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Classification of a Class of Agricultural Images Using Multi Guided Multicolor Coherence Feature

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Abstract: Classification of particular group of agricultural images into semantically meaningful categories is a challenging task. Recently color coherence vector has become popular for image mining. This study makes use of multicolor coherence feature with multiple guide images (MGMCF) for classification of agricultural images like coconut and palm trees. The classification results using neural network is promising. Hence, image mining/image retrieval tasks can be done at good precision/recall by using MGMCF features.

Key words: Multi guided multicolor coherence feature, greenery images, coconut tree, palm tree, classification, neural network

INTRODUCTION

With the rapid development of the internet and the World Wide Web, the amount of digital image data accessible to users has grown enormously. At present the size of image repository is growing in exponential and it is accessed by huge number of applications and users. So, there is a growing need for good image retrieval system in terms of retrieval time and accuracy (Flickner *et al*., 1995; Huang *et al*., 1997; Ogle and Stonebraker, 1995; Pass *et al*., 1996; Smith and Chang, 1996; Pentland *et al*., 1996; Gudivada and Raghavan, 1995).

The global color distribution in an image can be obtained using color histograms which are popular solutions to retrieve an image from a large database (Swain and Ballard, 1991; Ogle and Stonebraker, 1995). Color histograms are insensitive to small changes in camera positions and liable to false positives since it does not include any spatial information. Several schemes for using spatial information about colors to improve upon the histogram method have been proposed. Smith and Chang (1996) partition an image into binary color sets using histogram back-projection (Swain and Ballard, 1991) and binary color sets along with their location information constitute the feature. Stricker *et al.* (1996) divide an image into five fixed overlapping regions and extract the first three color moments of each region to form a feature vector for the image.

Huang *et al.* (1997) propose another color feature for image indexing/retrieval called the color correlogram that take into account the local spatial correlation as well as the global distribution of this spatial correlation. The revised version of color correlogram is called autocorrelogram (Huang *et al*., 1997), which consider spatial correlation between identical colors only and it requires less space compare to correlogram method. Pass and Zabih (1996) partition histogram bins by the spatial coherence of pixels called as Color Coherence Vector (CCV).

In general, the natural images are more complex and classifying natural images into particular group is more challenging task in image processing (Szummer and Picard, 1998) and there is a high need of good features for image retrieval system. Moreover, classification of agriculture images is the first step in any automatic disease identification system. Hence, this paper introduces Multi Guided Multicolor Coherence Feature (MGMCF) for a class of agriculture images like coconut and palm trees.

COLOR COHERENCE VECTOR

Color coherence (Pass *et al*., 1996) measures the number of connected similar color pixels. If the size of the similarly connected regions are greater than or equal to threshold (τ) value then they are called coherent regions otherwise they are incoherent. These coherent features are having significant importance in classifying natural images.

Computing a CCV is very simple. First blur the image lightly which eliminates small variations between neighboring pixels. Now quantize the color's space into n (bucket size) distinct colors in the image. Then find similarly connected regions and classify them into coherent and incoherent to form CCV as:

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$$\{(\alpha_0, \beta_0), \ldots\ldots, (\alpha_{n-1}, \beta_{n-1})\}$$

where α_j is the number of coherent pixels and β_j is the number of incoherent pixels of the jth discretized color, respectively.

Color Image retrieval based on two indexes namely ΔH and ΔG has been proposed by Pass *et al*. (1996), with the constraints that:

$$\Delta H \leq \Delta G$$

Where:

$$\Delta H = \sum_{j=0}^{n-1} \left| \left(\alpha_j^1 + \beta_j^1\right) - \left(\alpha_j^2 + \beta_j^2\right) \right| \quad (1)$$

$$\Delta G = \sum_{j=0}^{n-1} \left(\left|\alpha_j^1 - \alpha_j^2\right| + \left|\beta_j^1 - \beta_j^2\right| \right) \quad (2)$$

where, (α^1_j, β^1_j) and (α^2_j, β^2_j) correspond to coherent and incoherent pixels of the first image (I_1) and second image (I_2), respectively.

