and b* indicate color along blue-yellow axis. RGB color space is device dependent where La*b* color space is device independent [3].

La*b* color space is designed to approximate human vision. It aspires to perceptual uniformity, and its L component closely matches human perception of lightness. So, La*b* color space model used for image segmentation. In proposed system, color value is generated for a given RGB image using color segmentation in La*b* color space. Table-1 shows different ranges of three channels used to generate segments of six different colors.

Table 1. La*b* color channel ranges for segmentation

Sr. No.	Color Name	L	a*	b*
1	Green	0-255	0-130	130-255
2	Blue	0-255	0-150	0-130
3	Yellow	100-255	110-150	150-255
4	Red	128-255	150-210	150-210
5	Pink	128-255	170-250	70-140
6	Brown	0-255	140-190	130-160

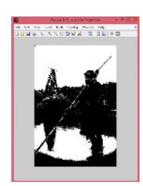
As proposed, system deals with images of sky, water and green land objects, correct image classification should have images with maximum numbers of green or blue color pixels. To extract the information about contribution of each color pixels in an image, ratio of total count of specific color pixels with respect to total count of all pixels in an input image is calculated. Calculated ratio is further compared with threshold. If value of the ratio satisfies the threshold criteria, then color segments will be considered for further analysis. Eq.-1 gives formula for ratio calculation.

$$Color\_seg\_ratio = \frac{Total\ No.Color\ Pixel}{Total\ No.of\ image\ pixel} \quad (1)$$

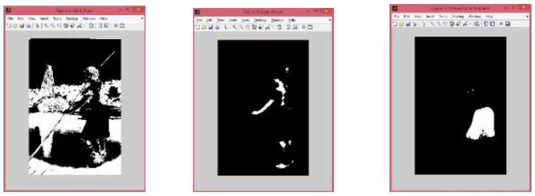
After that it compares the ratio of pixels for selected segments with each other and assigns the color value of segment to image whose color pixel contribution is largest in image.

Figure 1 shows the result of segmentation using above mentioned color values of La*b* color space. Proposed system generates four segments for given input image color; blue, green, brown, and yellow. For given input image, segments are not generated for orange/red and pink color.

(a)



(b)



(c) (d) (e)

Figure 1. Segments using La*b* color ranges
(a) Original image, (b) Blue, (c) Green, (d) Brown, (e) Yellow

B. Statistical Texture Features Extraction and its role in Image Classification :

Texture of sky and water is smooth and that of green land (forest / green lawn) is rough. Grid based statistical texture features are used to generate global texture features of an object. Initially, image is divided into grids of 100x100. Statistical texture features i.e. energy, homogeneity, contrast and correlation are calculated for each grid. Further, the mean of each texture feature is calculated which will be considered as global texture features for an object image. All four statistical texture features are tested individually and so also in combinations to recognize the object images.

The process of texture based image recognition is divided into two phases: Training and Testing.

Algorithm: Statistical Texture Feature based Image Classification

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a. Training phase:

1. Take RGB color image of Sky body/Water body/Green land as input.
2. Divide complete image into grids of 100 x 100.
   i. Let G= {Grd_1, Grd_2, Grd_3 … Grd_n |where 'Grd' is grid of size 100x100 and 'n' is total no. of grids}
   ii. Let Grd = {p_1,p_2,p_3, ………, p_m |where 'p' is pixel value of grid}
3. Calculate statistical texture features (Energy, Homogeneity, Contrast and Correlation) of each grid.
   i. Let Feat = {F_1, F_2, F_3, ………., Fn| where 'F' represents vector of statistical texture feature for each grid of image}
   ii. Let F={f_1, f_2, f_3, f_4 | where 'f' represents statistical texture features}
4. Calculate mean of each texture feature extracted from all grids.
5. Repeat steps 1-4 for all training images
6. Train the PNN (Probabilistic Neural Network) with all statistical features of all training images.

b. Testing & recognition phase:

1. Take RGB color image as an input.
2. Repeat steps 1 to 4 of Training phase.
3. Test the features using network generated by PNN.

C. Horizontal line texture feature and its role in image classification :

Statistical texture features are tested for recognition of sky, water and green land objects. Discrimination of green land against sky and water object is moderately achieved but these features could not reduce the rate of misclassification of sky and water object images as both classes have approximately same color and texture features.

