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# Novel Colour Clustering Method for Interlaced Multi-colored Dyed Yarn Woven Fabrics

## Abstract

In this paper, a novel colour clustering method based on the K-means clustering algorithm is developed for interlaced multi-colored dyed yarn woven fabrics which can be used to sort the colour of the dyed yarn for the development of a quick response fabric system. Firstly fabric images captured by a flat scanner could be decomposed into three sub-images in red, green and blue channels, respectively. Secondly median filters with different template sizes were selected to process the sub-images in the three color channels separately. Thirdly filtered images in the RGB colour space, reconstructed from the three sub-images, can be converted into the Lab colour format. Ultimately the results of colour segmentation and classification can be obtained based on the Lab color space using the improved K-means clustering algorithms. Our experimental results indicated that our method proposed works better than the conventional method based on subjective and manual operations with the aid of simple tools in terms of both accuracy and robustness.

**Key words:** colour clustering, Lab colour space, K-means algorithm, dyed yarn woven fabrics, image analysis.

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## Introduction

Colour clustering can be used to segment and classify the colours inside fabrics, which has been regarded as a vital and indispensable procedure during the fabric manufacturing and analysis processes. Previous researchers [1, 2] have always focused on analysing grayscale fabric images, although digital image analysis techniques for fabrics have developed and evolved very quickly. Nevertheless the visual perception of colour images is much more significant than for grayscale ones, thus it is necessary to develop an automatic colour clustering method for dyed yarn woven fabrics. Generally the methods proposed [3-5] based on image analysis (or computer vision) in this field can be divided into three categories: fuzzy C-means clustering, neural-network, and histogram based thresholding methods.

One way of the colour identification in dyed yarn fabrics is based on an unsupervised analysis method and, as pointed out in reference [6], a fuzzy C-means (FCM) clustering algorithm and a specific cluster-validity criterion (sc criterion) can be used to analyse the colours and patterns of printed fabrics in a RGB colour space. However, this kind of colour clustering method is suitable for dyed yarn fabrics; it could describe the variation in image intensity. Once the yarns have different colours possessing similar intensity, but with different hue values, colour classification is difficult to be done in the RGB colour space. In this situation, a novel method based on an improved FCM algorithm and HSL colour space was proposed to identify the coloured yarns in woven fabrics [7]. The membership degree and cluster center of H, S & L were

the efficiency of the FCM algorithm. By validating the optimal cluster number, the number of yarn colours in the woven fabrics was automatically recognised. Nonetheless the HSL colour space is not effective for colours with an analogous hue and lightness value, but with different saturation values. Accordingly, an FCM algorithm was proposed to classify the colours for dyed yarn fabric in a Lab colour space [8]. A single-system-mélange colour fabric, captured by a flat scanner, could be divided into different blocks using the FCM algorithm based on the Lab colour space. Finally the yarns could be located in different means and the number of yarns could be counted. Along similar lines, two different dyed yarn fabrics: a light colour fabric (LCF) and dark colour fabric (DCF), were studied for validation of this method [9]. It was reported that the colour yarns, which were difficult to disperse with others in the RGB and HSL colour spaces, were successfully classified in the Lab colour space using the FCM algorithm.

On the other hand, neural networks have proved that it has the advantages of parallelism and good robustness to disturbances. Thus it makes them suitable for real-time applications and provides reliable predictions. A computerised colour classification system based on a backward-propagation neural network to separate the rich colour of a printed fabric pattern was put forward to conduct the colour separation of a printed fabric RGB sub-image [10]. The experiment results proved that this supervised colour separation method could differentiate the colours of a printed fabric image. Similarly a back-propagation neural network was adopted to make fuzzy clustering analy-

sis of an image texture feature acquired based on the image's hue and value [11]. As indicated by their experimental results, this system could recognise plain, twill and satin weave textures in woven fabrics, single and double jersey in knitted fabrics, and nonwoven fabrics accurately.