Later Balamurugan and Rajesh (2007, 2008a, b) proposed ΔI for greenery and non-greenery image classification with the constraints that:

$$\Delta I \leq \Delta H \leq \Delta G$$

Where:

$$\Delta I = \sum_{j=0}^{n-1} \left| \left(\alpha_j^1 - \alpha_j^2\right) \right| - \left| \left(\beta_j^1 - \beta_j^2\right) \right| \quad (3)$$

GUIDED MULTI-COLOR COHERENCE FEATURES

The multi guided multi color coherence features correspond to the color coherence vector of images represented in multi color model with reference to a multiple guide images for the classification of images. For Example, ΔI_1 is derived from Eq. 3 with guide image g_1,

$$\Delta I_1 = \sum_{j=0}^{n-1} \left| \left(\alpha_i^{g_1} - \alpha_i^k\right) \right| - \left| \left(\beta_i^{g_1} - \beta_i^k\right) \right|, \ \forall k \quad (4)$$

where, $\left(\alpha_i^{g_1}, \beta_i^{g_1}\right)$ and $\left(\alpha_i^k, \beta_i^k\right)$ corresponds to coherent and incoherent pixels of the guide image (g_1) and the kth image (I_k) in the database, respectively. Similarly, ΔH_1 and ΔG_1 can be calculated for the guide image g_1. Thus color coherence feature indexes namely (ΔI, ΔH and ΔG) are calculated for three guide images g_1, g_2 and g_3 thereby forming Multi-guided color feature (ΔI_1, ΔH_1, ΔG_1), (ΔI_2, ΔH_2, ΔG_2) and (ΔI_3, ΔH_3, ΔG_3), respectively. These MGCF, namely:

$$\bigcup_{i=1}^{3} \{\Delta I_i, \Delta H_i, \Delta G_i\}$$

are calculated for different colors in RGB, HSI and Indexed color spaces and forming Multi-guided Multi-color Coherence Feature (MGMCF). Moreover these MGMCFs are calculated for two threshold values ($\tau = 50{,}100$) with two bucket sizes ($b = 26{,}64$) for RGB and HSI color spaces and with four bucket sizes ($b = 26{,}64{,}128{,}256$) for indexed color space. Thus forming $(9\times6\times2\times2)+(9\times1\times4\times2) = 288$ features.

EXPERIMENTS AND RESULTS

The data set consists of 900 images which includes 300 greenery, 300 coconut and 300 palm images of 100×100 pixel size. 50% of images are used for training. The experiment is repeated by interchanging the testing and training set of images.

Mining of coconut images: This section focuses on the mining of coconut tree using Adaptive Neuro Fuzzy System (ANFIS) (Gonzalez *et al*., 2004; Jahne, 2002; Jang, 1993). Four set of features namely (ΔH, ΔG), (ΔH, ΔI), (ΔG, ΔI) and (ΔH, ΔG, ΔI) in various color spaces, bucket sizes, threshold values and guided images are given as input to the classification system for understanding the mining performance. ANFIS uses a hybrid learning algorithm to identify the membership function parameters of single-output, Sugeno type Fuzzy Inference Systems (FIS). A combination of least-squares and backpropagation gradient descent methods are used for training FIS membership function parameters to model a given set of input/output data. Each input variable is mapped into two membership functions.

Experiment 1: Understanding the classification performance due to the combination of features in RGB color space.

Classification results of greenery and coconut images using guided color coherence vector in RGB color scale with one, average of two and average of three guide images are shown in Table 1. The highest classification rate 89% is obtained for the combination (ΔH, ΔI) with bucket size(n) = 25, threshold (τ) = 50 and three guided images.

