Comparison between HSV and YCbCr Color Model Color-Texture based Classification of the Food Grains

Neelamma K. Patil
Dept. of Telecommunication Engineering
KLES College of Engineering & Technology, Belgaum, Karnakata, India

Ravi M. Yadahalli
Dept. of Electronics & Communication Engineering
PES Institute Technology & Management, Shivamogga, Karnakata, India

Jagadeesh Pujari
Dept. of Information Science Engineering
SDM College of Engineering & Technology, Dharwad, Karnakata, India

ABSTRACT
This paper presents the comparative study among HSV and YCbCr color models in the classification of food grains by combining color and texture features without performing preprocessing. Also, the paper deals with the effect of training set, block size and K-value in the process of classification. The proposed method is performed in two phases; the feature extraction phase and classification phase. The K-NN and minimum distance classifiers are used to classify the different types of food grains using color, local and global features. The classification of food grains involves the computation of features locally and globally using the Haralick features and the cumulative histogram respectively. The non-uniformity of RGB color space is eliminated by HSV and YCbCr color space. The good classification accuracy is achieved using both the color models.

General Terms
Pattern Recognition, Algorithm, Features, Classification.

Keywords
Feature Extraction, Co-occurrence Matrix, Global Features, Cumulative Histogram, RGB, HSV, YCbCr color models.

1. INTRODUCTION
The type of food grains and their quality are identified manually by visual inspection. This evaluation process is however, tedious and time consuming. Hence, manual identification of food grains requires automation and there is a need for the development of image processing systems that can be helpful to identify the types of food grains, classify & then being analyzed.

Machine Vision Systems are successfully used for Identification and Classification of plants, leaves, flowers, bulk grain samples [9-13]. Anami et al. and Visen et al. have used an artificial neural network approach to identify and classify the bulk grain samples [1-3]. A novel method for the recognition of images using textural features is described in Haralick et al. [6]. A method for the classification and gradation of different grains (for a single grain kernel) such as groundnut, Bengal gram, wheat etc. is described in Anami et al. [1]. Determining the potential of morphological features to classify different grain species, classes, varieties, damaged grains, and impurities, using statistical pattern recognition techniques, have been the main focus of much of the published research work [7-9]. Neuman et al. and Majumdar et al, have tried to use color features for grain identification [14,15,11]. Only limited work has been done to incorporate textural features for classification purposes [8, 2]. Efforts have also been made to integrate all these features in terms of a single classification vector for grain kernel identification [13]. Neelamma et al. have performed classification on food grains using HSI color model and achieved 83.66% using 50% training set with 512x512 and 256x256 block size [5]. The Sanjivini et al., have carried out the experiment on rice grains and performed preprocessing process which is tedious [18].

The above study shows that the classification accuracies are high and depending on the features extracted. The texture features provide good classification result. In this paper, the effect of color models, training set, K-value and block size have been observed. Total 12 features are extracted and are used for classification. The food grain images are captured under natural light and are stored in database. The minimum distance classifier (K=1) and the K-NN classifier are used for classification. This work also gives clear knowledge about correct and erroneous classification in terms of percentage and confusion matrix respectively. The paper presents algorithms for feature extraction and classification and finally discusses the experimental results.

2. FEATURE EXACTION
Pattern recognition system consists of two stage process. The first one is features extraction and second is classification. The features are the set of description about an image which helps to classify. In this paper, the features are extracted locally and globally from color and texture information. The robustness of the system depends on the features extracted. In this paper, total 12 features are extracted including global, local and color features.

2.1 Color Model Conversion
Color is the most vital visual feature for humans. By color representation we mean the overall color of image content when used as a “global” feature. The non-uniformity of RGB color space is eliminated by HSV and YCbCr color space before extracting the features.