In addition, the histogram based thresholding method is one of the techniques most used for colour clustering. A segmentation algorithm used in a watershed algorithm to segment either the two-dimensional (2D) or three-dimensional (3D) colour histogram of an image was presented for colour fabric images [12]. The LUV colour space was used for perceptual coarsening of the colour histogram in compliance with the way humans perceive colour. Another framework for colour image segmentation was presented for the combination of colour histogram analysis and the region merging approach. It can be used to segment an image around material boundaries while ignoring the spatial colour of uniform objects, caused by accidents of illumina-

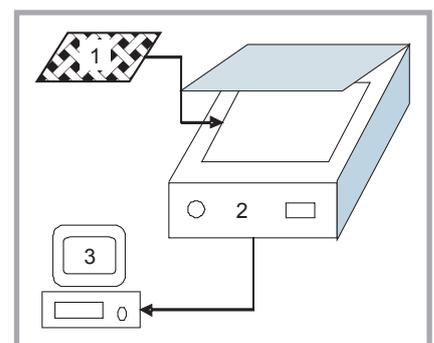
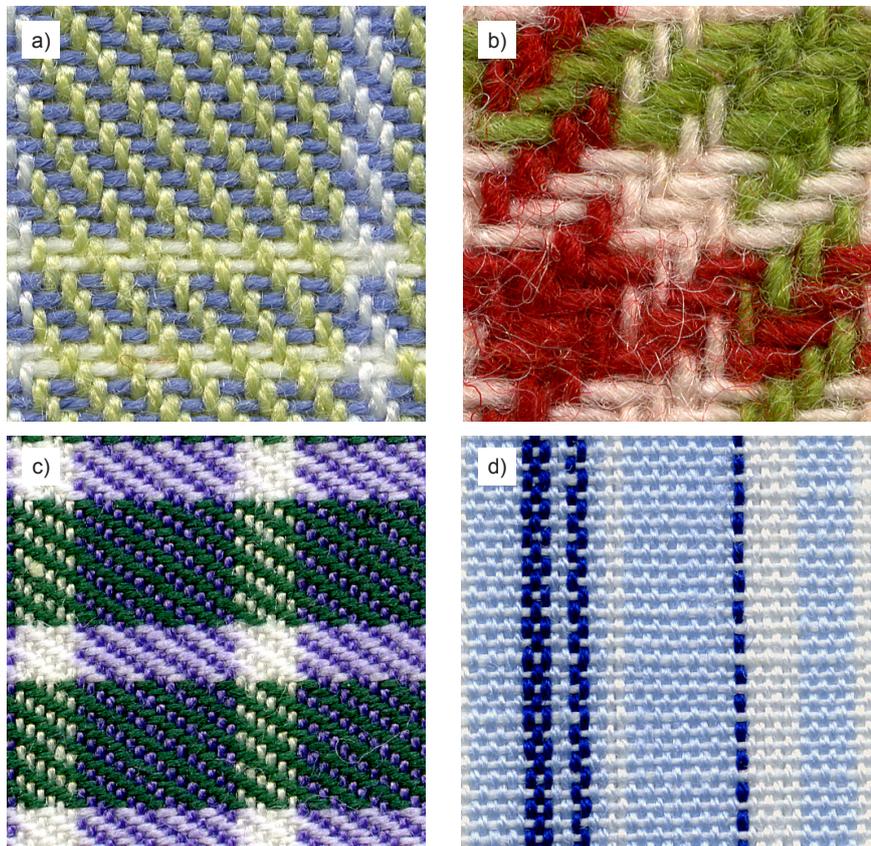


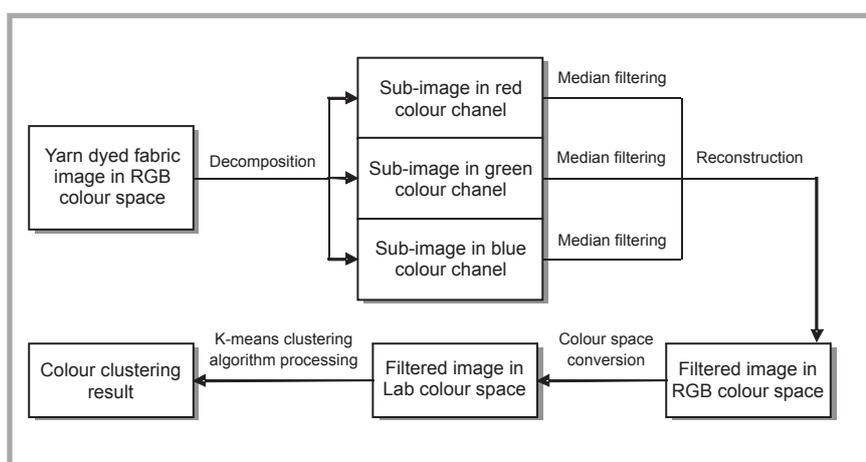
Figure 1. Overview of the image acquisition system; 1) sample, 2) flat scanner, 3) computer.

