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An Automated Image Based System for Colour Assessment of Prints and Textiles in Light Booth

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Abstract: Colour is a subjective perception, and in an industrial environment using colour, objectivity is of great significance. In pursuit of improvising the measurement approaches inheriting the scientific progressions, this research emphasis on the development of an automated system with image processing and machine learning techniques for non-contact colour assessment of both prints and textiles under user-defined daylight conditions in the light booth. The system consists of a light booth with tunable LED daylight luminaire to set the day-lighting conditions of D50, D65 and D75 with adjustable illuminance as per colour assessment standards of ISO/ASTM. The feature vectors of the sample images are extracted using colour histograms through histogram quantization. Colour classification is performed using K-Nearest Neighbor (KNN) algorithm trained with 140 shades of Macbeth colour checker chart SG. The proposed system is compared with visual and instrumental measurement methods for experimental validation. The results demonstrate an accuracy rate of 86% in colour classification of prints. Correlating to the lightness of textile samples an accuracy rate of 86% (very dark colour), 83% (medium light colour), 100% (very light colour) found.

Keywords: Colour assessment; Colour histograms; K-Nearest Neighbor; Light booth; Machine learning techniques; Prints; Tunable LED daylight luminaire; Textiles; Visual assessment

1. Introduction

Colour measurement is a crucial and sophisticated task in textile and printing industries as it decides the quality of prints and fabrics. It plays a significant role in pre-production, production and quality assurance stages. Pre-production stage involves colour assessment of customer sample. Production stage involves verification of colours of produced textile/prints to ensure the colour repeatability in successive batches. Lastly, the quality assurance stage includes the check for colour difference between the colours of produced textile/prints and the required. Therefore, considering the above, accurate colour measurement techniques are necessary to reduce rejection and rework, along with increasing productivity [1].

Colour assessment of textiles and prints are generally performed using two techniques: Visual or instrumental. In visual, the assessment process entirely relies on the human eye. Even with the best-designed man-machine interface, the probability of human error cannot be zero. The drawbacks of this method are [2-3]:

- Tedious process even for the best-trained experts;
- Requires training and takes time to expertise;
- Slower than machines;
- Creates tiredness inducing lack of visual focus;
- Subjective method where reproducibility of results not possible;

- Variation of results due to a difference in perception;
- Difficult to interpret the observed colour difference.

Therefore, to increase the accuracy in colour assessment instrumental methods like flat-bed scanner, Spectrophotometer, DigiEye are used. The advantages of these methods in comparison with the human visual system are [2] [4-5]:

- Produce results with increased accuracy and consistency;
- Results can be in RGB, XYZ, CIELAB or CIELUV coordinates;
- An objective method where repetition of results possible with the same precision;
- Shorter production time and reduce labour costs with an increase in manufacturing efficiency.

These devices also have some disadvantages. The scanner makes contact with the sample, and their measurements vary based on the scanning position and alignment of the sample. Spectrophotometer makes contact with the sample restricting the area of analysis to approximately 2.5mm diameter through a small aperture. The DigiEye uses a light box, camera, and convoluted software to make measurements. It can measure larger areas with reasonable accuracy without making contact with the sample. But, owing to the device cost as well as the cost and time involved in training a person on the device usage, their extensive use among small scale manufacturers remains restricted. Hence, abiding the technological advancements and as an alternative to the human visual system, many computer vision systems with image processing methodologies for colour assessment of textiles and prints have emerged in academia for different kinds of materials [1].

In 2000, Verikas et al. [6] deliberated a corrective system to reduce the colour deviations produced due to the disproportion of inks in halftone images of newspapers. From the preprint copy taken using CCD camera, RGB values extracted. These values then converted to nine binary images representing different classes of CMYK vectors giving the percentage of areas covered under each ink. Artificial neural networks used to train and make corrective decisions on ink-feed adjustments for a reference print. Bergman et al. [7] proposed a similar method using unsupervised segmentation and clustering algorithm for identifying the mixing proportions of four different inks in prints used in newspapers, magazines and catalogues. Luo and Zhang [8] proposed an automated process for inspecting the colour of prints using neural networks for image classification and colour histograms for image processing. Colour histograms are sensitive to illumination variations hence illumination correction of RGB values to standard illuminants was carried out using colour charts to maintain constancy in an inspection under varying illumination. Brown et al. [5] suggested an automated system to monitor the gravure printing process continuously, by inspecting the printing sample with machine vision using an area scan camera and using a fuzzy knowledge-based system with tolerance limits. Eerola et al. and Pedersen et al. [9-10] signified a novel approach of using a digital camera for the estimation of human visual quality measures. Similarly, Nebouy [11] proposed a test bench for the estimation of human visual quality using the values obtained by scanning a printed image by a flat-bed scanner. Nussbaum [4] proposed several techniques to improve the print quality in different processes like soft proofing and coldest offset newspaper. Also, a comparison of the accuracy of spectrophotometers and CCD camera measurements for print quality assessment in the printing workflow discussed.