2.1.1 RGB to HSV color model conversion

The HSV stands for the Hue, Saturation and Value. The value represents intensity of a color, which is decoupled from the color information in the represented image. The hue and saturation components are intimately related to the way human eye perceives. The transformation equations for RGB to HSV color model conversion is given below

$$V = \max(R, G, B)$$

$$S = \frac{V - \min(R,G,B)}{V}$$

$$H = \frac{G-B}{6S} \quad , \quad if \quad V = R$$

$$H = \frac{1}{3} + \frac{B-R}{6S} \quad , \quad if \quad V = G$$

$$H = \frac{2}{3} + \frac{R-G}{S} \quad , \quad if \quad V = B$$

2.1.2 RGB to YCbCr color model conversion

Y is the luminance component and C_b and C_r are the blue-difference and red-difference chroma components. The conversion equations from RGB to YCbCr color model is given below.

$$[\mathrm{Y}\ \ \mathrm{Cb}\ \ \mathrm{Cr}] = \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112.00 \\ 112.00 & -93.786 & -18.214 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + [16 \quad 128 \quad 128]$$

2.2. Color, Global and Local Features

2.1.1 Color Features

Color features like mean and standard deviation are extracted from color channels in HSV and YCbCr color models. The mean and standard deviation are calculated using formula given below.

Standard Deviation = $$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}.$$

Mean = $$\mu = \frac{1}{N}\sum_{i=0}^{N-1} x_i$$

2.1.2 Global Features

Global features are extracted from cumulative histogram. The mean, standard deviation and slope of the regression line are the three global features which are extracted from cumulative histogram.

2.1.3 Local Features

The food grains may have similarity in color but exhibit different texture patterns. This motivated us to include texture feature act as local features. We have adopted co-occurrence matrix to obtain texture features. The five local features are extracted from co-occurrence matrix known as Haralick features. The features are homogeneity (E), contrast(C), correlation (Cor), entropy (H) and local homogeneity (LH) and are listed in table 2.1.

Table 2.1. List of Haralick features

S. N.	Haralick Features	Equation
1.	Homogeneity	$E = \sum_i \sum_j (M(i,j))^2$
2.	Contrast	$C = \sum_{k=0}^{m-1} k^2 \sum_{\lvert i-j \rvert = k} M(i,j)$
3.	Correlation	$Cor = \sum_i \sum_j \frac{(i-\mu_i)(j-\mu_j)M(i,j)}{\sigma_i \sigma_j}$
4.	Entropy	$H = \sum_i \sum_j M(i,j) \log (M(i,j))$
5.	Local homogeneity	$LH = \sum_i \sum_j \frac{M(i,j)}{1+(i-j)^2}$

3. CLASSIFIERS

3.1 K-NN Classifier

In pattern recognition, the K-nearest neighbor algorithm (K-NN) is a method for classifying objects based on closest training examples in the feature space. The K-nearest neighbor algorithm is amongst the powerful and simplest of all machine learning algorithms: an object is classified by a majority “votes” of its neighbors, with the object being assigned to the class most common amongst its K nearest neighbors (K is a positive integer, typically small). If K = 1, then the object is simply assigned to the class of its nearest neighbor.

In the K-NN classifier, the class of the test sample is decided by the majority class among the K nearest neighbors. The K indicates the consideration of top values in the classification vector array. K should be odd in order to avoid ties and it should be kept small, since a large K tends to create misclassifications unless the individual classes are well separated.

3.2 Distance Classifier

The Canberra distance measure is used to compute the distance between the images. It is calculated and used for classification when K=1. The Canberra distance measure is given by

$$D(M) = \sum_{i=1}^{N} \frac{|f1_i - f2_i|}{|f1_i| + |f2_i|}$$

where f_1 and f_2 are feature vectors for training and testing, N is total images present and D(M) is distance calculated between each testing and training image.

