Electronic Food Grain Identifier for Visually Challenged People

[1]P Sai Vivek, [2]R Lakshmi Priya, [3]S Nishanth, [4]K. Mounika, [5]Ramkakrishna Kohir, [6]Ibrahim Patel

[1,2,3,4,5]Bachelor's degree in BME Dept, [6]Member IEEE Associate Prof. Dept of ECE
[1,2,3,4,5]Dr. B. R. Raju Inst. of Tech. Narsapur Medak (Dist) A. P.India
Email: [1]pogulasaivivek@gmail.com, [2]rangaraju.lpriya@gmail.com, [3]nishanthzz999@gmail.com, [4]karmanchimounika12@gmail.com, [5]ramky.kohir@gmail.com, [6]Ibrahim.patel@bvrit.ac.in

Abstract- This paper presents the study of identification and classification of different food grains using different colour models, the purpose is evaluation of both software and hardware colour identification tools which is used to assist complete blind and colour-blind people in their daily activities. Blind people face a number of challenges to interact with their environments because so much information is encoded visually. Texture and colour features are the important features used in the classification of different objects. The local features like Haralick features are computed from co-occurrence matrix as texture features and global features from cumulative histogram are computed along with colour features. The experiment was carried out for different classes of food grains. Minimum distance classifier is used to identify and classify the different types of food grains using local and global features. The non-uniformity of RGB colour space is eliminated by L*a*b, HSV, HSI and YCbCr colour space. The correct classification result achieved for different colour models is quite good.

Keywords: colour identification tools, co-occurrence matrix, Haralick, histogram, RGB, L*a*b, HSV, HSI, YCbCr.

I. INTRODUCTION

It is estimated that 161 million people around the world (about 2.6% of the population) are visually impaired. This figure consists of 124 million people who have low vision and 37 million who are blind. According to the World Health Organization (WHO), low vision is defined as visual acuity of 20/200 or less in the better eye with best correction possible. (WHO, 2004). Approximately 10% of the male population in Europe suffers from some form of colour blindness, the most usual case being an inability to distinguish between certain colours (e.g. red/green, blue/yellow). In extreme situations, only shades of grey might be distinguishable. Normal people use colour to perform everyday tasks. In the present grain-handling scenario, grain type and quality are identified manually by visual method. Normal human beings can recognize fruits, grains, flowers and many other agriculture and horticulture produce based on shape, size, colour and patterns. But the visually impaired people can't conclude by these properties they encounter problem with similar shaped food grains, so they face difficulty in choosing right food grains, this project aids them in recognizing the desired result. Hence, these tasks require automation and develop imaging systems that can be helpful for choosing different food grain, In order to perform this task of pattern recognition by device, considerable design effort is necessary. Literature survey has been conducted to explore usage of these methods in different fields. Focus has been made on food grain samples like maize, wheat, corn, cow peas, green gram, horse gram, Bengal gram, pearl millet, red gram and peas shown fig.1.

II. SYSTEM OVERVIEW AND PROPOSED WORK

The robustness of the system depends on the features extraction. In this paper, the experiment was carried out on 10 different classes of food grains. The process of classification is performed in two phases; the first one is the computation of features and second is the classification of food grains with the help of extracted features by the use suitable classifiers. The original images used for the experimentation are captured under natural light and are resized to 1024x1024. The K-NN and minimum distance classifiers are used for classification using extracted global, local and colour features.

2.1 Colour Model Conversion

Colour is the most vital visual feature of human. By colour representation we mean the overall colour of image content when used as a "global" feature. A colour space is defined as a model representing colour in terms of intensity values. There are different colours models: RGB, Lab, HSV, HSI, YCbCr, etc. Each of these has got specific applications and also has got advantages and drawbacks. Based on our application we need to convert from one colour space to another. All the images are in RGB colour model, because of the non-uniformity of RGB colour space we need to convert them to the suitable colour space. The HSV and L* a* b* models are commonly used in colour image retrieval system. The non-uniformity of RGB colour model is eliminated by L*a*b, HSV, HSI and YCbCr colour models.