Experiment 2: Understanding the classification performance due to the combination of features in HSI color space. Classification results of greenery and coconut images using guided color coherence vector in HSI color scale with one, average of two and average of three guide images are shown in Table 2. The highest classification rate 93% is obtained for the combination (ΔH, ΔG, ΔI) with bucket-size (n) = 63, threshold (τ) = 100 and three guided images.

Experiment 3: Understanding the classification performance due to the combination of features in Indexed color space. Classification results of greenery and coconut images using guided color coherence vector in indexed color scale with one, average of two and average of three guide images are shown in Table 3. The highest classification rate 93% is obtained for the combination (ΔH, ΔG) with bucket size (n) = 256, threshold (τ) = 100 and two guided images.

CLASSIFICATION OF COCONUT AND PALM IMAGES

Experiment 1: Understanding the classification performance due to the combination of features in RGB color space. Classification results of coconut and palm images using guided color coherence vector in RGB color space with one, average of two and average of three guide images are shown in Table 4. The highest classification rate 88% is obtained for the combination (ΔH, ΔI) with bucket size (n) = 63, threshold (τ) = 50 and two guided images.

Experiment 2: Understanding the classification performance due to the combination of features in HSI color space. Classification results of coconut and palm images using guided color coherence vector in HSI color space with one, average of two and average of three guide images are shown in Table 5. The highest classification rate 90% is obtained for the combination (ΔH, ΔG, ΔI) with bucket size (n) = 63, threshold (τ) = 100 and three guided images.

Experiment 3: Understanding the classification performance due to the combination of features in Indexed color space. Classification results of coconut and palm

Table 1: Classification results of greenery and coconut images using color coherence vector in RGB model with three guide images (GI)

			Red of RGB			Green of RGB			Blue of RGB		
Feature	Bucket size (b)	Threshold (τ)	GI-I	GI-II	GI-III	GI-I	GI-II	GI-III	GI-I	GI-II	GI-III
[ΔH, ΔG]	63	100	73	57	68	70	56	59	63	70	71
[ΔH, ΔI]	63	100	67	59	65	66	76	60	74	66	63
[ΔG, ΔI]	63	100	69	63	65	67	72	66	73	70	68
[ΔH, ΔG, ΔI]	63	100	76	64	71	72	73	65	78	74	68
[ΔH, ΔG]	63	50	75	56	65	67	60	59	63	68	69
[ΔH, ΔI]	63	50	71	57	65	77	82	81	75	66	64
[ΔG, ΔI]	63	50	65	60	66	79	82	79	75	68	66
[ΔH, ΔG, ΔI]	63	50	77	63	73	80	85	80	77	69	69
[ΔH, ΔG]	25	100	69	59	53	63	70	62	61	66	60
[ΔH, ΔI]	25	100	75	68	82	83	86	88	71	67	67
[ΔG, ΔI]	25	100	77	73	77	80	81	88	68	63	64
[ΔH, ΔG, ΔI]	25	100	77	74	77	82	87	88	72	65	68
[ΔH, ΔG]	25	50	67	53	49	66	66	59	61	66	63
[ΔH, ΔI]	25	50	69	72	76	80	88	89	68	77	71
[ΔG, ΔI]	25	50	72	73	73	78	83	85	68	77	66
[ΔH, ΔG, ΔI]	25	50	71	70	74	76	86	85	70	78	69

Table 2: Classification results of greenery and coconut images using color coherence vector in HSI model with three guide images (GI)