Chung et al. [12] suggested an automatic colour inspection system for printed fabrics. A general scanner used to extract the RGB values, and neural networks algorithm utilized to perform the non-linear transformation of RGB to XYZ as well as compensate the positional error of scanner. Zang and Li [13] projected a computer colour matching method to improve the accuracy of textile dyeing. Human visual assessment of textile samples for dye colourant preparation leads to errors between the sample, dye concentration and dyed material. Hence a training data set of dyed textile samples were created using scanners, and numerical analysis performed for determining the mixture of colourants. Similarly, to reduce the visual assessment error Liu et al. [14] using computer colour matching, analysed the relationship between dye concentration and the dyeing sample with large training dataset. Almodarresi et al. [15] proposed a colour matching system to match the colour of dyed fabric with its dye concentration using artificial neural networks. The samples scanned using a scanner, and the CIELAB values extracted followed with histogram conversion. The algorithm was trained and tested with the L*a*b* values from fabric images and actual fabric obtained using a spectrophotometer. A colour difference of < 1.5 obtained for 80% of testing data. Celik et al. [16] suggested a computer vision system for detection and classification of the defect in fabrics using artificial neural networks. For extracting the input data, the texture feature extraction method was used, achieving an average accuracy of 96.3%. Vitthal et al. [17] demonstrated a system to perform the colour assessment in fabrics using machine learning techniques, involving Image acquisition using a digital camera followed with RGB feature extraction. From the analysis of Euclidian distance and k-means colour clustering method, the later was found to be better. In 2017, Matusiak et al. [18] made a comparative study of the colour measurements of woven fabric using a spectrophotometer and DigiEye. Both the instruments had a good statistical correlation between them, but unfortunately, the actual colour difference with CIELAB values were not determined. Kumah et al. [19] using mean shift algorithm, performed an unsupervised segmentation of printed fabrics of plain cotton woven patterns using Matlab and obtained the colour measurements over the segmented regions using RGB to LAB conversion. The images were captured using a DigiEye system and validated with the comparison of root mean square values between segmented and un-segmented patterns.

In comparison with all the above techniques, the distinct features of the proposed system are:

- This system serves as a common platform for colour assessment of both print and textile samples
- It is an automated system with no human intervention required
- The system performs colour assessment under recommended daylight and illumination levels as per ISO/ASTM standards
- Accuracy of the proposed colour prediction system validated in comparison with visual and spectrophotometer measurements.

2. Materials and Methods

2.1. System Hardware Description

The system consists of two modules: a designer module and press operator/dyer module as shown in Figure 1. The designer module serves as a wireless user interface consisting of PC/ mobile to give the user preferences, visualize the predicted colour and monitor the entire process. Press operator/dyer module comprises of the image acquisition unit and the processing unit. A light booth installed with tunable LED daylight luminaire with dimmable LED driver and Digital Single Lens Reflex Camera (DSLR) Canon EOS 750d are the components of the image acquisition unit.

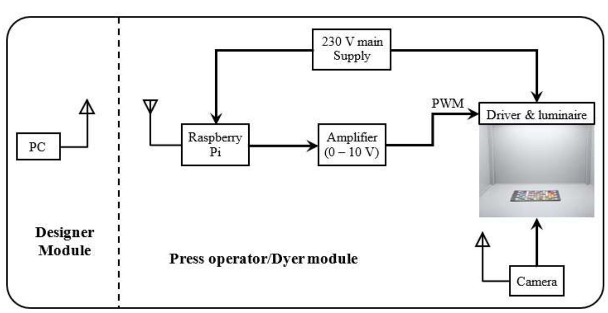


Figure 1. Block diagram of the proposed system.

As per Commission of International Illumination (CIE) 051.2 and ISO 3664, D50 daylight is recommended for printing industries for colour quality testing of products. As per ASTM D1729, D65 daylight is recommended for textile industries [20-22]. D75 was used before the standardization of D65. For the benefits of researchers and manufacturers, they are still in existence. Also, Table 1 gives the standard illumination ranges for colour assessment.

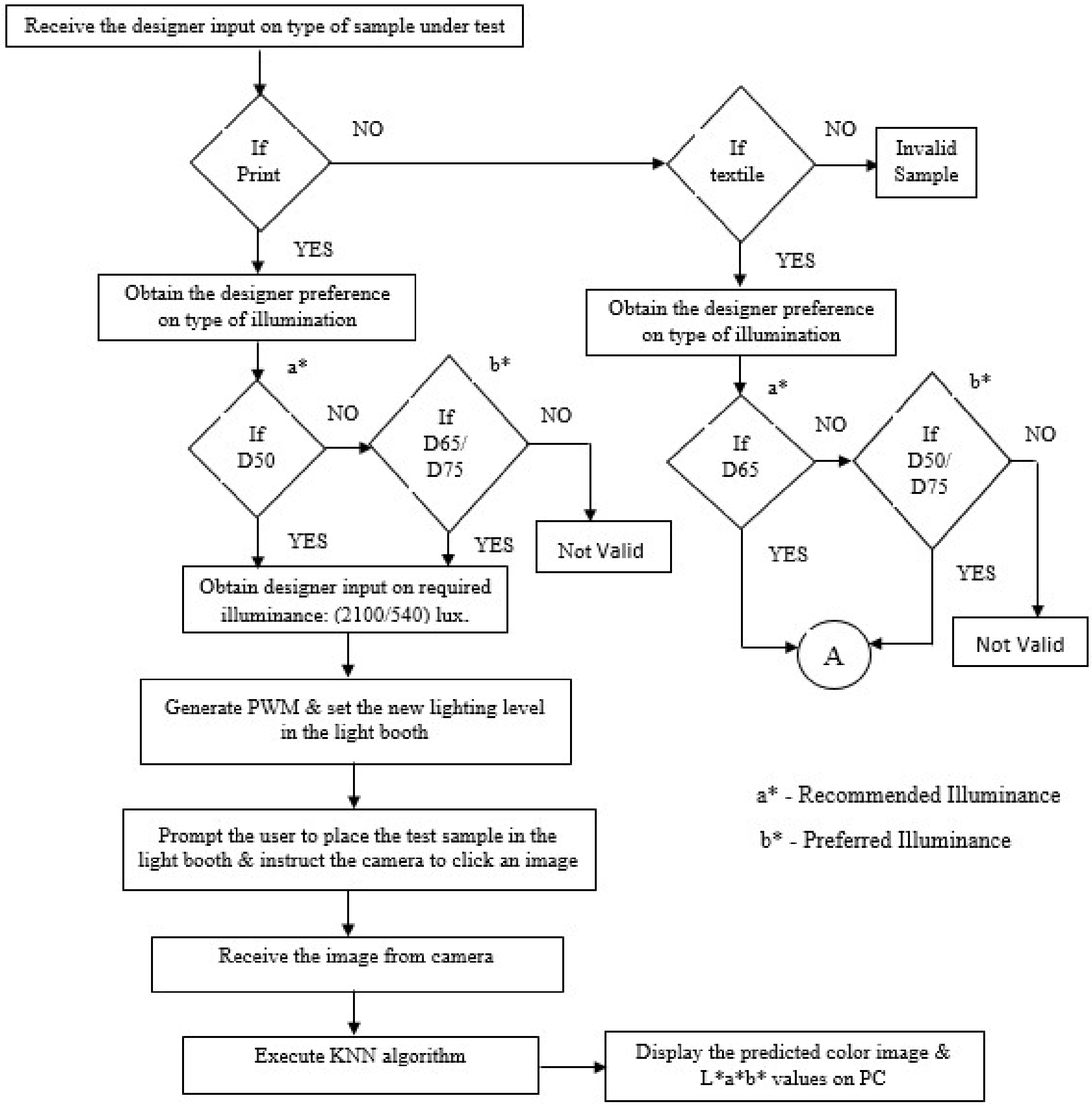
Table 1. Standard Illumination Levels.