Gain sample Jawar　Gain sample Corn,　Gain sample Cow Peas　Gain sample Red gram

Gain sample: Green gram　Gain sampleHorse gram,　Gain sampleBengal　Gain sample Peas

Figure 1: Food grain samples

1) RGB to L*a*b colour model conversion:

L*a*b* is an international standard for colour measurements, adopted by the Commission International d'Eclairage (CIE) in 1976. This colour model creates a consistent colour regardless of the device used to generate the image. 'L' is the luminance or lightness component, which ranges from 0 to 100, and parameters a'' (from green to red) and 'b' (from blue to yellow) are the two chromatic components, which range from -120 to 120.

The transformation equations for RGB to Lab colour model conversionby a margin of 0.4 cm. Your paper must adhere to the length stipulated on the event website. Pages should be numbered centrally at the bottom of the page.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.42356 & 0.362390 & 0.179347 \\ 0.21267 & 0.715160 & 0.072169 \\ 0.01933 & 0.119193 & 0.950227 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

$$L = 116\left(g\left(\frac{Y}{Y_n}\right)\right), \quad a = 500\left(g\left(\frac{X}{X_n}\right)\right) - \left(g\left(\frac{Y}{Y_n}\right)\right),$$

$$b = 200\left(g\left(\frac{Y}{Y_n}\right)\right) - \left(g\left(\frac{Z}{Z_n}\right)\right)$$

$$g(t) = \begin{cases} t^{1/3} & for\ t > 0.00882 \\ 7.83 + \frac{16.3}{117} & for\ t \le 0.00882 \end{cases} \quad -- (1)$$

2.2 RGB to HSV colour model conversion

The HSV stands for the Hue, Saturation and Value. The value which represents intensity of a colour, which decoupled from the colour information in the represented as image. The hue and saturation components are intimately related to the way human eye perceives. HSV is often called HSB (B for brightness). Hue varies between 0 and 1 .when colour goes from red to green then to blue and back to red. H is then defined modulo 1 as colour is seldom mono chromatic, saturation(S) represents the amount of white colour mixed with the monochromatic colour. Value (V) does not depend on the colour, but represents the brightness. So H and S are chrominance and V is intensity.

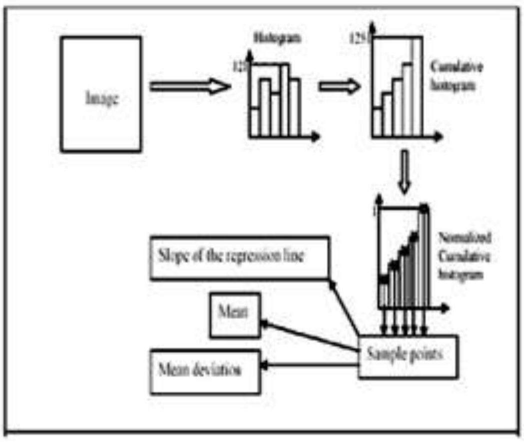

Fig 3.1. Cumulative Histogram

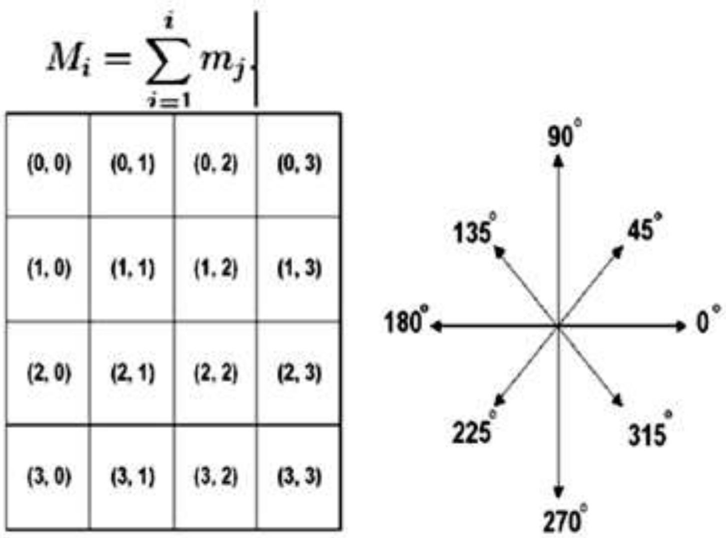

Fig 3.2. Co-occurrence matrix formation

The transformation equations for RGB to HSV colour model conversion

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

$$H = \frac{G-B}{6S}, \text{ if } V=R; \quad H = \frac{1}{3} + \frac{B-R}{6S}, \text{ if } V=G; \quad H = \frac{2}{3} + \frac{R-G}{S}, \text{ if } V=B$$