			Hue of HSI			Saturation of HSI			Intensity of HSI		
Feature	Bucket size (b)	Threshold (τ)	GI-I	GI-II	GI-III	GI-I	GI-II	GI-III	GI-I	GI-II	GI-III
[ΔH, ΔG]	63	100	77	77	72	61	68	64	69	61	69
[ΔH, ΔI]	63	100	77	79	82	89	90	93	65	68	65
[ΔG, ΔI]	63	100	78	78	84	83	82	91	68	73	66
[ΔH, ΔG, ΔI]	63	100	84	85	83	88	89	93	72	71	72
[ΔH, ΔG]	63	50	75	78	76	59	65	61	68	57	68
[ΔH, ΔI]	63	50	72	77	82	88	85	91	61	71	66
[ΔG, ΔI]	63	50	73	77	83	86	79	90	65	72	66
[ΔH, ΔG, ΔI]	63	50	78	82	85	87	86	91	71	72	69
[ΔH, ΔG]	25	100	84	89	72	60	62	63	59	54	61
[ΔH, ΔI]	25	100	64	64	73	67	72	68	82	78	87
[ΔG, ΔI]	25	100	75	74	73	62	62	70	78	78	86
[ΔH, ΔG, ΔI]	25	100	88	89	69	66	68	69	78	77	84
[ΔH, ΔG]	25	50	83	87	76	61	68	61	61	53	62
[ΔH, ΔI]	25	50	66	66	71	65	69	74	72	77	77
[ΔG, ΔI]	25	50	67	63	67	62	61	65	69	78	78
[ΔH, ΔG, ΔI]	25	50	89	86	75	67	68	72	66	74	75

Table 3: Classification results of greenery and coconut images using color coherence vector in indexed model with three guide images (GI)

			Indexed model		
Feature	Bucket size (b)	Threshold (τ)	GI-I	GI-II	GI-III
[ΔH, ΔG]	256	100	80	93	78
[ΔH, ΔI]	256	100	83	86	83
[ΔG, ΔI]	256	100	82	84	83
[ΔH, ΔG, ΔI]	256	100	81	92	84
[ΔH, ΔG]	256	50	82	87	79
[ΔH, ΔI]	256	50	87	82	84
[ΔG, ΔI]	256	50	87	82	84
[ΔH, ΔG, ΔI]	256	50	89	87	82
[ΔH, ΔG]	128	100	72	71	60
[ΔH, ΔI]	128	100	91	88	77
[ΔG, ΔI]	128	100	89	85	75
[ΔH, ΔG, ΔI]	128	100	91	87	75
[ΔH, ΔG]	128	50	72	69	60
[ΔH, ΔI]	128	50	78	78	62
[ΔG, ΔI]	128	50	72	70	62
[ΔH, ΔG, ΔI]	128	50	80	75	63
[ΔH, ΔG]	63	100	51	45	60
[ΔH, ΔI]	63	100	49	60	63
[ΔG, ΔI]	63	100	52	58	65
[ΔH, ΔG, ΔI]	63	100	50	58	66
[ΔH, ΔG]	63	50	46	55	48
[ΔH, ΔI]	63	50	59	48	66
[ΔG, ΔI]	63	50	46	52	60
[ΔH, ΔG, ΔI]	63	50	55	54	64
[ΔH, ΔG]	25	100	60	60	66
[ΔH, ΔI]	25	100	48	59	61
[ΔG, ΔI]	25	100	62	60	57
[ΔH, ΔG, ΔI]	25	100	58	62	65
[ΔH, ΔG]	25	50	52	68	63
[ΔH, ΔI]	25	50	50	59	61
[ΔG, ΔI]	25	50	51	70	59
[ΔH, ΔG, ΔI]	25	50	56	68	67

Table 4: Classification results of coconut and palm images using color coherence vector in RGB model with three guide images (GI)

