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Quality Assessment of Black Tea on the Basis of Colour using Machine Vision

G. S. Gill
Department of instrumentation, Kurukshetra University Kurukshetra Haryana, India

Abstract- Tea is a valuable cash crop throughout the world. It is a major export product of India. As far as social aspect is concerned, about 1.2 million people are directly employed as labour in tea industry.At present, tea quality is validated by professional 'Tea Tasters' who charge exorbitantly for every sip they take. Conventionally, these experts evaluate tea quality by use of organolepticmethods during fermentation and sorting stage. In addition to this, gas chromatography and colorimetry are employed for chemical analysis of tea liquor and for colour analysis, respectively, at various stages oftea processing. Theseevaluation methods are subjective and suffer from high labourcosts, inconsistency and variability. In the Present work, colour estimation was carried out for discriminating the different grades on the basis of colour of tea liquor. Grade assignment was done on the basis of extracted colour featuresusing the RGB colour model and 100% accuracy was observed using MLP classifier. Statistical analysis by ANOVA (Analysis of Variance) highlighted the relevance ofcolour features as significant attributes for discrimination between various grades.

Keywords- Tea, Machine Vision, Quality, Colour, ANOVA

1. Introduction

Tea is a popular beverage throughout the world. The production and trade of tea has become an important business for centuries. In 1990, the tea growing area in the world reached 2.45 million hectares with total yield of 2.51 million tons. India is the largest producer, with a total production of tea approaching one million tonnes in 2013-14 and exports of 2,49,900 metric tons (GOI, 2015). India is also a major exporter of tea globally having exportshare of 4873 crores in the year 2013-14 (GOI, 2015). World tea consumption has increased steadily over the years. Over 3 billion cups of tea are consumed, globally, on daily basis.Black tea is preferred by majority of consumers (more than 75%)followed by other types of tea.Factors considered by consumers for selection of a particular type of tea are its availability, taste, cost, and noticeable health benefits (Bhattacharya *et.al.*,2014). Because of the high popularity of tea, the relationship between tea and health has come out as one of the most attractive topics in biomedical sciences (Jain *et. al.*, 1999; Chen, 2005).

The increasing incomes and awareness, growing number of consumers giving high priorities to food quality in addition to increasing exports of agricultural produce have emerged as vital factors for growingconcernfor quality assessment of raw and processed agricultural produce after Green Revolution in India. The same applies to tea, as well, and tea industry in India needs to pay increased attention to quality of its produce because of growing trade competitiveness. Weaknesses in quality assessment and grading systems can cost high to tea industry and the economy of the country.

The grading system for agricultural products ensures enhanced marketability and a better price to the producer by fixing up rates on the basis of quality. Recognizing this need, the Indian government introduced the procedures to standardise of agro-produce so as to ensure that maximum benefits of grading are passed on to the farming communityas per the

Agricultural Produce Grading and Marking Act which came into force as early as 1937. In the past, India suffered massive setbacks due to stiff competition in the international market as various consignments of agricultural produce from India were rejected on the basis of poor quality. For instance, a 16-million kg tea market, Libya, imposed a five year ban on tea imports in protest against the export of three million kg of 'substandard tea' from India in 1998-99, and in the following years Libya started importing tea from Sri Lanka (Bose, 2004). India's share in the world exports for tea has dropped from 33.4% in 1970 to 10.5% in 2013. India as a growing economy can't afford to lose its export orders for the cash crop like tea for which it is the world leader in production and exports. So there is strong need of indigenously developed modern and sophisticated technique for quality assessment of agricultural produce in order to withstand the global competition.

2. Assessment of Tea Quality

Assessment of quality of tea is a multifarious phenomenon and there are no particular terms to describe overall quality of tea. It may also vary according to choice of diverse individuals. The tea tasters follow certain terminology to explain the quality. At present, two approaches are being followed for quality indexing tea industry. While one involves the evaluation of biochemical indicators of tea either at fermentation stage of or post-production stage, the other one is a purely subjective method involving subjective judgment through professional tea tasters. The subjective evaluation is based on certain physical attributes, namely, physical appearance, aroma, taste etc. The TF-TR (Theaflavin-Thearubigin) based chemical analysis is the most commonly used method by the tea industry for quality assessment (Gill *et.al.*, 2013). The TF:TR ratio is used as a descriptor of quality of made black tea. However, the subjective evaluation is most commonly used approach by tea industry.