2. **3 RGB to HSI colour model conversion**

The HSI stands for the Hue, Saturation and Intensity. The HSI colour space is very important and attractive colour model for image processing applications because it represents colour 's' similarly how the human eye senses colours. The HSI colour model represents every colour with three components: hue (H), saturation (S), intensity (I).

Before converting from RGB to HSI colour model, we normalize RGB values as follows. r = R / (R + G+B) , r = G / (R + G+B) , r = B / (R + G+B)

Each normalized H, S and I components are obtained by the following expressions

$$h = \cos^{-1}\left\{\frac{0.5\cdot\left[(r-g)+(r-b)\right]}{\left[(r-g)^2+(r-b)(g-b)\right]^{1/2}}\right\} \qquad h \in [0, \pi] \text{ for } b \le g$$

$$h = 2\pi - \cos^{-1}\left\{\frac{0.5\cdot\left[(r-g)+(r-b)\right]}{\left[(r-g)^2+(r-b)(g-b)\right]^{1/2}}\right\} \qquad h \in [\pi, 2\pi] \text{ for } b > g$$

2.4 B. K-NN Classifier

In pattern recognition, the K-nearest neighbour algorithm (K-NN) is a method for classifying objects based on closest training examples in the feature space. K-NN is a type of instance-based learning where the function is only approximated locally and all computation is deferred until classification. The K-nearest neighbour algorithm is amongst the powerful and simplest of all machine learning algorithms: an object is classified by a majority "votes" of its neighbours, with the object being assigned to the class most common amongst its K nearest neighbours (K is a positive integer, typically small). If K = 1, then the object is simply assigned to the class of its nearest neighbour.

The neighbours are taken from a set of objects for which the correct classification is known. This can be thought as the training set for the algorithm, though no explicit training step is required. The training examples are vectors in a multidimensional feature space, each with a class label. The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples.

In the classification phase, K is a user-defined constant and an unlabelled vector (a query or test point) is classified by assigning the label which is most frequent among the K training samples nearest to that query point. The best choice of K depends upon the data; generally, larger values of K reduce the effect of noise on the classification, but make boundaries between classes less distinct. 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. In our experiment, K= 1,3,5 and 7 were selected. With K=1, minimum distance classifier is used for classification.

III. FEATURE EXTRACTION

3.1 Colour Features Extraction

The colour conversion is performed before extracting colour features. The colour images are recognized by quantifying the distribution of colour throughout the image and change in the colour. The quantification is obtained by computing mean and standard deviation for a given image. The colour features represent the global characterization of an image.

The mean and standard deviation are the features extracted as colour features. The standard deviation and mean are calculated using the formulae as given below.

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

The total four colour features are extracted from each of two colour channels from colour model. In L*a*b colour model, 'a' and 'b' are the colour channels hence two features from each colour channel are extracted. Similarly, 'H' and 'S' in HSV and HSI colour models and 'Cb' and 'Cr' from YCbCr colour model respectively.