			Red of RGB			Green of RGB			Blue of RGB		
Feature	Bucket size (b)	Threshold (τ)	GI-I	GI-II	GI-III	GI-I	GI-II	GI-III	GI-I	GI-II	GI-III
[ΔH, ΔG]	63	100	77	69	74	70	64	73	72	64	72
[ΔH, ΔI]	63	100	81	71	85	76	60	83	79	87	84
[ΔG, ΔI]	63	100	83	75	85	79	61	83	78	83	84
[ΔH, ΔG, ΔI]	63	100	85	76	86	76	65	80	78	86	86
[ΔH, ΔG]	63	50	77	65	74	76	62	78	74	62	73
[ΔH, ΔI]	63	50	82	76	83	78	63	83	79	88	84
[ΔG, ΔI]	63	50	84	78	85	81	64	81	78	85	82
[ΔH, ΔG, ΔI]	63	50	83	77	82	81	62	81	76	86	85
[ΔH, ΔG]	25	100	79	72	80	73	62	73	79	71	80
[ΔH, ΔI]	25	100	79	71	80	76	57	77	73	73	82
[ΔG, ΔI]	25	100	83	73	80	81	65	79	75	68	78
[ΔH, ΔG, ΔI]	25	100	82	77	83	81	64	81	76	75	84
[ΔH, ΔG]	25	50	81	70	80	71	59	71	79	67	78
[ΔH, ΔI]	25	50	82	66	81	77	59	79	76	66	77
[ΔG, ΔI]	25	50	84	68	80	82	67	81	75	66	71
[ΔH, ΔG, ΔI]	25	50	83	72	85	83	66	81	77	65	76

images using guided color coherence vector in indexed color space with one, average of two and average of three guide images are shown in Table 6. The highest classification rate 87% is obtained for the combination (ΔH, ΔG) with bucket size (n) = 25, threshold (τ) = 100 and three guided images.

NEURAL NETWORK BASED SYSTEM FOR CLASSIFICATION OF IMAGES

This section describes the mining of tree using neural network (Park *et al*., 2004; Gonzalez *et al*., 2004; Jahne, 2002). Totally 288 guided color coherent features of different color space, bucket sizes, threshold values and guided images are given as training parameters. These training parameters are used by training algorithm called scaled conjugate gradient to learn from sample and test with 20 neurons for 1000 epochs.

Experiment 1: Classification of greenery and coconut images: The success rate of 98.3% is obtained for the classification of greenery and coconut images as shown in Table 7. The confusion matrix is given in Table 8. It informs that, out of 150 coconut trees, one is

Table 5: Classification results of coconut and palm images using color coherence vector in HSI model with three guide images (GI)

			Hue of HSI			Saturation of HSI			Intensity of HSI		
Feature	Bucket size (b)	Threshold (τ)	GI-I	GI-II	GI-III	GI-I	GI-II	GI-III	GI-I	GI-II	GI-III
[ΔH, ΔG]	63	100	62	81	83	72	71	79	74	66	73
[ΔH, ΔI]	63	100	59	61	83	78	78	87	77	66	78
[ΔG, ΔI]	63	100	64	64	83	84	83	89	76	72	80
[ΔH, ΔG, ΔI]	63	100	63	77	82	80	80	90	78	71	79
[ΔH, ΔG]	63	50	63	82	84	76	74	82	74	68	74
[ΔH, ΔI]	63	50	60	62	84	76	77	86	80	72	80
[ΔG, ΔI]	63	50	62	63	84	86	81	89	80	78	80
[ΔH, ΔG, ΔI]	63	50	66	79	82	81	81	89	79	76	79
[ΔH, ΔG]	25	100	83	87	79	83	77	80	76	69	75
[ΔH, ΔI]	25	100	74	77	78	67	61	70	77	70	75
[ΔG, ΔI]	25	100	71	70	77	80	76	77	82	77	77
[ΔH, ΔG, ΔI]	25	100	81	85	75	82	79	81	82	76	81
[ΔH, ΔG]	25	50	83	88	76	79	70	81	74	65	77
[ΔH, ΔI]	25	50	74	76	78	66	65	70	81	66	80
[ΔG, ΔI]	25	50	74	75	81	79	72	78	81	70	80
[ΔH, ΔG, ΔI]	25	50	83	84	75	78	71	79	83	72	81

Table 6: Classification results of coconut and palm images using color coherence vector in indexed model with three guide images (GI)

