CHAPTER 7

FRUIT COLOUR

7.1 INTRODUCTION

The colour of an object is determined by wavelength of light reflected from its surface. Colour is one of the most significant criteria related to fruit quality. It indicates properties like ripeness, maturity, freshness, defects etc., of the fruits. The appearance of the fruit affects the consumer acceptance and the value addition.

Usually, sorting of fruits by colour is performed by quality graders through visual inspection. Owing to the structure of human eye, all colours are seen as variable combinations of three so-called primary colours, red (R), green (G) and blue (B).

Researchers carried out extensive work for developing reliable colour matching systems using image processing. However most of the work was related to man-made products and not for natural products like fruits. RGB colour space was used for colour classification of apples (W.V. Thomas and C. Connoly 1986). Usage of HSI colour space was suggested for apple classification (S.A Shearer and F.A Payne 1990). Entropy and probability methods were employed for colour analysis (R.K. McConnell et al 1991). The colour classification of apples was carried out based on histogram comparison (Y.Tao et al 1995). Researchers (E. Ding et al 1990, P. Heinemann et al 1994, 1995 and Robinson 1998) experimentally found that HSI model was most suitable for finding out colour matching samples. Linear discriminant analysis (M.G. Kendall and Stuart 1979, D.F. Morrision 1990) was used as a tool to sort apples based on colour.

Present section discusses two methods for colour analysis namely histogram analysis and linear discriminant analysis, utilising HSI colour space. Section 7.2 briefly describes different colour models. Section 7.3 discusses the details of histogram analysis. Section 7.4 and 7.5 discuss colour discrimination using histogram analysis and linear discriminant analysis respectively along with results. Section 7.6 presents the conclusions.

7.2 COLOUR MODELS

Different image processing systems use different colour models for different reasons. A colour model or colour space is a specification of a 3D coordinate system where each colour is represented by a single point. It is a way of representing colours and their relationship to each other. A colour model is adopted depending on specific application. Image processing systems generally adopt RGB, HSI or CIE colour spaces in their applications.

7.2.1 RGB Colour Space

The primary colours red (R), green (G) and blue (B) are defined for standardization purpose. Combination of these three primary colours can generate all colours. Colour cameras used in machine vision systems represent the colour information in terms of RGB components. This RGB model, shown in Figure 7.1, is represented by a three dimensional cube with red, green and blue at the corners on each axis.

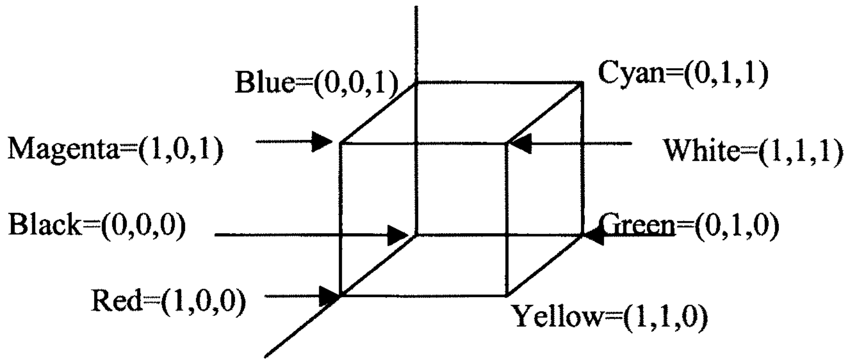


Figure 7.1 RGB colour cube

7.2.2 CIE Colour Space

The CIE system as shown in Figure 7.2 characterizes colours by a luminance parameter Y and two colour coordinates x and y which specify the point on the chromaticity diagram.