**Table 1.** Specifications of fabric samples.

ID	Fabric structure	Composition	Yarn density ( yarns per inch)	
			Warp	Weft
1	Twill 2/2	65% polyester + 35% rayon	70.10	56.39
2	Twill 2/2	100% cotton	34.04	31.51
3	Twill 1/2	100% cotton	137.67	97.54
4	Plain 1/1	55% linen + 45% cotton	109.22	64.01



**Figure 2.** Images of the interlaced dyed yarn woven fabrics (4 samples); a) ID 1, b) ID2, c) ID3, d) ID4.



**Figure 3.** Flowchart of the colour clustering processing for the yarn dyed woven fabric

tion and distortion of the viewing geometry [13]. Furthermore a novel histogram thresholding-fuzzy C-mean hybrid (HT-FCM) approach was proposed to apply the histogram thresholding technique to

obtain all possible uniform regions in the colour image. Then the Fuzzy-C-means (FCM) algorithm was utilised to improve the compactness of the clusters forming these uniform regions [14].

However, most of these research works are focused on printed fabrics and solid coloured fabrics. In this paper, we attempt to develop a new colour clustering method for interlaced multi-coloured dyed yarn woven fabrics. The purpose of our study is to establish a quick response system for the development and quality evaluation of dyed yarn woven fabric. The colour numbers and exact colour sorts of the interlaced multi-coloured dyed yarn woven fabrics could be determined based on our method. Firstly, the fabric images captured by a flat scanner could be decomposed into three sub-images in R, G and B channels, respectively. Secondly median filter can be generated to process sub-images in the three channels separately. Thirdly the filtered image in the RGB colour space, reconstructed from the three sub-images, can be converted into a Lab colour space. Ultimately segmentation and classification results can be obtained using an improved K-means clustering algorithm.

## Methodology

### Image acquisition system set-up

To digitalise the interlaced multi-coloured dyed yarn woven fabrics, one set-up of the image acquisition system has been illustrated in *Figure 1* (see page 107). It comprises two components: 1) a high-resolution flat scanner, which is used to capture the reflective surface images of fabric samples, 2) a personal computer with software for image capturing and analysis; the software is developed by Microsoft Visual Studio 2010 in the Windows 7 operating system.

In this research, three twill fabrics and one plain fabric were selected for this investigation. These four fabric samples were firstly analysed by means of a traditional manual method to identify the fabric structure and densities along the warp and weft directions separately. All these fabric samples were multi-coloured, composed of three different colour yarns. Detailed information is listed in *Table 1*.

Reflective images of the fabric samples selected were digitalised by an Epson flat scanner, which could be transferred to a personal computer for image recording. The image resolution in our experiment was 1200 pixels per inch, and all images were cropped into 512 × 512 pixels, as shown in *Figure 2*.

$f(i-1,j-1)$	$f(i,j-1)$	$f(i+1,j-1)$
$f(i-1,j)$	$f(i,j)$	$f(i+1,j)$
$f(i-1,j+1)$	$f(i,j+1)$	$f(i+1,j+1)$

**Figure 4.** Template of a  $3 \times 3$  median filter template.

### Development of colour clustering algorithm

Once the reflective images of the multi-coloured dyed yarn woven fabrics were captured, colour clustering could be accomplished by the following procedures illustrated in **Figure 3**. The decomposition is aimed to divide the fabric image into red, green and blue colour channels identically. Subsequently the median filter is utilised to process the sub-images in three colour channels. After reconstructing the images by combining the three colour channels, a filtered image in the RGB colour space is achieved. By converting the image from RGB to a Lab colour space, a filtered image in the Lab colour space could also be obtained. Finally by analysis of the image based on the improved K-means clustering algorithm, classification and segmentation of the results could be achieved.