			Indexed model		
Feature	Bucket size (b)	Threshold (τ)	GI-I	GI-II	GI-III
[ΔH, ΔG]	256	100	62	58	51
[ΔH, ΔI]	256	100	64	71	68
[ΔG, ΔI]	256	100	64	70	68
[ΔH, ΔG, ΔI]	256	100	68	72	71
[ΔH, ΔG]	256	50	67	59	62
[ΔH, ΔI]	256	50	62	70	67
[ΔG, ΔI]	256	50	62	73	67
[ΔH, ΔG, ΔI]	256	50	70	76	75
[ΔH, ΔG]	128	100	66	64	68
[ΔH, ΔI]	128	100	60	61	60
[ΔG, ΔI]	128	100	57	60	56
[ΔH, ΔG, ΔI]	128	100	69	66	68
[ΔH, ΔG]	128	50	67	63	66
[ΔH, ΔI]	128	50	61	59	62
[ΔG, ΔI]	128	50	60	50	65
[ΔH, ΔG, ΔI]	128	50	67	64	69
[ΔH, ΔG]	63	100	79	73	68
[ΔH, ΔI]	63	100	56	58	73
[ΔG, ΔI]	63	100	74	71	81
[ΔH, ΔG, ΔI]	63	100	80	71	77
[ΔH, ΔG]	63	50	75	64	70
[ΔH, ΔI]	63	50	63	60	72
[ΔG, ΔI]	63	50	76	64	77
[ΔH, ΔG, ΔI]	63	50	77	67	76
[ΔH, ΔG]	25	100	74	67	87
[ΔH, ΔI]	25	100	59	70	74
[ΔG, ΔI]	25	100	71	66	77
[ΔH, ΔG, ΔI]	25	100	75	70	86
[ΔH, ΔG]	25	50	73	68	80
[ΔH, ΔI]	25	50	63	72	74
[ΔG, ΔI]	25	50	63	70	61
[ΔH, ΔG, ΔI]	25	50	73	73	82

Table 7: Classification results for mining coconut tree images using neural network classifier based on 288 multi guided multicolor coherence feature (MGMCF)

Classification problem	Classification results (%)	Time (sec)	No. of neurons	Performance function
Greenery vs. coconut	98.3	7-10	20	MSE
Coconut vs. palm	96.7	4-5	20	MSE

Table 8: Confusion matrix for mining coconut tree images in neural network classifier using multi guided multicolor coherence feature (MGMCF)

	Predicted class			Predicted class	
Actual class	Coconut trees	Greenery images	Actual class	Coconut images	Palm images
Coconut trees	149	1	Coconut images	150	0
Greenery images	2	148	Palm images	3	147

misclassified as greenery images. Likewise out of 150 greenery images, 2 images are misclassified as coconut trees.

Experiment 2: Classification of coconut and palm images: The success rate of 96.7% is obtained for the classification of coconut and palm trees as shown in Table 7 and the corresponding confusion matrix is given in Table 8. It seems that out of 150 coconut trees, all are correctly classified as same class and of 150 palm trees, 3 are misclassified as coconut trees.

INTERPRETATION

The above experiments shows that in most of the cases (1) the guided color feature ΔI gives better result along with ΔH or ΔG or both ΔH and ΔG (2) the performance of the classification with average of more than one guide image is better than the single guide and (3) neural network classifier gives prominent result for mining of coconut images. Hence, MGMCF can be considered as good feature for image mining/image retrieval with the help of more than one guide/similar images.

CONCLUSION

Multi Guided Multicolor Coherence Features (MGMCF) are more good at getting higher classification rate due to the presence of guide images which are chosen from target class images. This feature is used for the classification of (1) Coconut trees vs. Greenery images and (2) Coconut trees vs. Palm trees. The result of classification using neural network is promising. Hence, MGMCF feature can be used for guided image retrieval/image mining.

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