Presently, sorting of black tea into diverse grades on the basis of variations in granule size is being followed in tea industries for quality evaluation. The tea is made to pass through a number ofsieves havingopeningsof different sizes, arranged one below another, with the sieve of largest sized opening at the top. These sieves are subjected to constant vibrations using some mechanical arrangement. The diverse tea grades are collected at outlet of the respective sieves. Based on size of the granules, tea is broadly categorized as leaf, brokens, fannings followed by dust, in decreasing order of their granule size (Borah et al., 2007). Some of the commonly used terms to describe black tea are 'attractive' or 'well-made' representing a well-made sample of granules with uniform colour and size; 'even' describing a sample containing tea granules of uniform size; 'mixed' representing the presence of different grades together in a sample; 'bold' indicating the presence of pieces of leaves and 'stalky' containing undue presence of stalk.

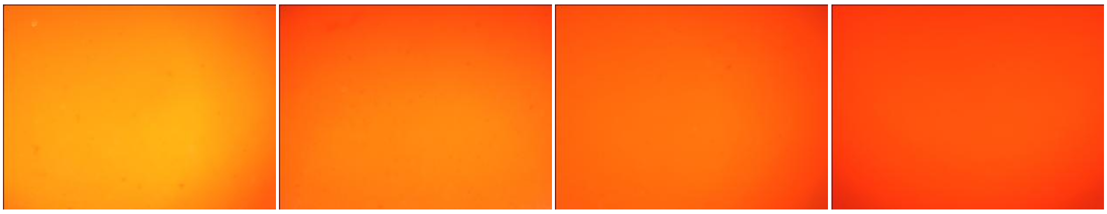
Machine vision based techniques have been employed in recent past for colour recognition in an image of food product and has been reported as an efficient technique for quality examination (Gunasekaran, 1996; Brosnan and Sun, 2002; Gill *et. al*, 2011). Colour is a significant feature on the basis of which an image can be analysed and classified. Since visual colour examination is affected by a variety of parameters such as nature of illumination, condition, direction of observation and individual variability in colour perception, the computer vision based colour analysis can provide an objective and reliable method of colour analysis. In this work, images of tea granules at the drier output stage have been analysed and graded based on their colour using machine vision based methods.The colour image of tea liquor can serve as a key indicator of its quality and grade. This is done during the process of tea manufacturing to identify the condition of optimum fermentation and at the final stage to assess its grade.

3. Methodology

Quality assessment of black tea has been done either at the tea industries before packing. Colour of tea liquor has been considered as one of the key parameters used to determine the grade of tea.

3.1. Image Acquisition and Experimental Set-up

The visual estimation of colour by the human sensory panel provides a reasonably accurate estimate in judgement of the colour. But, while imaging with the CCD cameras, a large numbers of parameters such as viewing distance, viewing angle and illumination condition play a very significant role. Theseparameters are generally adjusted by human operator as per his judgement and skill. In computer vision based system,if proper care is takenduring imaging, it can enhance the system performance significantly. For instance, same colour might appear to be different during imaging if the direction of illumination, intensity of illumination or distance of image capturing is different (Gevers, *et. al.*,1999).Although these parameters can be attuned to some extent by image pre-processing operations but maintaining identical set of conditions all through the imaging process is always beneficial. The imaging system comprised of a 3CCD colour camera(JAI-CV-M9-CL, National Instruments, Austin, TX, USA), animage capture board (National Instruments, PCI 1430e) along with associated computerhardware and software (Gill, *et.al.*, 2011; Wang & Sun, 2002). The camera was enclosed in aphotic housing and working distance was kept to be 135mm. For estimation of tea grades on the basis of colour, three grades of tea leaf, fannings and dust were evaluated. The captured images of brewed tea liquor for various grades are shown in fig. 1.



Leaf Brokens Fannings Dust

Figure 1: Acquired images of brewed liquor for different tea grades

3.2 Sample Preparation

The sample preparation for extracting colour information was prepared according to British Standard BS-6008. According to this standard, by weight 2 grams of tea is brewed per 100 mlof fresh boiling water for 6 minutes. The brewed liquor was then filtered and collected in a sample holder plate made up of clear glass. Borosil sample holder was used for this experiment

3.3 Colour Feature Extraction

The tea liquor was brewed for all four grades of black tea. An image database was generated and ten images were obtained for each grade of tea. The RGB colour model was preferred over other models in the current problem as RGB colour image is presumed to be composed of individual monochrome images of primary colours and due to this the computational complexity associated with evaluation of intensities is greatly reduced for the system based on RGB model.In addition to this,RGB colour scheme offers much bright compared toother models. Also more of the visible spectrum can be utilized with RGB scheme since it works on principle of transmission compared to reflection used by CMY. Further, RGB model being straight forward in nature is,typically, the most well suited model for hardware and software implementations. Though it has been criticised as incompatible with human perception, it matches well with human vision's strong response to primary colours. RGB was preferred choice for this work due to its computational simplicity and its hardware and software compatibility.