4. EXPERIMENTAL SETUP

4.1 Sample Set of Food Grains Images

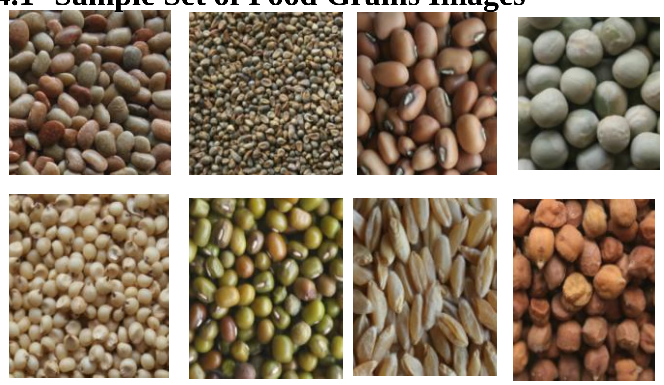

Fig 4.1. Images of food grains

Totally 20 different classes of food grains are collected and samples of them are shown in fig 4.1. Images are captured under natural light in photo studio maintaining fixed background and same distance between grains and camera. Through data cable these images have been transferred and resized to 1024x1024 by cropping and stored in database as JPEG image.

4.2 Methodology

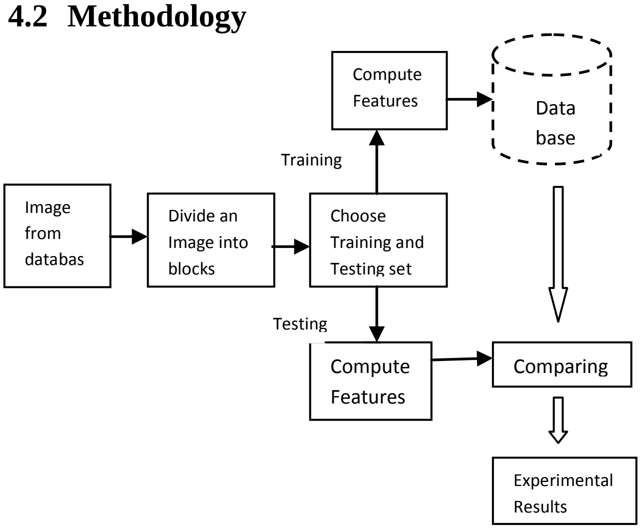

Fig 4.2. Block diagram of proposed work

Fig 4.2 shows the block diagram of the proposed work. Each image stored in the database is divided into small blocks of size 256x256 and 512x512. The computation of features is performed for each block of image and stored in database**.** The 12 features computed are mean and standard deviation for color information, 5 Haralick features for intensity information and 3 global features from cumulative histogram. The image is divided into blocks of different size; half part (50%) of an image and 25% of image part is used for training which acts as standard database and remaining part is used for testing which is verified against training set. Training and testing results are compared and output is expressed in terms of percentage of classification. The variation in the classification is referred as semantic gap which can be analyzed in the form confusion matrix.

4.3 Algorithm for Computation of Features

The color conversion from RGB to HSV and YCbCr color models is performed before extracting features. The following steps show the flow of computation of features.

Input: 1024x1024 size image from database.

Output: Computed features stored in database.

Start:

Step-1: Read an image and convert RGB to HSV and YCbCr color models.

Step-2: Divide an image into number of blocks with block size 512x512 and 256x256.

Step-3: Co-occurrence matrix is formed for texture information 'V' in case of HSV and 'Y' in YCbCr color models.

Step-4: Compute Haralick features for co-occurrence matrix.

Step-5: Mean and Standard Deviation are calculated for Chrominance information 'H' and 'S' in case of HSV and 'Cb' and 'Cr' in YCbCr color models.

Step-6: Cumulative histogram is formed to extract global features; viz. mean, standard deviation and slope of regression line.

Step-7: Store all 12 computed features in database.

Step-8: All the above steps are repeated for all the images present in all classes.

Stop

4.4 Algorithm for Classification

The following steps explain the flow of classification process.

Input: Features stored in database.

Output: Percentage of Classification.

Start:

Step-1: Set the value of K (K=1,3,5,7)

Step-2: Select training and testing blocks (50% and 25% Training set).

Step-3: Set the path where the computed features have been stored in the database.

Step-4: Distance is calculated between training and testing features.

Step-5: Sort all the calculated distances in an ascending order.