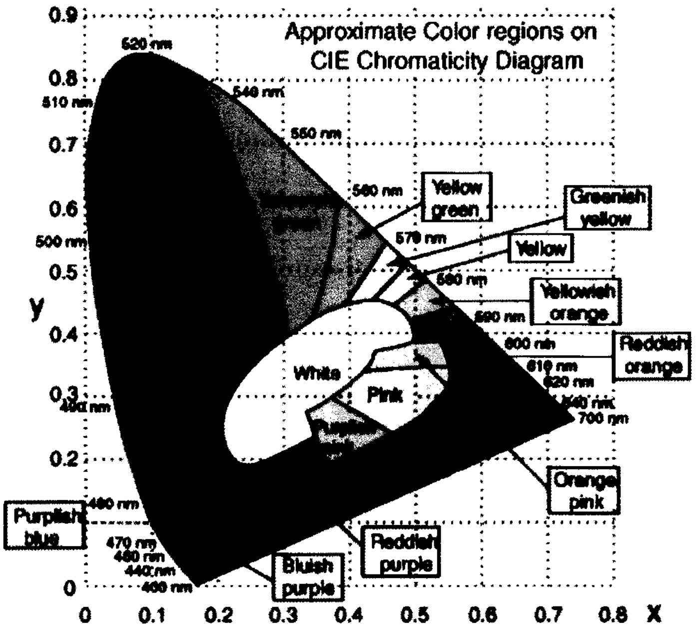


Figure 7.2 The C.I.E. Chromaticity Diagram

7.2.3 HSI Colour Space

HSI is modelled with cylindrical coordinates, as shown in Figure 7.3. Hue (*H*) is represented as an angle, varying from 0° to 360°. Saturation (*S*) corresponds to the radius, varying from 0 to 1. Intensity (*I*) varies along the (*z*) axis with 0 being black and 1 being white. Hue is a colour attribute that describes a pure colour, whereas saturation gives a measure of the degree to which a pure colour is diluted by white light and finally intensity gives the effectiveness of the colour. Most machine vision systems use HSI colour space for identifying the colour of objects. Image processing applications such as histogram operations, intensity transformations, and convolutions operate on only an image's intensity. These operations are performed much easier on an image in the HSI colour space.

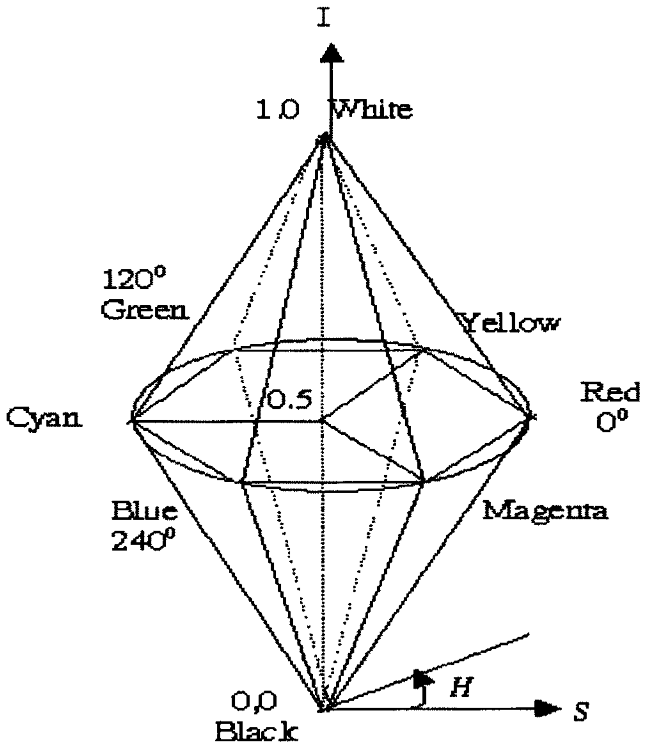


Figure 7.3 Double cone model of HSI colour space

7.3 HISTOGRAM ANALYSIS

Histogram is a graphical representation of the distribution of a variable over an area. From histograms of an image for a given colour space, the following are some of the statistical data that can be obtained. Histogram in RGB colour space is taken as example.