This case is resolved as follows. Though water objects have smooth texture, it contains horizontal lines of ripples on it. This characteristic of water object can be used for discrimination of water object from sky object. To extract the information about presence of horizontal lines along with its density, a new edge based texture feature; termed as horizontal line texture feature is designed.

The process of horizontal line texture feature generation starts with the conversion of RGB image into grey color image. Sobel edge filter used to detect the edges which are further used to extract horizontal and non-horizontal lines along with its count using horizontal line filter (HLF). The density of horizontal lines is calculated using ratio of horizontal line to non-horizontal line. This ratio will be further used as one of the feature of image in training and testing using PNN.

Algorithm: Horizontal Line Filter

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1. Convert RGB color image to grey color image.
2. Detect edges using 'Sobel' edge filter
3. Remove noise by using Gaussian filter
4. Extraction of Horizontal line texture feature
   a. Traverse image column wise.
   b. Check value of each pixel is '0' or '1' and mark each traversed pixel as visited pixel.
   c. If value of pixel is '1' then check for its neighbour pixel with value '1'
   d. If neighbour pixel is '1' then calculate and store the angle between 1st pixel and neighbour pixel and mark it as visited, so it will not get consider in next iteration.
   e. Traverse neighbour pixel of each neighbour pixel and calculate angle between 1st pixel and the current pixel under consideration.
   f. Repeat steps 'c','d' & 'e' till we get a pixel with value '0' for all neighbours.
   g. Compare count of total traversed pixel of value '1' i.e. length of line with threshold value. If the length of line greater than threshold value, then consider it as line otherwise consider it as noise.
   h. Calculate count of angles between range 0^o to 35^o.
   i. Calculate ratio of count of angles between 0^o to 35^o and total count of angles. If the ratio is greater than threshold value, then increment the count of horizontal line.

j. Calculate ration between total horizontal lines and image size. If it satisfies ratio then classify image segment as 'water body' otherwise 'sky body'.

D. Probabilistic Neural Network :

Classification of images can be done by various types of classifiers however, Probabilistic neural network gives better accuracy when compared with other classifiers like Bays classifier, K-Nearest neighbourhood, Minimum mean distance and MLP classifier [19]. PNN is a feed forward network. It uses a supervised training set to develop probability density functions within a pattern layer. PNN adapted for classification because of its advantages like good accuracy, small training time, robustness to weight changes, insensitivity to outliers and negligible retraining time[20][21]. Figure 2 shows the architecture of probabilistic neural network. This network includes three layers; Input layer, Radial Basis layer and Competitive layer. Input layer takes the actual input vector of features for training and testing images. During training phase input weight matrix IW is computed in hidden layer which will be used in testing phase to calculate distance between training and testing vector. Layered weight matrix LW in competative layer is also generated using target class values provided during training. This matrix is used in testing phase to identify the class of testing vector.

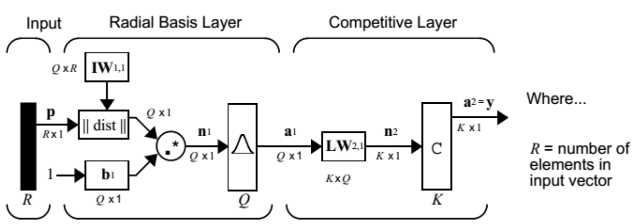

Figure 2. Architecture of Probabilistic Neural Network [23].

Input Layer: Input layer denoted by 'p' is presented as black vertical bar in figure. Its dimension is given by Rx1. Here, the value of R equals 3. R represents 3 features; color, statistical texture and horizontal line texture feature which are extracted from the given image.

