Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 03, No. 01, Dec 2022-Jan 2023
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.31.11.17

Comparison of the Components of Different Colour Spaces to Enhanced Image Representation

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Received: 01 September 2022 **Accepted:** 19 November 2022 **Published:** 12 December 2022

Abstract: In many applications, the comparison of the visual appearance of real-world materials is crucial. In this article, we look into the issue of selecting an appropriate colour representation for food photographs, weigh the benefits and drawbacks of several colour spaces, dispel some myths about how to use them, and suggest a number of "best practices" for colour conversion. To put the debate into practice, we created a brand-new dataset of various foods, which we utilized to compare and assess the effectiveness of colour spaces methodically in a methodical manner. According to the results of the investigation, the H component provides more discriminative information about the colour of food items with clearly distinct item pixels than other components

Keywords: Colour, Image, Dataset, Linear,Transformations

1. INTRODUCTION

Colour space representation is defined as a computerized representation of colours, that further allows the reproduction of the represented colour with the aid of both digital and analogue devices [1]. Images contain pixels, the pixels based on colour space to represent colour. In any colour definition, three elements should contribute to the light source, and these consist of the reflectivity of the sample and the visual sensitivity of the observer [2]. Images, in general, can be represented with one of three levels of representation: binary (black and white), grey, and colour [3]. It is obvious the degree of the more available colour in the representation the more information exists in the image. As a result, adopting colour representation for the applications of computer vision such as segmentation [4], [5], feature extraction [6] and, pattern recognition is useful for providing sufficient information [7], [8].

In this paper [9] extracted RGB colour space, S component from HSV colour space, I component from YIQ colour space, Cb component from YCbCr colour space, and Z component

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from XYZ colour space are used to eliminate the effect of disturbing factors for Segmentation. In [10] The authors proposed five colour spaces were used: CIELAB, HSV, YUV, YCbCr, and HLS. The result shows that A in LAB and H in HLS are better to produce segmentation than other colour channels. Also, the authors in [11] developed a multi-agent-based food recognition system based on extracting a large set of features colour. Colour features are extracted from HSV, CIE LAB, RGB, normalised RGB, and opponent colour spaces.

The common colour representation is to represent any colour as a mixture of three components Red, Green, and Blue (RGB) [12]. This is enough to represent any colour that the human eyes can perceive according to the tristimulus theory. However, RGB is not the only colour representation; there are other colour representations such as HSV, I1I2I3, Normalise RGB, YCbCr, LAB, and YUV [13]. Each of them can be used in the application of image segmentation with the power of capturing a different aspect of the colour information than the other. Any of them can be derived from RGB by using linear or non-linear transformation. The goal of this effort, Comparing different colour spaces to choose the best one for image representation. The following describes the structure of this essay: In Section 2, a basic overview of the various colour spaces is given. Section 3 of this article outlines the suggested detection method, while Section 4 presents comprehensive results and explores the components of various colour spaces. This work is concluded and, offers suggestions for additional research in Section 5.

2. Types Of Colour Spaces

There are different types of colour spaces extracted for classification such as

2.1 Linear Transformations

Analogue video signal for dimensional colour distribution over both U and V as well as luminance (YUV), I1I2I3, and Digital Video Signal on Dimensional Colour Distribution across Cr and Cb (YCbCr) are three common colour representations derived based on linear transformations from RGB. The advantage of deriving using linear transformation is useful for the reduction of computational complexity and applying them in real time applications [14].

2.2 Nonlinear Transformations

There are several types of non-linear RGB transformed colour space representations; some of them are explained in the following [15]. Normalise RGB Colour Space: this is a non-linear transformed colour space where components values are always constrainedts between [0, 1].

$$r = \frac{R}{(G + R + B)} \tag{1}$$

$$b = \frac{B}{(G + R + B)} \tag{2}$$

$$g = \frac{G}{(G + R + B)} \tag{3}$$

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- HSV (Hue, Saturation, Value), another non-linear transformed colour space from RGB is HSV [16], [17] . Conversion is done by Equations below.

$$V = max\,(G,\ \mathrm{R},\ B) \tag{4}$$

$$S = \frac{V\ - min\,(G,\ \mathrm{R},\ B)}{V} \tag{5}$$

$$H = \begin{cases} 3 + \dfrac{(B-R)}{V - min\,(G,\ \mathrm{R},\ B)} & for\ V = G \\ 1 + \dfrac{G-B}{V - min\,(G,\ R,\ B)} & for\ V = R \\ 5 + \dfrac{R-G}{V - min\,(G,\ R,\ B)} & for\ V = B \end{cases} \tag{6}$$

Hue, saturation, and intensity are the three channels used in this colour space. The term "pure colour" refers to the hue, which represents the predominant frequency of light, "saturation," which refers to the quantity of white light incorporated into the pure colour, "intensity," which refers to the colour's overall brightness.