### Median filtering

In order to eliminate the noises usually caused by the hairiness or a single fibre spreading over the fabric surface, a spatial domain median filter can be applied to enhance the image quality, thus improving the accuracy of the colour analysis in this paper.

The main idea of the median filter is to run through the signal entry by entry, replacing each one with the median of neighboring entries. If the pattern of neighboring ones has an odd number of entries, it is simply the middle value after all the entries in the window are sorted numerically [15]. Here a  $3 \times 3$  neighborhood has been chosen as the filter template (**Figure 4**).

Assuming  $f(x,y)$  and  $g(x,y)$  represent the original sub-image and filtered image

$$g(i,j) = \text{Med} \begin{pmatrix} f(i-1,j-1), f(i,j-1), f(i+1,j-1), f(i-1,j), f(i,j), \\ f(i+1,j), f(i-1,j+1), f(i,j+1), f(i+1,j+1) \end{pmatrix} \quad (1)$$

**Equation 1.**

respectively,  $f(x,y)$  is the central element and the adjacent eight elements are described in the template. When the filter template is utilised to process all the pixels of the sub-image point by point, the median value of each template will be reserved as illustrated in **Equation 1**. Finally the original sub-image,  $f(x,y)$  will be replaced by the filtered image  $g(x,y)$ .

### CIE-Lab colour space

The Lab colour space [8] illustrated in **Figure 5** is more similar to human vision in comparison with the RGB colour space in its perceptual uniformity. The  $L$  component accommodates approximately human perception of lightness. Accordingly in components  $a$  and  $b$  the output curves can be modified to achieve accurate colour balance corrections. Furthermore the  $L$  component can be used to adjust the lightness contrast. However, it is difficult to realise the above advantages in an RGB colour space.

To use the Lab colour space for further processing, conversion from an RGB colour space to Lab colour space should be completed [16]. To accomplish the conversion, the fabric image in the RGB colour space should be transferred to an XYZ colour space. The specific conversion procedures [17, 18] are described as follows:

$$r = R/255 \quad (2)$$

$$\text{if } r > 0.04045 \text{ then } r = \left( \frac{r + 0.055}{1.055} \right)^{2.4}, \quad (3)$$

$$\text{else } r = r/12.92$$

Similarly,  $g$  and  $b$  can be calculated from components  $G$  and  $B$  in the same way.

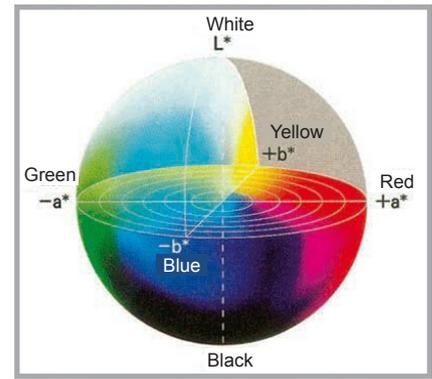
$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4125 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} \cdot \begin{bmatrix} r \\ g \\ b \end{bmatrix} \quad (4)$$

Then the image can be converted to a Lab colour space from the RGB colour space by the aid of an XYZ colour space.

$$\text{if } X > 0.008856 \text{ then } x = X^{1/3} \quad (5)$$

$$\text{else } x = 7.787 \times X + 16/116 \quad (6)$$

Analogously  $y$  and  $z$  can be calculated from components  $Y$  and  $Z$  using the above equations.



**Figure 5.** The diagram of Lab colour space [16].

$$\begin{cases} L = 116 \times y - 16 \\ a = 500 \times (x - y) \\ b = 200 \times (y - z) \end{cases} \quad (7)$$

Once the conversion has been finished, values  $L$ ,  $a$ ,  $b$  will range from -128 to +128. Therefore the clustering method can be used to classify and segment the multi-coloured dyed yarn woven fabrics with the Lab colour space.

### K-means clustering algorithm

The K-means clustering method aims to minimise the sum of the squared distance between all points and the cluster centers. This procedure is composed of the following steps: [19, 20].

1) Choose  $K$  for initial cluster centers  $Z_1(1), Z_2(1), \dots, Z_k(1)$ .