Standards	Centre Illuminance
ISO3664	1750 to 2250 lux
ASTM D1729	Medium Light: 1080 to 1340 lux (critical) and 810 to 1880 lux (normal) Very Light: min 540 lux Critical and normal Very Dark: max 2150 lux

According to these standards, a tunable and dimmable LED daylight luminaire that can produce D50/D65/D75 with colour rendering index (CRI) > 90 was previously designed and installed in the light booth as shown in Figure 1. The centre illuminances of the LED luminaire (2350 lux) D50, (2517 lux) D65 and (2600 lux) D75 in comparison with table 1 are higher than required but can be controlled by dimming using a typical three-channel 24W constant current mode AC to DC converter, one channel per daylight spectra. Canon EOS is a 24.2 Megapixels camera with an image resolution of 14 bits/pixel. The processing unit contains Raspberry Pi 3, B+ along with a (0-10) V amplifier to match its PWM compatibility with the LED driver. Raspberry Pi 3 is wirelessly interfaced using Wi-Fi with the camera and designer module for data acquisition and execution of colour classification algorithm. W-Fi connectivity gives simultaneous display of colour assessment results to both the designers and the press operator thereby eliminating the need for long cable installations within the production house.

The complete work flow of the hardware system is shown in Figure 2. For print sample assessment, under the preferred lighting condition of D50/D65/D75, a choice of 2100 lux for critical or 540 lux for general evaluation is given by raspberry pi to the user as per ISO 3664. Based on the selected illuminance corresponding pulse width modulated (PWM) signal is generated by raspberry pi, thereby setting the required lighting level in the light booth. The press operator is then prompted by raspberry pi to place the print sample in the centre of light booth for which a predetermined time of 3 minutes is given by raspberry pi. At the end of this preset time, the camera is prompted to take an image by raspberry pi. This test image is automatically sent to raspberry pi and stored in a folder from where it is extracted by the classification algorithm.

For textiles, the colour prediction has to be made based on the lightness of the sample. Hence, once the user preference for the lighting condition is obtained by raspberry pi, a command is displayed to the press operator to place the textile sample in the centre of light booth. After a preset time of 3 minutes, following the command of raspberry pi an image is taken by camera under a default illuminance of 2100 lux. From the extracted (L*) feature vector of the image which corresponds to lightness value as per CIELAB colour space the Raspberry pi classifies the sample as very dark colour, medium light colour and very light colour. The limits for very dark classification is (0-50), medium light is (51-84) and very light is (85-100) on a lightness scale of (0-100). According to this classification, the illuminance level in the light booth is varied as 2100 lux for dark colours, 1100 lux for medium-light colours and 540 lux for very light colours as per ASTM D1729. Under the new illuminance, the camera is prompted to take the second image, which is then sent to raspberry pi for colour classification. The CIELAB L*a*b* values of the test sample are recorded in a text file.


Receive the designer input on type of sample under test
If Print
NO
YES
If textile
NO
Invalid Sample
YES
Obtain the designer preference on type of illumination
a*
If D50
NO
YES
b*
If D65/ D75
NO
YES
Not Valid
Obtain the designer preference on type of illumination
a*
If D65
NO
YES
b*
If D50/ D75
NO
YES
Not Valid
A
Obtain designer input on required illuminance: (2100/540) lux.
Generate PWM & set the new lighting level in the light booth
Prompt the user to place the test sample in the light booth & instruct the camera to click an image
Receive the image from camera
Execute KNN algorithm
Display the predicted color image & L*a*b* values on PC
a* - Recommended Illuminance
b* - Preferred Illuminance