- Distribution and lightness Dimensional colour distribution across A and B (LAB). This color space aims to closely resemble how people see color. CIELAB employs three channels. L stands for a color's luminosity, or brightness; A for where it is on a scale from red to green; and B for where it is on a scale from blue to yellow. Represents a colour coding system that results from RGB based on two stages [18].

1- Convert from RGB to XYZ spaces.
2- Conversion from XYZ spaces to LAB model.

- Greyscale: greyscale images were composed of different shades of grey ranging from 0 to 255. 0 is a black colour at the weakest intensity. 255 is the strongest intensity which is white [19], [20]. The conversion formula from RGB to greyscale is:

$$Grey = 0.2999 * Red + 0.5870 * Green + 0.1140 * Blue \tag{7}$$

3. METHODOLOGY

The experiments of this article have been done on dataset combined of 100 images. In this dataset, images are acquired by IPhone mobile with 16 mega pixels with different conditions such as colours lighting, and background. The image was taken in RGB format. The image was converted from RGB to the other colour spaces to extract features from different colour spaces. The colour spaces are I1, I2, I3, normalised R, normalised G, normalised B, H from HSV, Cb, Cr, A and B from LAB. Statistical features are extracted such as mean: average or mean value, standard deviation, and skewness. Figure 1 shows the algorithm that is suggested in this paper.

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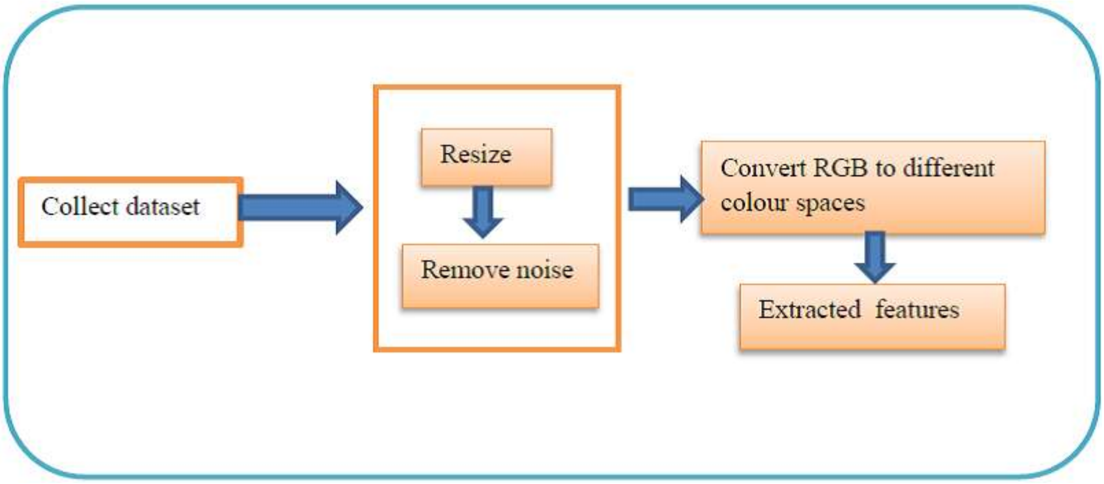

Figure 1: Diagram of the Proposed Algorithm

The following colour components' average values, are determined for each region to be categorised in as an equation (8).

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{8}$$

where N stands for the number of pixels in the image and x_i represents the value of the I th colour component of the image pixel i . The definition of the standard deviation for a random variable vector with N scalar observations is as follows:(9).

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N} |x_i - \mu|^2} \quad . \tag{9}$$

The asymmetry of the data around the sample mean is measured by skewness. Equation (10) gives the following definition of skewness:

$$s = \frac{E(x-\mu)^3}{\sigma^3} \quad , \tag{10}$$

where $E\,(x)$ represents the anticipated value of the quantity x and, μ the mean of x , and, $\sigma$the standard deviation of x, respectively This population value is computed using a sample version of skewness.

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4. RESULTS AND DISCUSSION

Figures 2 and 3, represent the results of numerous experiments. The results show some components are better than others. The component R is cannot distinguish between items. The items areas are mostly absent in component V. Component G and B are not clear to segmented items, The B normalize, G normalize, S from HSV and I3 from LAB, Cb, and Cr not visible. The Z component contains all the edge details of the lesion. Other components in representing colour information were reached because these components have item pixels that are clearly different among each other. H carries more discriminative information on the colour of the food items which have item pixels that are clearly different compared with S and V and other components.