Step-6: Minimum distance classifier is used for K=1 and K-NN classifier is used for K=3, 5 and 7 to find out each image does belong to particular class.

Step-7: Display the confusion matrix.

Step-8: The percentage for each class is calculated.

Step-9: Average is calculated.

Step-10: All the above steps are repeated for different combinations of blocks.

Stop

5. EXPERIMENTAL RESULTS

Each image is of resolution 1024x1024 and is divided into blocks of size 256x256 or 512x512. For each texture class, half of the image is used for training and the remaining half samples for testing in the first case. Later, 25% of image is used for training and 75% of image is used for testing. Minimum distance classifier and K-NN classifier are used to analyze the classification performance and the value of K is taken as 1, 3, 5 and 7.

Table 5.1. Experimental results for block size-256x256, 50% training set, HSV color model

S.N.	Training set (Tr) & Testing(Ts) set	Average correct classification in Percentage			
		Using Min.Dist	Using K-NN Classifier		
		K=1	K=3	K=5	K=7
1	Tr-2,4,6,… Ts-1,3,5,…	68.99	70.38	70.62	70.87
2	Tr-3,4,7,8,.. Ts-1,2,5,6,..	69.79	69.36	68.43	67.52
3	Tr-1,3,5,7,... Ts-2,4,6,8,...	72.60	69.35	70.94	71.59
4	Tr-5,6,7,8,... Ts-1,2,3,4,...	70.54	73.09	71.54	69.77

Table 5.2. Experimental results for block size-512x512, 50% training set, HSV color model

S.N.	Training set (Tr) & Testing (Ts) set	Average correct classification in Percentage			
		Using Min.Dist	Using K-NN Classifier		
		K=1	K=3	K=5	K=7
1	Tr-2,4 Ts-1,3	82.50	85.63	85.00	80.00
2	Tr-3,4 Ts-1,2	80.07	77.85	76.59	79.10
3	Tr-2,3 Ts-1,4	88.75	82.50	85.62	85.00
4	Tr-1,3 Ts-2,4	82.50	83.125	83.12	83.75

From table 5.1 and 5.2 it is evident that maximum classification accuracy of 73.09% for K=3 and 88.75% for K=1 have been achieved for HSV color model with 50% training set with block size 256x256 and 512x512 respectively.

Table 5.3. Experimental results for block size-256x256, 50% training set, YCbCr color model

S.N.	Training set (Tr) & Testing(Ts)	Average correct classification in Percentage			
		Using Min.Dist	Using K-NN Classifier		
		K=1	K=3	K=5	K=7
1	Tr-2,4,6,… Ts-1,3,5,…	58.52	58.80	58.96	58.80
2	Tr-3,4,7,8,.. Ts-1,2,5,6,..	54.24	55.61	56.21	57.46
3	Tr-1,3,5,7,... Ts-2,4,6,8,...	56.16	58.49	58.80	59.43
4	Tr-5,6,7,8,... Ts-1,2,3,4,...	61.98	61.63	62.39	62.93

Table 5.4. Experimental results for block size-512x512, 50% training set, YCbCr color model

S.N.	Training set (Tr) & Testing(Ts)	Average correct classification in Percentage			
		Using Min.Dist	Using K-NN Classifier		
		K=1	K=3	K=5	K=7
1	Tr-2,4 Ts-1,3	71.87	70.62	70.62	73.12
2	Tr-3,4 Ts-1,2	82.50	80.62	80.62	81.87
3	Tr-2,3 Ts-1,4	83.75	83.75	83.75	82.50
4	Tr-1,3 Ts-2,4	84.37	81.87	79.37	81.87

Referring to the table 5.3 and table 5.4, the maximum accuracy of 84.37% is achieved with block size of 512x512 for K=1.The experimental results for 50% training set are shown in table 5.1 through table 5.4 for HSV and YCbCr color models. The total 20 different classes of food grains are selected for the experiment and the correct classification depends on block size, K value, different combinations of training and testing set.