Percentage of colour component,

$$r,g,b = \sum(\textit{gray level} \times \textit{number of pixels in that gray level})$$

$$\text{variance} = \sum\left(y(x - X)^2/n\right) - \left[\sum y(x - X)/n\right]^2 \qquad (7.1)$$

where,

x = **gray level ranging from 0 – 255**

y = **number of pixels corresponding to grey level** x

X = **mean of** x

n = **total number of pixels**

standard deviation = $\sqrt{\text{variance}}$

mean of red = r/n

mean of green = g/n

mean of blue = b/n

co-variance= 100 (standard deviation / mean)

Correlation factor for two colour images, image-1 and image-2:

$$\text{where, } \frac{\sum(xy) - \left(\sum x \sum y / n\right)}{\sqrt{\left\{\left[\sum x^2 - \left(\sum x^2 / n\right)\right]\left[\sum y^2 - \left(\sum y^2 / n\right)\right]\right\}}} \qquad (7.2)$$

x = **gray level ranging from 0 – 255** for image-1

y = **gray level ranging from 0 – 255 for image - 2**

n = **total number of pixels**

The intensity mean and variance (or standard deviation) are the two properties frequently used because of their relevance to the appearance of an image. The mean is the measure of average brightness and the variance is a measure of contrast. Correlation factor between two images gives the measure of how well one image matches with the other.

The histogram analysis using RGB colour space has some limitations. The pixel value in colour image is a vector in 3D colour space. Thus, equalisation of colour requires processing of all the three RGB components at once, which makes the process complex. The second problem is that RGB colour space does not correspond to the human perception of colour. The overall important aspect of colour image processing is that the algorithms developed should be able to produce the least amount of detectable colour distortion. Also, the processed quantities should be mapped as closely as possible to those that are perceptually important (Y.Tao et al 1995).

Researchers (E. Ding et al 1990, P. Heinemann et al 1994, 1995 and Robinson 1998) experimentally found that HSI model is most suitable for finding out the ripeness of fruits, vegetables, colour matching samples etc. Here, the intensity is decoupled from the colour information of the image, and hue and saturation components are intimately related to the way in which human beings perceive colour.

In HSI colour space, the hue frame alone can be used for colour evaluation. Thus the transformation from RGB to HSI reduces the complexity of colour analysis from a three dimensional RGB space to a one-dimensional H space. In view of the above our analysis uses only HSI colour space.

7.4 HUE HISTOGRAM ANALYSIS

The basic image capturing system is a CCD camera and a frame grabber card, which provides the image in RGB colour space. After normalization, the RGB data is converted into HSI data using the following equations for hue, H, and saturation, S, (R.C. Gonzalez 1988).

$$H = \frac{255}{360}\left(90^0 + \tan^{-1}\left[\frac{(2R - G - B)}{\sqrt{3}(G - B)}\right](180^0 if\ G < B)\right) \quad (7.3)$$

$$S = \frac{255}{360}\{1 - [1 - \min\ (R, G, B)/I]\} \quad (7.4)$$

This method of colour analysis basically involves comparison of hue histograms. Initially, the histograms representing the colour attributes of known or reference items are prepared. Similarly the histograms of the same attributes of the test fruit are also prepared. The test fruit histogram is compared with that of the reference for the best match and classified in to a group whose histogram is most similar to that of the test item (R.K. McConnell et al 1981 and R.K. McConnell et al 1991). The average information per histogram output is denoted by $E(h) = -\sum_k p_{Tk} \log_b(p_{Rk})$, where p_{Tk} and p_{Rk} is the fraction of the attributes from test distribution (T) and reference distribution (R), which fall in the kth histogram cell respectively. As per the information theory (C.E. Shannon 1948), T_R is the average amount of information per sample necessary to identify a single sample taken from distribution (T) for identifying samples from distribution (R) and T_T is the entropy of distribution (T) (R.K. McConnell et al 1992). $(T_R - T_T)$ is a measure of dissimilarity of distributions (T) and (R) and if $(T_R - T_T) = 0$, then (T) and (R) are identical.