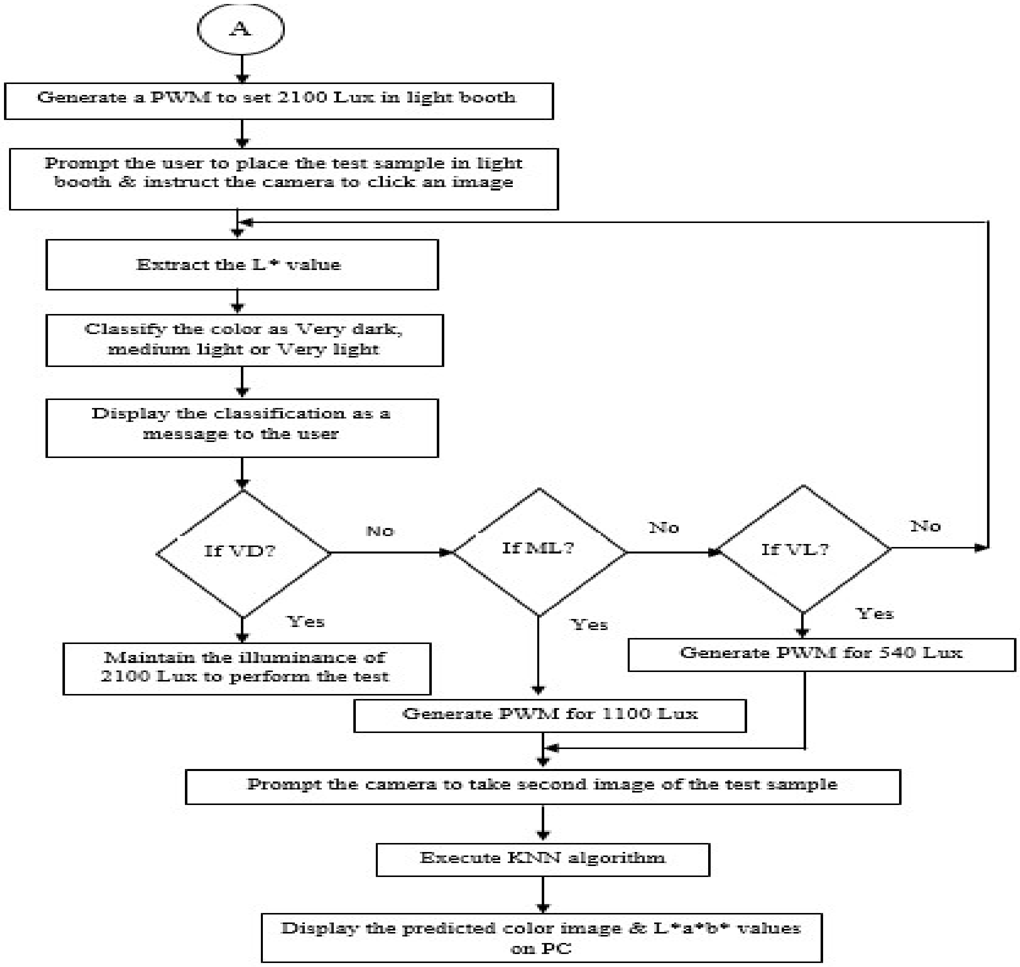


Figure 2. Workflow of the system.

2.2. System Software Description

The proposed classification method is illustrated in Figure 3. It is divided into two phases: the training phase and the prediction phase. The training and prediction phases comprise of four fundamental stages which are Histogram creation, Histogram quantization, feature extraction and colour space conversion. The OpenCV library in python 3 is used for software programming.

Colour histograms are two-dimensional plots used to obtain the statistical measurements of colour distribution over an image. Hence, it is independent of variations in viewing positions or orientations and even scene background [8]. In this work, three histograms are created to represent the colour composition of each channel in the print/textile image: Red histogram, green histogram and blue histogram. Histogram quantization is performed by representing each entry in the histogram by a range of intensity values, referred to as binning [23]. The total colour space of the image is divided into three bins into which the red, green and blue channels/pixels are segregated. Since, the images captured by the camera are 8-bit in sRGB colour space, each bin size is $2^8 = 256$; (0-255) sRGB range. Figure 6(b) shows the histogram plot for a sample print image. From the three channel histogram, the peak intensity values of sRGB are extracted as the feature vectors. Feature vector (FV) is represented as a three dimensional data as in (1)

$$FV = [Hist_{red}, Hist_{green}, Hist_{blue}]$$

Where $Hist_{red}$ is the bin value of red channel, $Hist_{green}$ is the bin value of green channel and $Hist_{blue}$ is the bin value of blue channel.

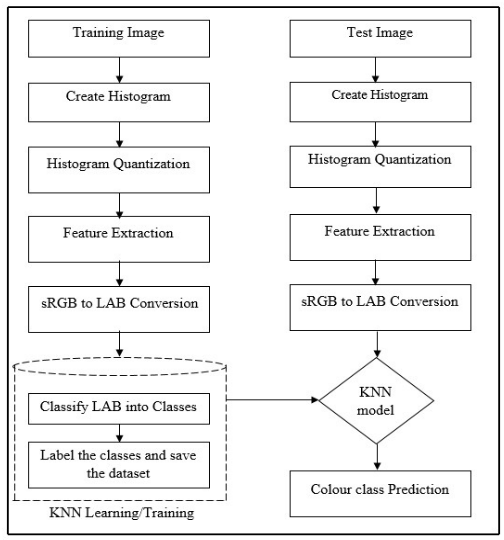


Figure 3. (a) Training Phase (b) Prediction Phase.