Extraction of the colour components or features is always a preliminary step in analysis and classification of colour images. In the simplest form, the colour content in an image can be represented by the pixel values in the red green and blue colour planes if an image is represented in RGB colour format. By definition, the notation followed for representing colour of a pixel is: 'Pixel value = (R-level, G-level, B-level)'. Each pixel is allocated an integer value, in 0-255 range and, in all, a total of more than 16 million colours can be achieved with different combinations of these values.

The three colour features, namely, average R, average G and average Bwere computed from the image database for various grades of tea. These features correspond to the average colour content of the respective colour component in the image. The image in all compatible formats, havingappropriate bit depth, can be usedwith the essential preliminary processing steps. True-colour image is transformed to greyscale image followed by resizing which imparts uniformity to the sample database. Further, the binary version of the image was created by changing greyscale image to a two tone image by selecting an appropriate threshold level. In the next step, colour analysis has been performed using RGB colour model. For estimation of the respective intensities of R, G and B components in an image the RGB colour model is preferred over HSI or CMY because RGB colour image can be segregated into set of constituent monochrome images. Due to this fact, the computational complexity associated with evaluation of intensities is greatly reduced for the system based on RGB model.Finally the mean of R intensity, G intensity, B intensity of each bulk image were extracted.

3.4 Feature Classification

It has been observed that various grades of black tea can be discriminated on colour based features and can be categorized into different grades by using ANN technique. In order to discriminate the grades on the basis of colour, MLP technique has been adopted.

MLP structure and implementation: MLP has been employed as a classification tool for discrimination between the diverse grades of tea on the basis of colour features. The image database used for network training comprised of images of four diverse grades viz., leaf, brokens, fannings and dust. The MLP network was developed having three input layer neurons, two hidden layers having 14 and 13 neurons and an output layer. The training function used was the LMbackpropagation (*trainlm*) which update its connection weights values according to LM optimization. GDM (*learngdm*) is used as learning while MSE as performance function. MSE estimates the performance of MLP in accordance with mean-square-errors. The network is trained using these functions. The hyperbolic tangent sigmoidal transfer function is employed for hidden while linear function is employed for output layer neurons. The network returned 80% correct classifications for the feature data base.

3.5 Grading based on colour features

Tea liquor can be graded according to quality on the basis of its colour. The colour attributes corresponding to the average intensity of red, green and blue colours were computed from the images of tea liquor for four grades of tea (Appendix I). For this purpose, a database of tea images comprising of five images for each grade was utilized. These images were captured under identical set of conditions and the samples for each of the ten images belonging to the same grade were drawn randomly from the same population. The fundamental reason of using more than one image for same grade was to ensure that any variations that may creep into the system due to various human factors may be reduced due to averaging effect.

For classifying the data based on colour features, multilayer perceptron architecture has been used with two hidden layers having 14 and 13 neurons. **Performance plot**(Fig.2)shows the mean square error dynamics for the datasets on logarithmic scale. Since the training MSE is showing a decreasing trend, so the validation and test MSE are the ones that have to be observed.