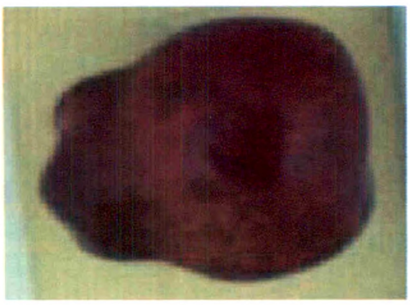
7.4.1 Experimental Results

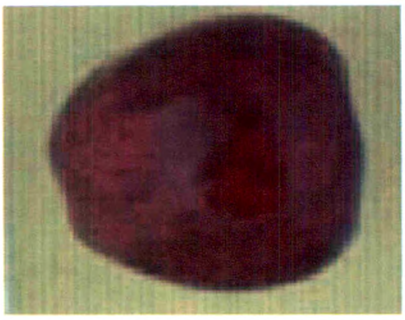
Reference histogram of a class is generated by accumulating histograms of different apples belonging to the class. Population of apples have multiple classes. Reference data is needed for subsequent classification, measurements and/or comparisons. Six different apples as shown in Figure 7.4 are taken to generate six reference sets (R) of data (classes). Histogram for each class is generated by taking 10 images on the same fruit. Each image is taken over specified region of interest [ROI] at different location on the fruit surface. The histograms of these images are accumulated to form the reference histograms of a class.

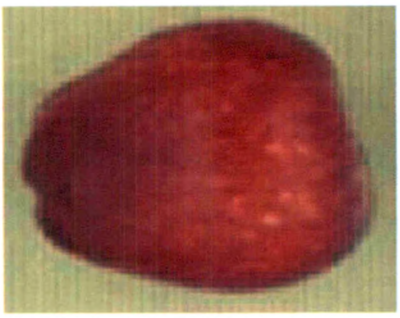
Classification is carried out by processing an ROI image taken randomly on an apple. The process is repeated for all the apples by random selection. The algorithm is found to correctly identify the class of the test apples presented for evaluation. Sample experimental results are presented in Tables 7.1 to Table 7.4.

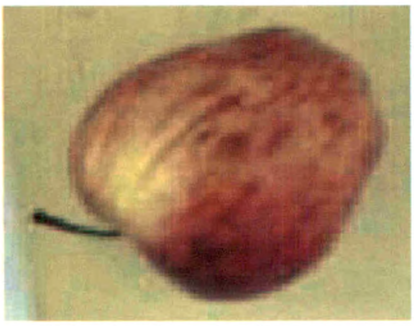
Table 7.1 Mean Colour and T_T during training

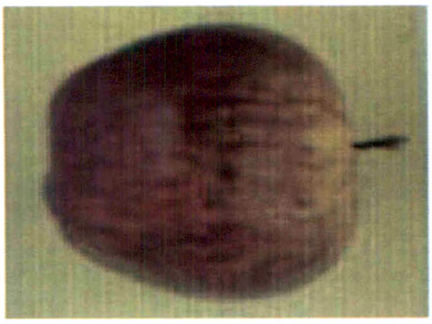
	Normalised R	Normalised G	Normalised B	T_T
Apple-1	R = 0.493	G = 0.293	B = 0.329	3.855
Apple-2	R = 0.547	G = 0.413	B = 0.411	3.672
Apple-3	R = 0.622	G = 0.309	B = 0.381	3.738
Apple-4	R = 0.717	G = 0.473	B = 0.400	3.648
Apple-5	R = 0.537	G = 0.390	B = 0.337	3.758
Apple-6	R = 0.861	G = 0.898	B = 0.560	3.301