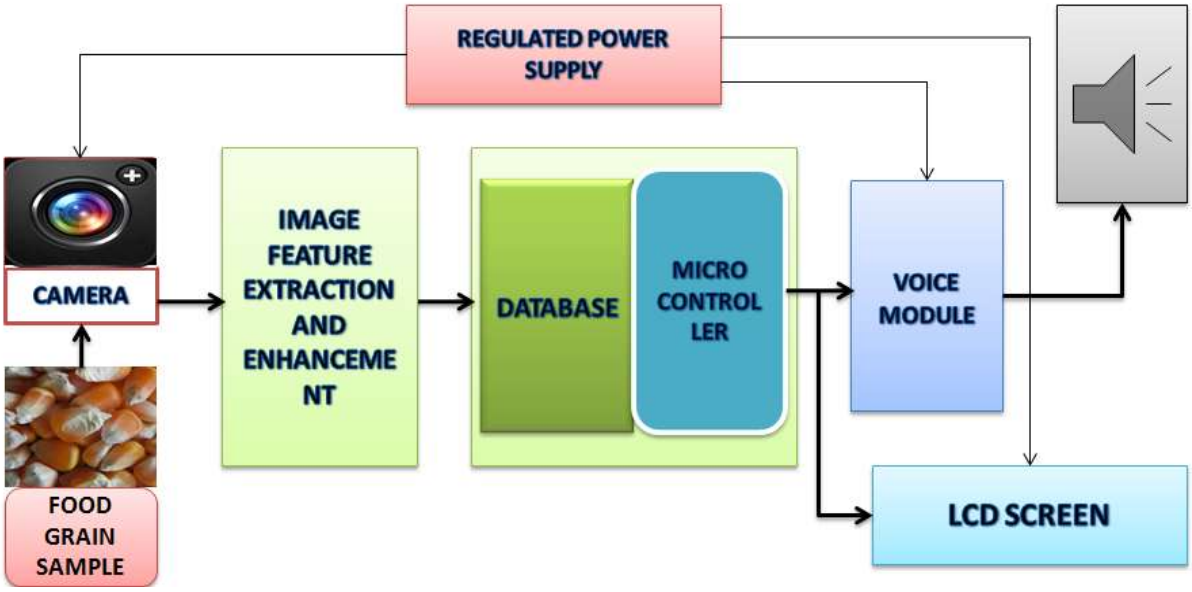

Fig. 3.3 Block Diagram for food grain identifier

3.2 Global Features Extraction

A cumulative histogram is a mapping that counts the cumulative number of observations in all of the bins up to the specified bin as shown in fig 3.2.The cumulative histogram M_i of a histogram m_j is defined as: The fig 3.1 shows the formation cumulative histogram from ordinary histogram. The mean, standard deviation and slope of the regression line are the three global features which are extracted from cumulative histogram.

3.3 Local Features Extraction

The food grains may have similarity in colour but differs in texture patterns. 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 fig 3.2 shows the formation of co-occurrence matrix. Co- occurrence method is classical in pattern recognition community and has extensively been used on gray scale images [19]. The co-occurrence matrix indicates the position of each pixel with respect to its eight neighbours those are surrounded by each pixel. Let I be a grayscale image coded on m gray levels. Let s ≡ (x, y) be the position of a pixel in I and t ≡ (x, y) be a translation vector. The co-occurrence matrix Mt is a m x m matrix whose $(i,j)^{th}$ element is the number of pairs of pixels separated by the translation vector t that have the pair of gray levels (i,j). This is a distance of one pixel in eight directions to take into account the eight nearest neighbours of each pixel. The eight matrices obtained were then summed to obtain a rotation invariant matrix M. Let us quote that since Mt(i,j)=M-t(j,i), M is symmetric [11]. Haralick assumed that the texture information is contained in this matrix and texture features are then calculated from it. Haralick extracted 14 parameters from the co- occurrence matrix, but only five are commonly used because it was shown that the five sufficed to give good results in a classification task and are listed in table 3.1. The process of classification is performed in two phases; the first one is the computation of features and second is the classification of food grains with the help of extracted features using suitable classifiers. The original images used for the experimentation are captured under natural light and are resized to 1024x1024. The K-NN and minimum distance classifiers are used for classification using extracted global, local and colour features. Fig. 3.3 show the block diagram of the proposed work. Images of different food grains are captured under natural light by maintaining fixed background and same distance between camera and food grains for all set of variety of food grains. The acquired images are resized to 1024x1024 and saved as JPEG image. The image is divided into small blocks of size 256x256. The 12 features computed are extracted from all the images and are stored in database. A part of an image is used for training set and remaining part is used for testing set which is tested against training set processed in image recognition module. Training and testing results are compared and output is given in terms of audio form by using voice module and speaker and displayed on LCD screen.