Table 5.5. Experimental results for block size-256x256 , 25% training set, HSV color model

S.N.	Training set (Tr) & Testing(Ts)	Average correct classification in Percentage			
		Using Min.Dist	Using K-NN Classifier		
		K=1	K=3	K=5	K=7
1	Tr-2,4,6,… Ts-1,3,5,…	69.41	69.59	69.64	68.99
2	Tr-3,4,7,8,.. Ts-1,2,5,6,..	66.27	66.40	64.69	64.84
3	Tr-1,3,5,7,... Ts-2,4,6,8,...	65.82	65.10	64.45	65.99
4	Tr-5,6,7,8,... Ts-1,2,3,4,...	66.79	66.52	65.69	66.05

Table 5.6. Experimental results for block size-512x512, 25% training set, HSV color model

S.N.	Training set (Tr) & Testing(Ts)	Average correct classification in Percentage			
		Using Min. Dist	Using K-NN Classifier		
		K=1	K=3	K=5	K=7
1	Tr-1 Ts-2,3,4	80.42	78.98	77.91	78.33
2	Tr-2 Ts-1,3,4	77.31	73.75	72.50	72.92
3	Tr-3 Ts-1,2,4	75.88	75.05	68.98	73.98
4	Tr-4 Ts-1,2,3	79.81	79.39	78.98	77.50

The experimental results for 25% training set are shown in table 5.5 and table 5.6 for HSV color model with block size 256x256 and 512x512. The average maximum correct classification of 80.42% in case of HSV color model is achieved for block size 512x512.

Table 5.7. Experimental results for block size-256x256 , 25% training set, YCbCr color model

S.N.	Training set (Tr) & Testing(Ts)	Average correct classification in Percentage			
		Using Min.Dist	Using K-NN Classifier		
		K=1	K=3	K=5	K=7
1	Tr-1,2,3,4 Ts-5,6,7,8,...	57.80	59.39	59.43	59.53
2	Tr-13,….16 Ts-1,…..12	56.11	56.61	57.02	56.55
3	Tr-3,4,7,8 Ts-1,2,5,6,9..16	60.39	62.55	62.14	62.50
4	Tr-9,10,13,14 Ts-1,2,…7, 8,11,12,15,16	61.61	61.06	61.43	61.04

Table 5.8. Experimental results for block size-512x512, 25% training set, YCbCr color model

S.N.	Training set (Tr) & Testing(Ts)	Average correct classification in Percentage			
		Using Min.Dist	Using K-NN Classifier		
		K=1	K=3	K=5	K=7
1	Tr-1 Ts-2,3,4	69.58	67.73	65.83	66.25
2	Tr-2 Ts-1,3,4	78.42	74.67	76.11	76.11
3	Tr-3 Ts-1,2,4	81.85	78.98	80.05	79.77
4	Tr-4 Ts-1,2,3	70.88	71.06	70.28	71.07

The experimental results for 25% training set are shown in table 5.7 and table 5.8 for YCbCr color model with block size 256x256 and 512x512. The average maximum correct classification result of 81.85% in case YCbCr color model are achieved for block size of 512x512 with K=1. From the experimentation results, it may be concluded that, K=1 which is optimum. The results in both the cases of 25% and 50% training set are quite good and hence, we can observe that the system and computed features are robust. The proposed work is implemented in MATLAB version 7.5.0.342. It is observed that when the size of the image increases the result of classification also increases.

The maximum average classification results for different block sizes and training set are shown in the form of graph in fig 5.1 and fig 5.2 for HSV and YCbCr color models.