Apple-1


Apple-2


Apple-3


Apple-4


Apple-5

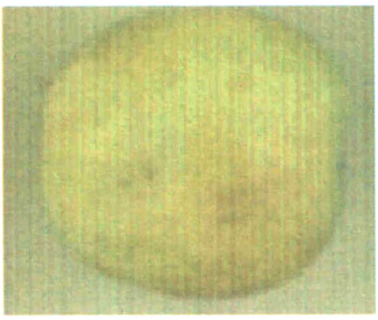

Apple-6

Figure 7.4 Six Test Apples images in one of their ten postures

Table 7.2 Verification of Apple-1 and Apple-2 as samples

	Apple-1			Apple-2		
	T_T	T_R	$(T_R - T_T)$	T_T	T_R	$(T_R - T_T)$
Apple-1	3.855	04.508	00.652	3.672	4.547	0.875
Apple-2	3.855	04.609	00.754	3.672	4.063	0.391
Apple-3	3.855	05.945	02.090	3.672	4.434	0.762
Apple-4	3.855	05.395	01.539	3.672	4.082	0.410
Apple-5	3.855	05.074	01.219	3.672	4.332	0.660
Apple-6	3.855	07.781	03.926	3.672	6.609	2.938
Analysis: $(T_R - T_T)$ being the smallest, confirms that the test apple is Apple-1				Analysis: $(T_R - T_T)$ being the smallest, confirms that the test apple is Apple-2		

Table 7.3 Verification of Apple-3 and Apple-4 as samples

	Apple-3			Apple-4		
	T_T	T_R	$(T_R - T_T)$	T_T	T_R	$(T_R - T_T)$
Apple-1	3.738	6.086	2.348	3.648	5.441	1.793
Apple-2	3.738	4.957	1.219	3.648	4.598	0.949
Apple-3	3.738	4.387	0.648	3.648	4.344	0.695
Apple-4	3.738	4.902	1.164	3.648	3.902	0.254
Apple-5	3.738	6.160	2.422	3.648	4.625	0.977
Apple-6	3.738	7.188	3.449	3.648	5.848	2.199
Analysis: $(T_R - T_T)$ being the smallest, confirms that the test apple is Apple-3				Analysis: $(T_R - T_T)$ being the smallest, confirms that the test apple is Apple-4		

Table 7.4 Verification of Apple-5 and Apple-6 as samples

	Apple-5			Apple-6		
	T_T	T_R	$(T_R - T_T)$	T_T	T_R	$(T_R - T_T)$
Apple-1	3.758	5.902	2.145	3.301	7.379	4.078
Apple-2	3.758	5.266	1.508	3.301	6.902	3.602
Apple-3	3.758	5.402	1.645	3.301	6.602	3.301
Apple-4	3.758	4.949	1.191	3.301	5.680	2.379
Apple-5	3.758	4.105	0.348	3.301	5.371	2.070
Apple-6	3.758	6.805	3.047	3.301	3.625	0.324
Analysis: $(T_R - T_T)$ being the smallest, confirms that the test apple is Apple-5				Analysis: $(T_R - T_T)$ being the smallest, confirms that the test apple is Apple-6		

7.5 LINEAR DISCRIMINANT ANALYSIS

A linear discriminant analysis program based on Mahalanobis distance is developed using MATLAB to classify apples based on colour. This method assumes that the reference data is distributed in a multi dimensional space and classifies the test data based on distance between the test data to the reference data sets.

The algorithm considers a two-class problem. For two reference classes having populations, N_1 and N_2, the mean values Xi are computed as

$$X_i = \sum_{j=1}^{N_i} x_j / N_i \qquad i = 1,2 \qquad (7.5)$$

For classifying a test data, Mahalanobis distances between the test data and the reference classes are computed as

$$d_i = (x - X_i)^T \text{cov}^{-1}(x - X_i) \qquad i = 1,2 \qquad (7.6)$$

where, cov is the pooled covariance of the two classes given by

$$\text{cov} = [\text{cov}_1 (N_1 - 1) + \text{cov}_2 (N_2 - 1)]/(N_1 + N_2 - 2) \qquad (7.7)$$

where cov_1 and cov_2 are covariances of the reference classes given as

$$\text{cov}_i = (x - X_i)(x - X_i)^T \quad ; i = 1, 2 \qquad (7.8)$$

The test data is classified into a class that gives minimum Mahalanobis distance.

The algorithm is implemented to classify apples based on colour into Green or Red coloured classes by analysing their colour images. The colour images are first converted from RGB into HSI colour space. The images are also segmented suitably to extract the region occupied by the apple in the image. Hue data of pixels lying inside the above extracted apple regions alone is used for analysis. This procedure is followed to generate hue data from colour images of reference as well as test apples. The algorithm first analyses the reference images of the two classes to extract the hue data and compute their mean values.