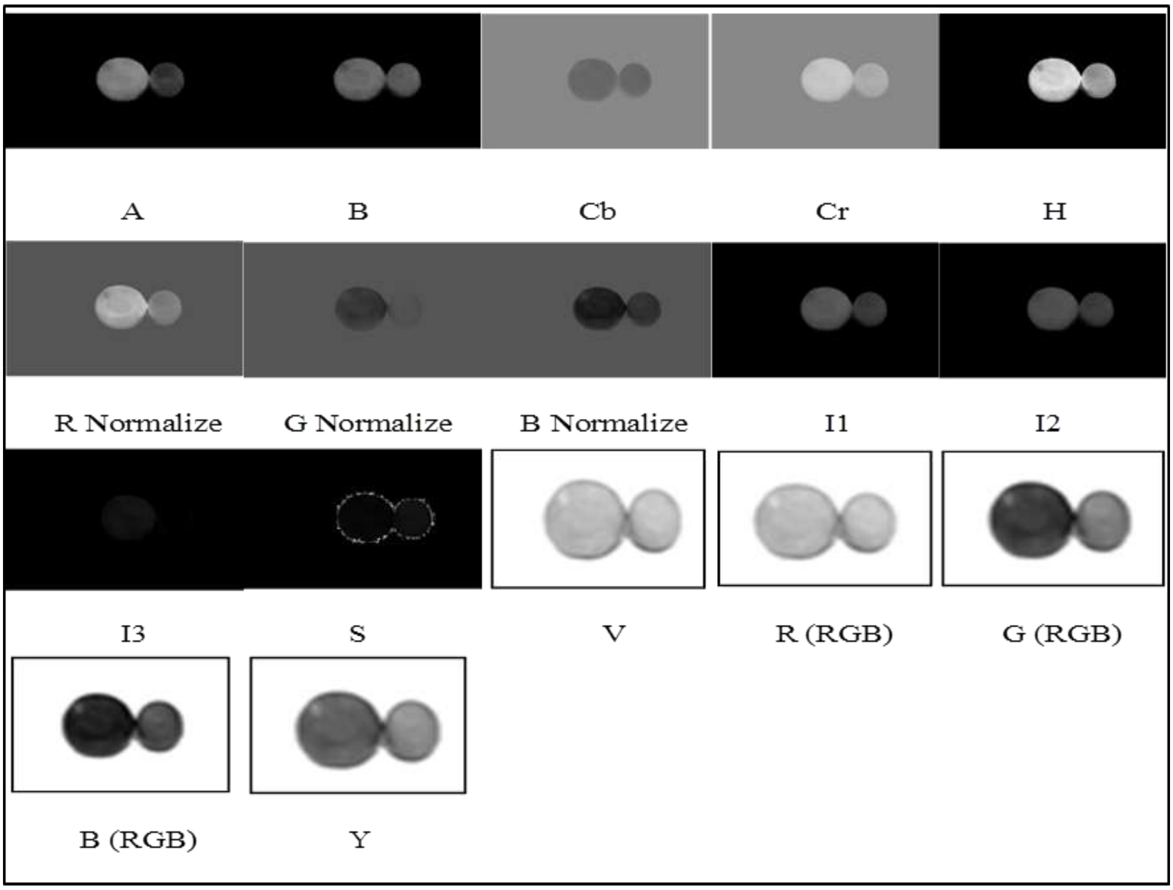

Figure 2: Experiments of Colour Features

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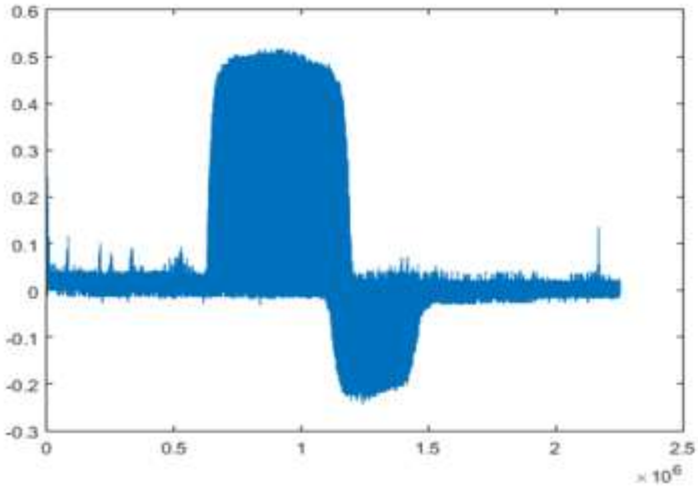

Figure 3: Histogram analysis of two items eggs and tomato

It is clear from Figure 3 that the pixels have been split into 2 distinguished areas of food items.

5. CONCLUSION

In this research, we have given a rigorous method for performance-based colour space comparison. The findings demonstrate that simple and inexpensive colour descriptors are extremely useful for the task under regulated illumination circumstances. H components from HSV spaces fared better than the competition. The validation of these findings in a bigger dataset in the future would be intriguing. Additionally, this work could be used for segmentation and classification.

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