Hidden Layer / Radial Basis Layer: This layer has one neuron for each case in training set. For our work Q is 32, as we are using total 32 images to train the system. Neuron stores the value of training feature vector along with its target class values. When presented with 'p' vector of input values from the input layer during testing phase , the ||dist|| between vector 'p' and each row of weight matrix 'IW' are calculated i.e. || IW-p||. Here, IW is a matrix of weights with dimension Q x R where Q is total number of training images and R is the size of feature vector. Here the vector distance ||dist|| is defined as dot product between two vectors i.e. dot product between 'p' and i^{th} row of IW matrix. This produces i^{th} element of distance vector ||dist|| whose dimension is Q x 1. Then the bias vector 'b1' is combined with ||dist|| by an element-by-element multiplication which is represented as ".*". This multiplication result is further sent to Radial basis function which calculates Euclidean distance of the test vector. An input vector close to training vector is represented by a number close to '1' in the output vector 'a1'. Resulting value is passed to neuron in the pattern layer. If an input is close to several training vectors of a single class, it is represented by several elements of 'a1' that are close to '1' [22][23].

Pattern Layer / Competitive layer*:* In this layer for each category of target variable, there is one pattern neuron. The actual target category of each training case is stored with each hidden neuron. The weighted value coming out of a hidden neuron is fed only to the pattern neuron that corresponds to the hidden neuron's type. The third-layer weights, LW are set to the matrix T of target vectors. Each vector has a '1' only in the row associated with that particular class of input, and '0' elsewhere. The vector 'a1' is firstly multiplied with layer weight matrix LW of size K x Q where K is number of classes of input data producing an output 'n2'. The competitive function denoted as 'C' produces a '1' corresponding to largest element of 'n2' and '0' elsewhere.

IV. RESULTS AND DISCUSSION

The previous section has discussed methods of Color, Statistical texture, Horizontal line texture features extraction and their use in classification of images using PNN. In this section all extracted features are tested individually and in various combinations with each other for their performance to classify the image using PNN.

Dataset:

A dataset of the sky, water and green land images have been created by collecting 'jpeg' images from Google image database. For texture and horizontal line features we have used total of 87 images with category-wise these counts are as follows: Sky-37, Water-23 and Green Land-27 (including images of Green forest and Green lawn). Initially system is trained with 8 images per category. For Green land, it is 16 i.e. 8 of forests and 8 of Green Lawns, i.e. 20%-30% for training. All remaining images are used for testing.

Table 2. Image Classification Result for Various Features of Image.

Class		Sky	Water	Green Land	Total
Count of images		37	23	27	87
With only Color Feature	TP	37	0	21	58
	FN	0	23	6	29
	FP	24	0	5	29
All Four Features in combine	TP	37	9	6	52
	FN	0	14	21	35
	FP	29	4	2	35
With Contrast, correlation & Homogeneity	TP	37	9	6	52
	FN	0	14	21	35
	FP	29	4	2	35
With Contrast & Homogeneity	TP	37	9	6	52
	FN	0	14	21	35
	FP	29	4	2	35
With Homogeneity	TP	36	14	14	**64**
	FN	1	9	13	23
	FP	7	7	9	23
With Contrast	TP	37	9	6	52
	FN	0	14	21	35
	FP	29	4	2	35
With Correlation	TP	3	16	13	32
	FN	34	7	14	55
	FP	1	27	27	55
With Energy	TP	26	17	5	48
	FN	11	6	22	39
	FP	0	20	19	39
With Homogeneity, Ratio of Horiz / Non_horiz_line_count	TP	33	19	17	**69**
	FN	4	4	10	18
	FP	6	10	2	18
With Homogeneity, Color and Horizontal Line Feature	TP	32	12	23	**67**
	FN	5	11	4	20
	FP	11	6	3	20

Table 3. Evaluation of Image Classification Result for Various Features of Image.