CIE has recommended three-dimensional uniform chromaticity spaces like CIELAB, CIELUV and CIEUVW for colour measurement and display. CIELAB introduced in 1976 is preferred over other colour spaces because it gives colour which is a good match of the colour perceived by human eyes. In this system the L* axis represents the lightness with white-black opponent pair, a* axis represents the chroma with red-green opponent pair (a*+ is red; a*- is green), and b* axis represents the hue with yellow-blue opponent pair (b*+ is yellow; b*- is blue) as shown in Figure 4. The lightness value ranges between (0-100) 0-black and 100-white, chroma and hue values range between (+128 to -128). Conversion of sRGB colour space to LAB colour space is performed using a two-step procedure given in [3].

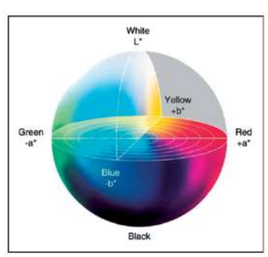


Figure 4. CIELAB Colour Space [3].

2.2.1. Training Database

K-Nearest Neighbor (KNN) is a fundamental supervisory machine learning algorithm that uses the training data stored in memory to predict the output. The training/learning of KNN algorithm is performed by classifying the extracted feature vectors (L*a*b*) into classes. These classes are then labelled and stored as the training dataset. In this work, Xrite Macbeth colour checker SG shown in Figure 5 consisting of 140 colours represented with horizontal and vertical indexing is used for creating the training dataset. 14 distinct classes (i.e 14 different colours) are considered from Macbeth colour checker

SG as they are the most widely used colours in textiles and prints as shown in figure 5. The remaining 126 colours in the macbeth chart are the slight varying shades of the above primary colours. To include these remaining colours in training dataset, under each main class 15 subclasses having similar feature vectors as that of the corresponding main class are assigned. Most of these subclasses are taken from the macbeth chart. These subclasses are labelled with the label of their corresponding main class. So, the total training dataset consists of 210 data points. Similar dataset consisting of 210 data points are created for each of D50, D65, D75 lighting conditions and illuminance of 2100 lux, 1100 lux and 540 lux.

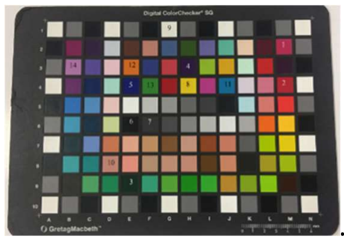
.

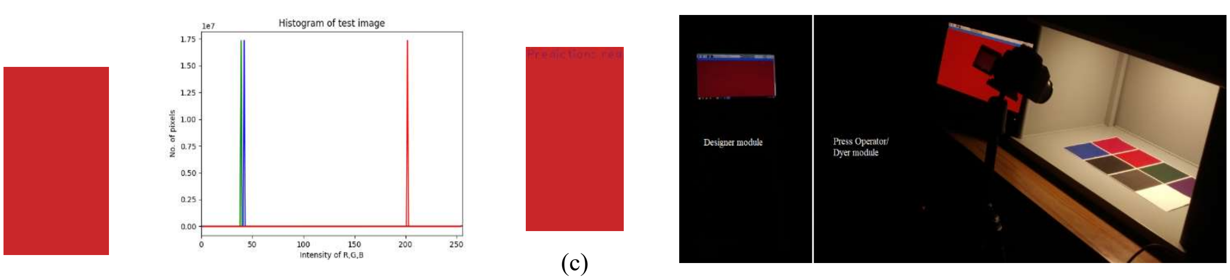
Figure 5. Macbeth SG Colour checker chart numbered with 14 selected classes**.**

2.2.2. K-Nearest Neighbor (KNN) Algorithm

KNN algorithm is based on feature similarity and classification, done using KNN classifier. This algorithm is widely used in pattern recognition, data mining and intrusion detection because of its accuracy [24-28]. To predict the colour of a test image, the algorithm performs the first four fundamental stages and extracts the L*a*b* values of test image. Then, the Euclidean distance from each of the training data set to the test data is calculated using (2).

$$\Delta E^{*}_{ab} = \sqrt{(\Delta L^{*})^{2} + (\Delta a^{*})^{2} + (\Delta b^{*})^{2}} \quad (2)$$

The K value of the classifier is empirically determined as 5; Among the 5 nearest neighbors, the class with majority votes and the subclass with min distance to the test data will be identified as the class of the test image. Generally, the ΔE^*_{ab} value range from (0-100). If ΔE^*_{ab} is within two, then "just noticeable colour differences" will not be perceived by human eyes [4]. Hence the algorithm selects the sub-class which has a distance of less than 2 from the test data. Finally, the test image is displayed to the designer and press operator with the predicted colour. The L*a*b* of the test image is recorded in a text file. Figure 6 shows the image of the prototype setup for a print sample. The obtained L*a*b* value of the red print sample is (L*=37.74, a*=55.82, b*=21.56).



(a) (b) (c) (d)

Figure 6. (a) Camera image of Print sample captured under D50 @ 540lux (b) Histogram (c) Image of the sample displaying the predicted colour (d) Experimental setup.

3. Results

3.1. Experimental Validation of the Proposed System

3.1.1. Test Sample Collection and Indexing

Figure 7(a)-(d) show the 14 randomly selected print and textile samples used for experimental validation. Note that, the patches marked with 'X' in Figure 7 (a)-(b) are not considered for our analysis. The size of the print sample is (3.8 by 5.6) inches, and the size of two folded textile sample taken for the test is (6 by 4.8) inches.

(a) (b) (c) (d)

Figure 7. (a) - (b) Print samples (c) - (d) Textile samples.