A number of images of the Green and Red coloured apples are utilized to generate reference hue data and mean values. Hue histograms of three sample apples each from Red and Green coloured groups are shown in Figure 7.5. It can be noted that hue data of green apples is centered around 72^O whereas the hue values of red apples appear partly near zero and partly near 360^O due to the cyclic nature of the hue spectrum. The latter hue distribution, although indicating a single (red) colour, gives rise to a misleading mean value representing a different colour. To avoid this problem, the histograms are wrapped around the X-axis by taking 180^O reference. This has transformed both the histograms into distinct clusters and helped in efficient classification. This transformation is employed to obtain reformed hue data from the reference and test apple images and utilized in the analysis. Comparison of hue data of the test apple image with the two reference data sets gives rise to two Mahalanobis distances, one to each class. The computed distances are compared and the test apple is classified into a class giving a lower Mahalanobis distance. The inverse of the computed distance, indicated as a relative percentage, is used as a measure of prediction confidence.

The developed computer program is verified by classifying three test apples having slightly-yellowish red surface colour. The hue histograms of these test apples are shown in Figure 7.5. The program classified all the three test apples into Red class with a confidence figure above 99%. .

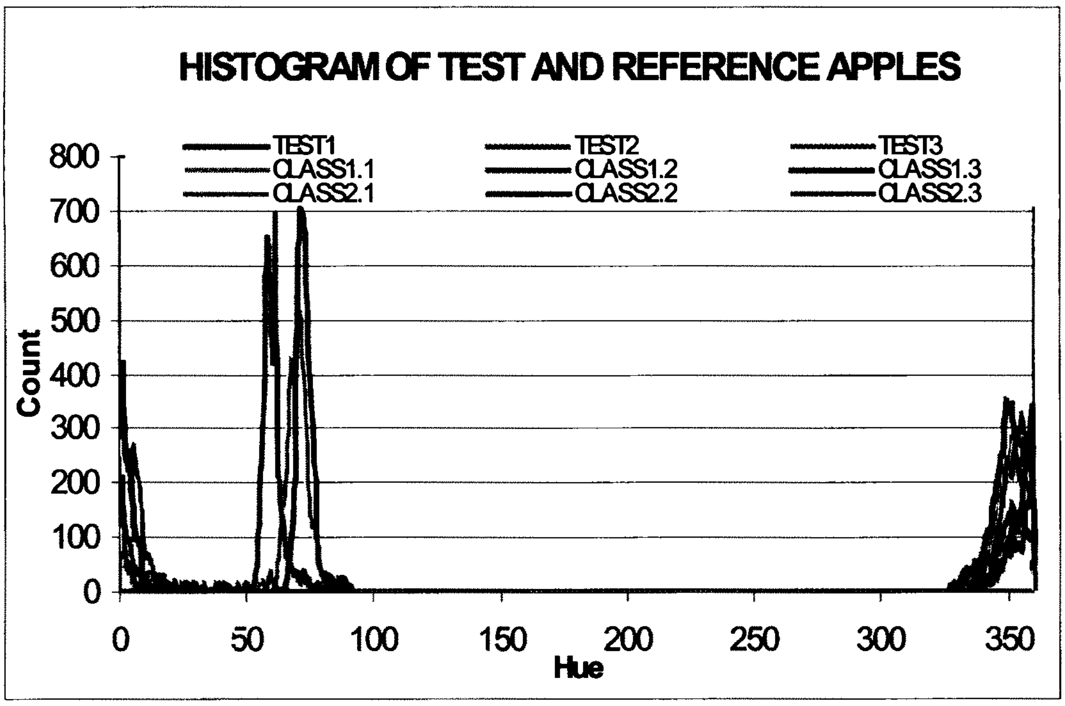


Figure 7.5 Hue histograms of reference and test apples

7.6 CONCLUSIONS

Two methods namely hue histogram method and linear discriminant method for classifying apples based on colour are suggested. Histogram method compares hue histograms for the purpose of classification. The linear discriminant method uses Mehalanobis distance criterion for classification. The later method can be extended to include other fruit quality parameters for overall classification of fruits.