Class	Evaluation Parameters	Sky	Water	Green Land	Total
Count of images		37	23	27	87
With only Color Feature	Precision	0.61	0.00	0.81	0.47
	Recall	1.00	0.00	0.78	0.59
	F-measure	0.76	0.00	0.79	0.52
All Four Features in combine	Precision	0.56	0.69	0.75	0.67
	Recall	1.00	0.39	0.22	0.54
	F-measure	0.72	0.50	0.34	0.52
With Contrast, correlation & Homogeneity	Precision	0.56	0.69	0.75	0.67
	Recall	1.00	0.39	0.22	0.54
	F-measure	0.72	0.50	0.34	0.52
With Contrast & Homogeneity	Precision	0.56	0.69	0.75	0.67
	Recall	1.00	0.39	0.22	0.54
	F-measure	0.72	0.50	0.34	0.52
With Homogeneity	Precision	0.84	0.67	0.61	**0.70**
	Recall	0.97	0.61	0.52	**0.70**
	F-measure	0.90	0.64	0.56	**0.70**
With Contrast	Precision	0.56	0.69	0.75	0.67
	Recall	1.00	0.39	0.22	0.54
	F-measure	0.72	0.50	0.34	0.52
With Correlation	Precision	0.75	0.37	0.33	0.48
	Recall	0.08	0.70	0.48	0.42
	F-measure	0.15	0.48	0.39	0.34
With Energy	Precision	1.00	0.46	0.21	0.56
	Recall	0.70	0.74	0.19	0.54
	F-measure	0.83	0.57	0.20	0.53
With Homogeneity, Ratio of Horiz / Non_horiz_line_count	Precision	0.85	0.66	0.89	**0.80**
	Recall	0.89	0.83	0.63	**0.78**
	F-measure	0.87	0.73	0.74	**0.78**
With Homogeneity, Color and Horizontal Line Feature	Precision	0.74	0.67	0.88	**0.77**
	Recall	0.86	0.52	0.85	**0.75**
	F-measure	0.80	0.59	0.87	**0.75**

In the proposed system, probabilistic neural network is trained with feature vector of training images. This trained network is tested with feature vectors of test images. Performance of various features is tested with evaluation parameters; namely, TP, FP and FN. Table-2 shows the values of these evaluation parameters. Table-3 shows the values of precision, recall and F-measures calculated from Table-2. Precision value gives information about how many of images that positively classified are relevant. Recall used to check how good a test is in detecting positives. F-measure is harmonic mean of precision and recall. It conveys balance between precision and recall. Higher values of precision, recall and F-measure show good performance of features.

When color features are used individually, it outperforms for sky object but all water objects are misclassified. When texture features are used individually, homogeneity feature performs good to classify sky object and it performs average to water and green land objects. When color, statistical texture and horizontal line features are used together to classify the image, it shows improvements in classification.

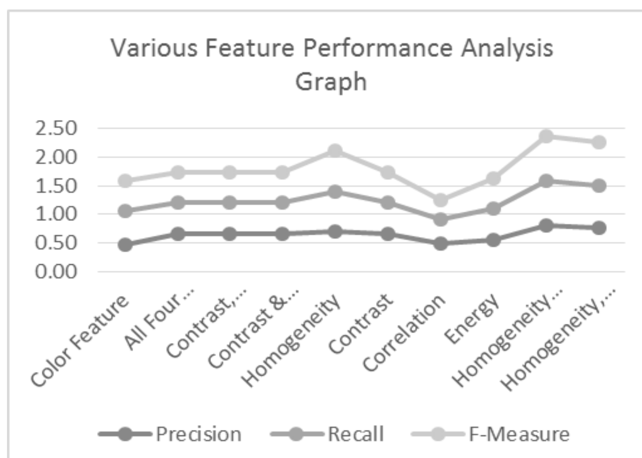

Figure 3. Feature Performance Analysis Graph

V. Conclusion and Future Scope

For the proposed scheme, we have observed encouraging results for image classification of sky, water and green land objects. Various features were tested individually and in combination with each other. It is observed from Table-2, Table-3 and Figure 3 that using only color feature for sky and water object image classification is not sufficient because it increases the misclassification. However, with using only statistical features individually or in combination, it improves the result of classification. It has been also observed that when color, statistical texture and horizontal line feature are used together, F-measure calculated for image classification is improved by 5% to 8%. In future we can take shininess feature of water into consideration to distinguish it from sky.

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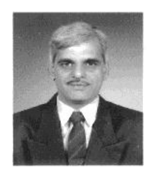
Authors Profile

Chaitali A. Laulkar has completed her BE (CSE) from BAMU, University, Aurangabad. She has completed her Masters degree, M.E.(C.E) from University of Pune, Pune. She is currently persuing her Ph.D from Shivaji university, Kolhapur and also working as Associate Professor in Department of Computer Engineering, Sinhgad college of Engineering, Pune. She has worked in image processing area on Biomedical imaging for her postgraduate project work. She has also completed ISRO funded and BCUD funded research project on satellite imaging. She has provided guidance to many UG & PG projects groups. Her main research work focuses on Image classification.



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