The selected textile samples are in combinations of very dark, medium light and very light colours. Since the Macbeth chart taken as the reference is semi-glossy, only shades of the semi-glossy, plain, print and textile samples are used for experimentation. In this work, Xrite i1 standard spectrophotometer measurements are considered as the reference hence before proceeding to the error analysis, two types of databases are created. First is the database of L*a*b* values of 140 colours of Macbeth chart using spectrophotometer under all three lighting conditions and illumination levels of 2100, 1100 and 540 lux. Second is the database of spectrophotometer measurements of the 14 random print and textile samples under the illumination levels mentioned above. The 14 random print and textile samples are indexed by searching the similar colours in Macbeth database with $\Delta E^*_{ab} < 2$ to that of the random sample. Table 2 shows the index numbers of the 14 random print and textile samples. As mentioned in section 2.1, as per ASTM D1729 the very dark textile colours need to assessed under 2100 lux, medium light under 1100 lux and very light under 540 lux. Accordingly, in table 2 sample index nos. M2 to G6 are considered as very dark colours; index nos. M7 to B2 are considered to be medium light colours and A10 is considered as very light colour based on their (L*) values.

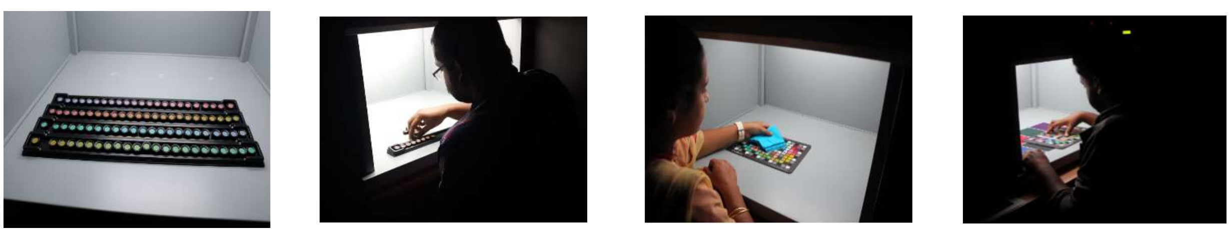
Table 2. Index Numbers of 14 Random Print and Textile Samples.

Print						Textile	
Samples	**Index No.**	**Samples**	**Index No.**	**Samples**	**Index No.**	**Samples**	**Index No.**
	M2		H4		M2		M7
	G4		E7		M4		I8
	E9		B6		H2		C5
	H3		E3		B4		L6
	E4		F4		F3		L9

J5	B3	I1	B2
F6	A4	G6	A10

3.1.2. Error Analysis of Visual Assessment Method

This analysis aims to determine the error rate (%) of observers in the visual assessment of colours in comparison with spectrophotometer measurements [4]. Farnsworth-Munsell 100 Hue Test was conducted to identify the superior observers for actual experimentation [29-30]. Ninety observers of different age groups involving age 20-30 (25 females and 25 males), age 31-40 (15 males and 15 female) and age 41-55 (5 males and 5 females) participated in the FM Hue test. The test was carried out in a dark room in the light booth under D65 lighting condition at 1000 lux. The observer chair was placed at a distance of 50 cm, in front of the light booth to maintain a 45^{o} viewing angle. The FM Hue test Kit consists of 4 boxes of metameric colours with each box consisting of 24 colour pallets as shown in Figure 8 (a). These colours represent perceptually uniform hue steps and form a natural hue circle. Each colour pallet has an integer number on its underside to help in identifying the position of the corresponding colour on the hue circle. For performing the test, the colour pallets in each of the four boxes were sorted one after the other in random order. Each box fixed with two extreme shades of the hue series on the left and right corner to serve as the reference for the observer. During the experiment, the observers had to rearrange the colour pallets in the box such that their hue attributes are continuous from one end of the box to other.



(a) (b) (c) (d)

Figure 8. Experimental setup (a) FM Hue Test Kit (b) Experimental scene (c)-(d) colour assessment of print and textile samples by observers**.**

Also, each observer was requested to rearrange all four hue boxes. Based on the arrangement of the observers, a test report was generated using the FM 100 Hue test scoring tool provided by Xrite showing the observers with superior colour discrimination. Based on the test report, around 20 superior observers were chosen for the actual colour assessment experiment. During the experiment, the selected 20 superior observers were asked to match the 14 random print and textile samples with colours on Macbeth colour checker chart under all three lighting conditions at required lux levels of 2100, 1100 and 540. Figure 8(c)-(d) shows the images of the experimental scene.

Figure 9 shows the observations made by the 20 observers for print samples under the lighting condition of D50 at 2100 lux in the form of a confusion matrix. The x-axis of the matrix represents the actual index of the print samples as given in table 2. Y-axis represents the index of the colours matched by the observers on the Macbeth chart. As can be seen in figure 5 each horizontal alphabetical series consists of 10 vertical index numbers. Hence, it is difficult to make one-to-one mapping of actual print index numbers with the various observed index numbers in matrix. Thus, in x-axis of the matrix A refers to A4; B refers to B6, B3; E refers to E9, E4, E7, E3; F refers to F6, F4; G refers to G4; H refers to H3, H4; J refers to J5; M refers to M2.

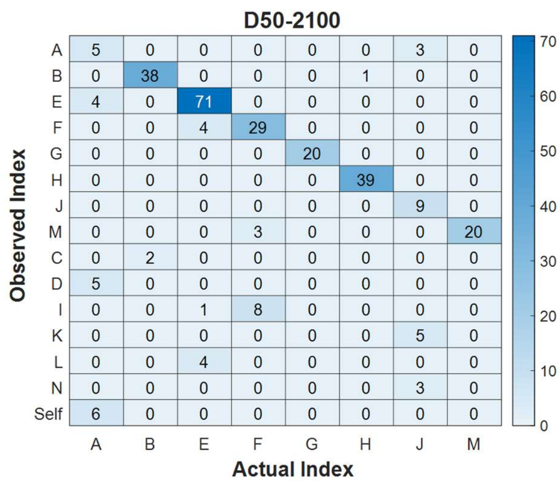


Figure 9. Confusion matrix showing the predictions of superior observers for print samples under D50 at 2100 lux.