Training (Tr) image blocks-640 and 480 i.e. 25% and 18.75% Testing image blocks -1920 and 2080 i.e. 75% and 81.25%								
Image Class	K=1		K=3		K=5		K=7	
	Tr set-25%	Tr set-18.75%	Tr set-25%	Tr set-18.75%	Tr set-25%	Tr set-18.75%	Tr set-25%	Tr set-18.75%
1	94.27	95.19	89.58	93.75	90.62	90.86	90.62	92.7885
2	82.29	77.40	92.70	90.86	96.87	97.59	96.87	96.15
3	98.43	97.11	98.43	97.59	95.83	95.19	95.83	94.71
4	94.79	96.15	93.75	96.15	95.31	94.71	95.31	94.23
5	98.43	98.55	97.91	95.19	95.31	95.30	94.79	95.67
6	86.45	83.65	95.83	83.65	91.66	88.46	91.66	92.30
7	90.62	94.71	92.70	90.86	93.22	93.26	90.62	92.30
8	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
9	100.00	100.00	100.00	96.63	100.00	100.00	100.00	100.00
10	98.43	98.55	98.43	98.55	98.95	99.03	98.95	99.03
Avg	94.37	94.13	95.93	95.04	95.78	95.33	95.46	95.72

Table 1.1 shows the percentage of correct classification in the experimentation on L*a*b colour model with 25% and 18.75% training set. It is evident from the table 5.1 that maximum average accuracy of 95.93% in case of 25% training set for K=3 and 95.72% in case of 18.75% training set for K=7 have been achieved.

Training (Tr) image blocks-320 and 160 i.e.12.5% and 6.25% Testing image blocks-2240 and 2400 i.e. 87.5% and 93.75%								
Image Class	K=1		K=3		K=5		K=7	
	Tr set-12.5%	Tr set-6.25%	Tr set-12.5%	Tr set-6.25%	Tr set-12.5%	Tr set-6.25%	Tr set-12.5%	Tr set-6.25%
1	95.08	90.00	88.83	79.16	88.39	77.50	91.51	82.50
2	63.83	52.08	80.80	63.75	92.85	69.16	80.80	74.16
3	97.76	97.91	97.76	98.75	96.87	95.00	95.08	93.33
4	94.19	94.58	92.85	91.66	94.64	91.25	94.64	87.50
5	94.19	92.50	93.30	92.91	92.85	90.41	92.41	90.00
6	76.78	76.66	88.39	90.83	87.50	87.50	91.96	92.50
7	92.85	90.83	91.51	90.00	91.96	91.66	91.07	93.75
8	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
9	99.55	98.75	100.00	100.00	100.00	100.00	100.00	100.00
10	97.76	98.33	97.76	96.66	96.42	96.66	96.42	92.08
Avg	91.20	89.16	93.12	90.37	94.15	89.91	93.39	90.58

Table 1.2 shows the percentage of correct classification in the experimentation on L*a*b colour model with 12.5% and 6.25% training set. It is evident from the table 5.2 that maximum average accuracy of 94.15% in case of 12.5% training set for K=5 and 90.58% in case of 6.25% training set for K=7 have been achieved.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

For each texture class, a portion of the image is used for training and the remaining portion is used for testing. Experiments are carried out in L*a*b, HSV, HSI and YCbCr colour models. Minimum distance classifier and K-NN classifier are used to analyse the classification performance and the value of K is taken as 1, 3, 5 and 7. The experimental results for different colour models and percentage of training sets are shown below in the form of table 5.1 through 5.8.

TABLE-1.1. EXPERIMENTION ON L*a*b COLOUR MODEL WITH 25% AND 18.75% TRAINING

SETTABLE-1.2. EXPERIMENTION ON L*a*b COLOUR MODEL WITH 12.5% AND 6.25% TRAINING SET

V. CONCLUSION

The smart food grain Identifier for Visually Impaired Persons can help the person be a little more independent than his normal self. Our main goal is to make the system inexpensive so that disable person could lead an independent and better life like a normal person by providing Grain identifier which can identify the pulses and different types of Grains. We hope it can be conveniently used by all those who are visually challenged. As innovation cannot be paralyzed, further in future work the portable device size can be reduced like a mobile phone, and at the end of the project we conclude that the disable persons specially the visually impaired persons can lead the better life and they can improve their standard of living with the help of this assistive technology devices.

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