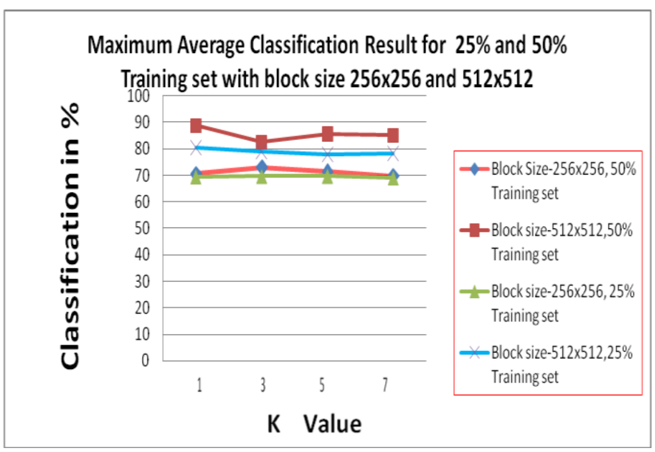

Fig 5.1. Maximum average clasification result for HSV color model

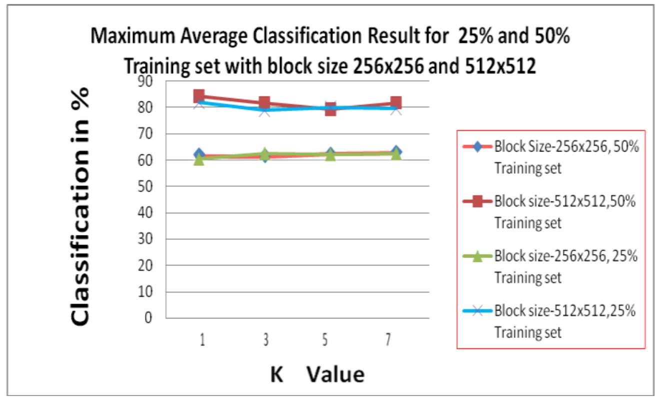

Fig 5.2. Maximum average clasification result for YCbCr color model

A confusion matrix contains information about actual and predicted classifications performed by a classification system. Performance of such systems is commonly evaluated using the data in the matrix which gives an idea about correct and erroneous classification. This is the gap between human vision and computer vision system which is known as semantic gap.

6. CONCLUSIONS

In this paper, a simple method for classification without performing preprocessing is proposed. The proposed work deals different food grains with different block sizes, percentage of training set and K value and also studied the effect of these in the classification process. The good correct classification result is achieved for both 50% and 25% training set for both the color models. This implies the robustness of the system and computed features. The features obtained are used for classification using minimum distance classifier and K-NN classifier. The robustness of the system depends on the features. Misclassification is identified in Confusion Matrix. The correct classification depends on K value present, Block size, selection and percentage of training set and testing set. The percentage of accuracy is increased by increasing the block size. From the experiment, we conclude that K=1 is optimum.

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8. AUTHORS PROFILE

Miss Neelamma K. Patil is working as Lecturer in the Department of Telecommunication Engineering in KLES College of Engineering and Technology, Belgaum, Karnataka, India. She has obtained her Bachelor degree in Electronics & Communication Engineering in the year 2010. Currently she is pursuing her Masters. Her areas of Research Interest are Image Processing and Pattern Recognition, Signal processing, Document Image Analysis and recognition and Medical Image processing. She has number of publications in peer reviewed International conferences.

Dr. Ravi M. Yadahalli is working as Professor and Head in Department of Electronics & Communication Engineering in PES Institute of Technology & Management, Shivamogga, Karnataka, India. He has obtained Bachelor degree in Electronics & Communications Engineering, M.E. Degree in Power Electronics and Ph.D in Microwave Electronics in the year 1990, 1993 and 2009 respectively. His research areas of interest are Microstrip Antenna and Biomedical Sensors. He has published more than 40 research papers in peer reviewed International Journals and conferences.

Dr. Jagadeesh Pujari is working as Professor in Department of Information Science & Engineering in SDM College of Engineering & Technology, Dharwad, Karnataka, India. He has obtained Bachelor degree in Computer Science & Engineering, M.S. Degree in Software Systems and Ph.D in Computer Science in the year 1990, 1999 and 2008 respectively. His research areas of interest are Image Processing, Content Based Image Retrieval and Pattern Recognition. He has published more than 25 research papers in peer reviewed International Journals and conferences.