The diagonal highlighted rows represent the correct predictions where the actual index alphabets with the exact index numbers are matched with the same alphabets with same index numbers. For example, Actual Index E is assessed 4 times by 20 observers giving a total of 80 predictions of which 71 are correct, matched to E9, E4, E7 or E3. The remaining rows and columns in the matrix represent the mispredictions where the actual index alphabets are matched with different alphabetical index by the observers. The "Self" row in the matrix represents the mispredictions where the actual index alphabets are matched with same alphabets but different index numbers. Similarly, the observations of superior observers for print samples under D65, D75 at 2100 and 540 lux are also recorded in different matrices. The inferences are discussed below.

- J5 (black), F6 (grey), A4 (white) were mismatched by majority of the observers under all lighting conditions and lux levels.
- M2 (dark magenta), E4 (dark blue), E3 (orange) were correctly matched by majority of the observers under all lighting conditions and lux levels.
- Remaining 8 colours have undergone mismatches under different lighting conditions and lux levels. (i.e.) If the colours were correctly predicted under one lux level their prediction failed under other.

In order to analyze error rate (%) we have considered the predictions of one single observer under D50 at 2100 and 540 lux as shown in Figure 10.

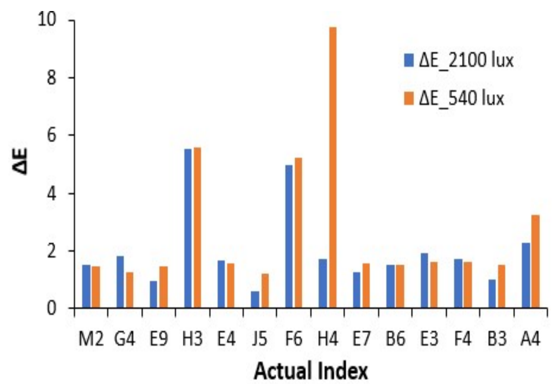


Figure 10. Comparison of a sample observer's colour assessment of print samples under D50 at 2100 and 540 lux.

The absolute colour difference ΔE is calculated by taking a difference of the L*a*b* values of the actual and observed index colours (using equation 2) measured using spectrophotometer. If ΔE is greater than 2 it is considered as mismatch. We observed that the number of colour mismatches are less at 2100 lux than at 540 lux due to good vision of observer at brighter light level. This observer has made consistent mismatch in H3 and F6 under different lux levels. But the mismatch in samples like H4 and A4 are inconsistent as the observer was able to rectify the error made in 540 lux, in 2100 lux. The error rate at 2100 lux is found to be 21% and 540 lux is 29%. When the analysis was repeated with other observers we observed that the type of mismatches were different but the rate of error was same under the considered lighting condition.

Figure 11 shows the observations made by the 20 observers for textile samples under the lighting condition of D65 at 2100 lux in the form of a confusion matrix. The x-axis of the matrix represents the actual index of the very dark textile samples as given in table 5. Y-axis represents the index of the colours matched by the observers on the Macbeth chart. In the x-axis of the matrix B refers to B4; F refers to F3; G refers to G6; H refers to H2; I refers to I1; M refers to M2, M4.

Figure 11. Confusion matrix showing the predictions of superior observers for textile samples under D65 at 2100 lux.

The inferences are discussed below.

- I1 (black) and G6 (grey) were mismatched by majority of the observers under all lighting conditions.
- M2 (dark magenta) and F3 (dark blue) were correctly matched by majority of the observers under all lighting conditions.

- Remaining 3 colours have undergone mismatches under different lighting conditions.

Similarly, from the predictions of observers for medium light colour textile samples at 1100 lux, we noticed that the observers faced difficulty in matching light materials similar to prints. Out of 6 index colours only L6 was matched correctly by majority observers. As the type of textile samples viewed under 2100,1100 and 540 lux are not the same, to analyze error rate we have considered the predictions of one single observer under D50, D65, D75 at 2100 lux as shown in Figure 12. We observed inconsistency in the assessment of this observer for M4, H2, G6 and I1 under varied lighting condition. The error rate at 2100 lux is found to be 29% for D50, 14% for D65 and 14% for D75. On repeating the analysis with other observers error percentage was found to be same.

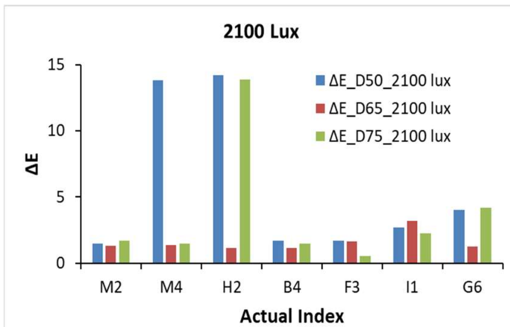


Figure 12. Comparison of a sample observer's colour assessment of very dark textile samples under D50, D65, and D75 at 2100 lux.