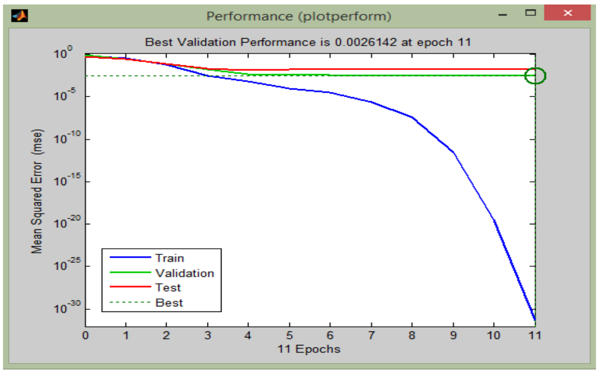


Figure 2: Performance plot of the ANN Classifier for Colour Parameters

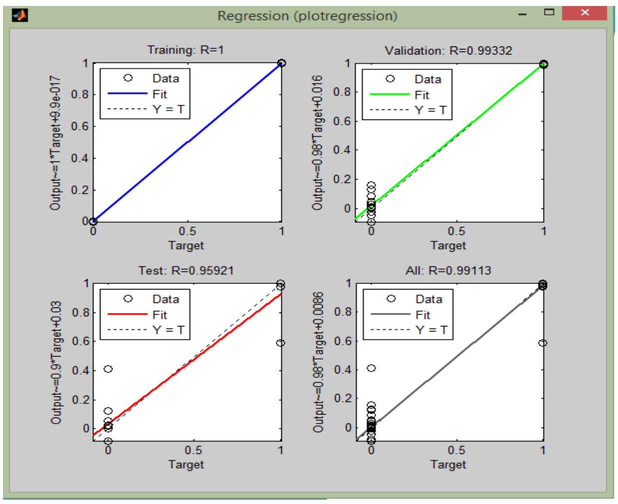


Figure 3: Regression plot of the ANN Classifier for Colour Parameters

The plot in this case shows a perfect training. Gradient value of 145e-16indicates that the network has reached the bottom of local minimum of the goal function without any validation check.

Further, regression plot (Fig. 3) indicatesperfect training with R=1. The four plots represent the training, validation, testing and overall data. The dotted line these plots correspond to ideal outcome where the outputs are equal to targets, while the bold lines symbolize the best-fit regression line. For the colour feature set, the validation and test results also show regression coefficient of 0.99332 and 0.95921, respectively.

In the end, statistical analysis is carried out by one-way analysis of variance (ANOVA) in which all the colour features have $F^* > F_{0.05}$ which means that the different grades can be considerably distinguished on account of each of the colour features (Table 1). The red colour had almost similar range for all grades, green colour proved to be the best one out of the all for discriminating amongst different grades closely followed by the blue. The grading efficiency achieved on the basis of colour was 100%, which endorses the suitability of proposed scheme for grading of tea.

Table 1: ANOVA results for Colourfeatures

Feature	Observed Variance Ratio (F*)	Theoretical Variance Ratio ($F_{0.05}$)
Red	121.45	2.84
Green	317941.13	2.84
Blue	4545.43	2.84

F*-Estimated (observed) variance ratio; $F_{0.05}$= theoretical value of at 5% level of significance

4. Conclusion

In this work, the potential of machine vision for quality assessment of black tea has been explored.In this context, the colour features were estimated for tea grading at the post processing stage and assessment of quality has been done on the basis of these parameters. The image data gathered by acquiring the images of graded tea samples have beenanalysed and relevant features were extracted using various image processing techniques and finally classified using an artificial neural network.Colour estimation was carried out for discriminating the different grades on the basis of colour of the brewed tea liquor. The RGB model has been used in this work for estimating the average red, green and blue components in the images. Grade assignment was done on the basis of colour features extracted and 100% accuracy was observed when the extracted colour features were classified using MLP having two hidden layers. For statistical validation of the extracted features, ANOVA has been employed, which further elaborated the features that contributed in a more pronounced manner for the discrimination of tea grades. ANOVA gave the extent of variance contributed by a particular feature towards the total variance. The salient features of this method are its objective nature, independence from human variability and biases, which were the key shortcomings of the conventionally followed human sensory panel that has been in use in tea quality assessment till now.

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APPENDIX I

Table 1: Colour features for various grades of Black Tea

Tea Grade	Red (on 0-255 scale)	Blue (on 0-255 scale)	Green (on 0-255 scale)
LEAF	252.5333	141.4844	19.4305
	252.5336	141.8668	19.4463
	252.5341	141.7301	19.4394
	252.5333	141.6534	19.4365
	252.5333	141.5708	19.4335
BROKENS	252.5317	95.9522	16.2653
	252.5294	95.7104	16.1996
	252.5307	95.8185	16.2233
	252.5312	95.867	16.237
	252.5315	95.9115	16.2514
FANNINGS	252.5068	90.8319	13.9596
	252.5248	91.4121	13.9697
	252.5194	91.1924	13.9649
	252.5157	91.0761	13.9631
	252.5116	90.956	13.9613
DUST	252.5309	70.2086	13.1434
	252.531	70.1143	13.1494
	252.531	70.1585	13.1468
	252.5309	70.1772	13.1453
	252.5309	70.1939	13.1444