3.1.3. Error Analysis of Proposed System

The objective of this analysis is to verify the error rate of the proposed system in colour assessment in comparison with spectrophotometer. The 14 print and textile test samples are placed in the LED light booth and images are taken under D50, D65 and D75 at required lux levels of prints and textiles. Using the KNN algorithm colour is predicted, and their CIELAB values obtained. Then the same samples are analyzed using a spectrophotometer, and their LAB value extracted. Taking the difference of these LAB values using equation 2, ΔE is calculated. Figure 13 shows the colour prediction of the proposed system for print samples under D50 at 2100 and 540 lux.

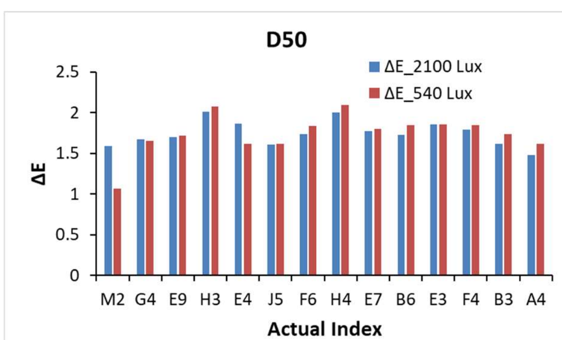


Figure 13. Colour assessment of the proposed system for print samples under D50 at 2100 and 540 lux.

From the analysis we observed that the proposed system produced ΔE slightly above 2 for H3 (purple) and H4 (skin). This means that the system has identified minor varying shade of purple and skin. In addition, the system is consistent in assessment (i.e.)

the mispredictions by the system under a particular lighting level and lighting condition was observed to be the same in other lighting levels and lighting conditions giving a consistent error rate of 14%. Figure 14 shows the assessment of textile samples under the three lighting conditions at 2100 lux. The system has made consistent mispredictions in identifying the exact shade of B4 (purple) giving an error rate of 14%.

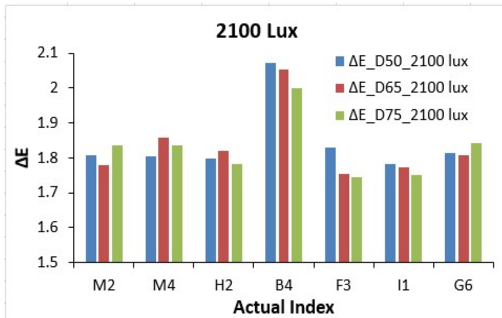


Figure 14. Colour assessment of the proposed system for textile samples under D50, D65, D75 at 2100 lux.

4. Discussion

From the results of Visual assessment method it can be notified that this method produces inconsistent results as it depends on the observer's perception under varied lighting condition and illuminances. Their predictions are correct if there are limited number of shades with which the test sample has to be matched. If there are many similar shades on the chart the observers get confused and end up in mismatch. Also, mismatch happens when they are asked to match light colours. The error rate of the observers for prints at 2100 lux is less compared to 540 lux as they rectified some of their errors made at 540 lux in 2100lux because of their clear vision at brighter light level. More specifically, the error rate varies under different lighting conditions and illuminances for print and textile samples.

But unlike the observer's perception, the proposed system produces less number of errors. Also the errors are consistent under different lighting levels and lighting conditions.

Table 3 shows the comparison of the error rate of visual assessment and the proposed system. Note that the error rate of both the systems are calculated in comparison with spectrophotometer considered as the reference. The error rate in each case is computed by dividing the number of mispredictions (ΔE^*_{ab} values > 2) by the total samples taken for the analysis. Accordingly, from table 3 it can be noted that proposed system produces a constant error rate of 14% in prints and 14%, 17%, 0% error rates at different lux levels for textiles. This comparison infers that the proposed system produces less number of errors in colour assessment compared to human observers.

Table 3. Comparison of Average Error of visual assessment with the Proposed System.

Type of sample	Illuminance (Lux)	Visual Assessment			Proposed system		
		D50	D65	D75	D50	D65	D75
		Error rate (%)	Error rate (%)	Error rate (%)	Error rate (%)	Error rate (%)	Error rate (%)
Prints	2100	21	14	21	14	14	14
	540	29	21	29	14	14	14
Textiles	2100	29	14	14	14	14	14
	1100	17	17	17	17	17	17
	540	100	100	100	0	0	0

5. Conclusions

The research portrays an objective image based method to access the colour of both textiles and prints under the ISO/ASTM standards. Apart from the recommended lighting (D50 for prints and D65 for textiles) the system also provides two other daylight options to allow the user to verify colour constancy of samples under different lighting conditions. In addition, the system is capable of adjusting the illuminance automatically based on the colour of the textile sample under test. Wireless connectivity would help the manufacturers, having their designer and dyer units placed far apart from each other by removing the long cable installations within the dyer unit and between the designer and dyer units. The KNN algorithm trained with 210 different colour shades predicts the sample colour satisfactorily. Unlike visual assessment method, the proposed system produces less and consistent errors under varied lighting conditions and illuminances. The proposed system does not require human intervention except for giving user preferences and placement of colour sample in the light booth. Hence, no system specific training required unlike the other instruments for assessing the colour of samples; reducing time and cost. From the experimental results it is evident that the proposed system produces L*a*b* values with colour difference ($\Delta E^*_{ab} < 2$) in comparison with spectrophotometer. The proposed system with the help of a stable and good colour rendering LED daylight luminaire provides colour prediction with 86% accuracy for prints. Like-wise an accuracy rate of 86% (very dark colour), 83% (medium light colour) and 100% (very light colour) obtained for textiles for a sample count of 14. The future scope of this research will be to work on unsupervised machine learning techniques to improve the accuracy rates, to verify the robustness of the system with print and textile materials of different textures, shapes and volumes.

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