2) At the  $k$ -th iterative step, distribute the samples  $\{x\}$  among the  $K$  clusters using the relation,

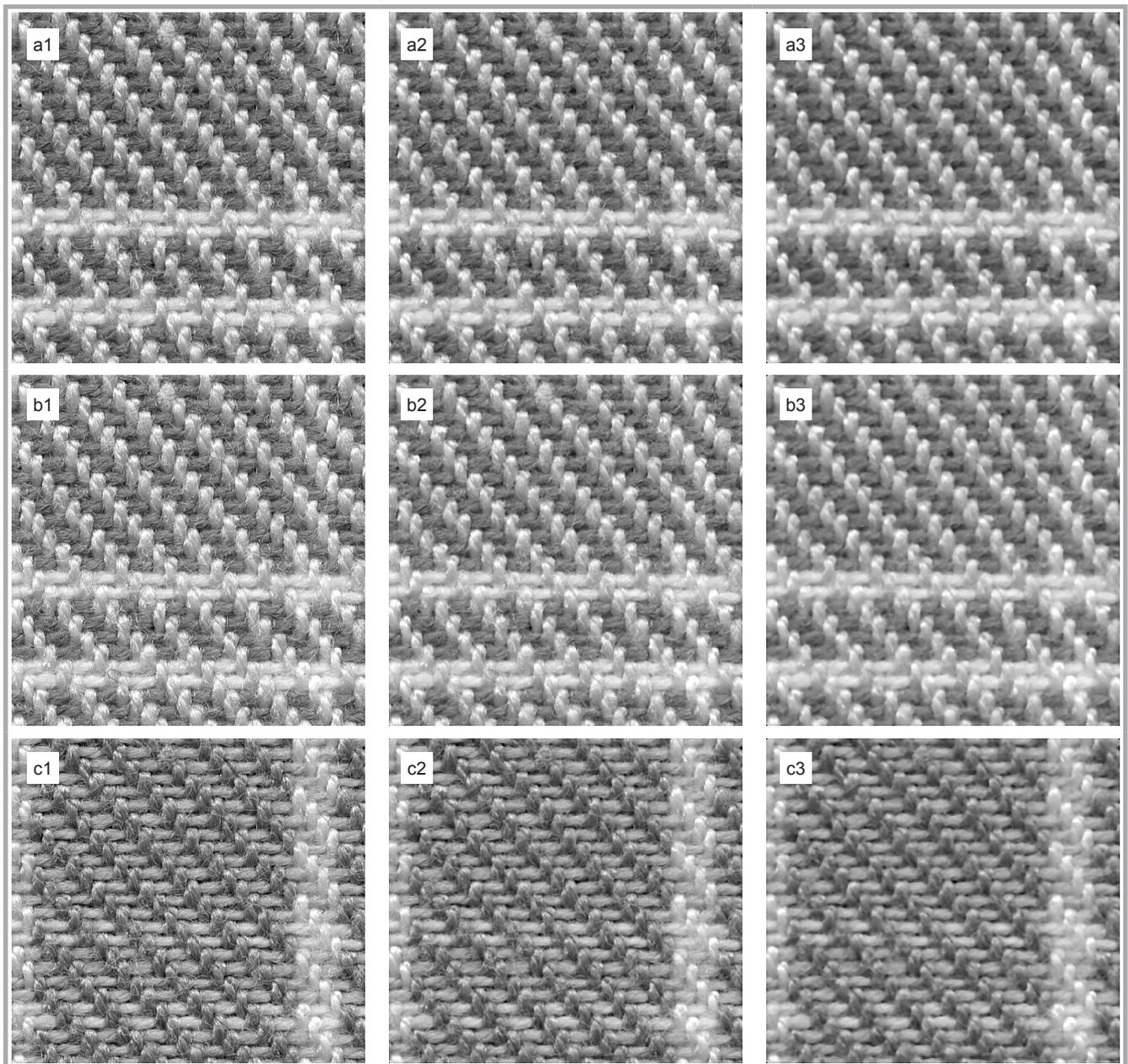
$$x \in C_j(k) \text{ if } \|x - z_j(k)\| < \|x - z_i(k)\| \quad (8)$$

for all  $i = 1, 2, \dots, K; i \neq j$ ; where  $C_j(k)$  denotes the set of samples whose cluster center is  $z_j(k)$ .

3) Compute the new cluster centers  $z_j(k+1), j = 1, 2, \dots, K$  such that the sum of the squared distances from all points in  $C_j(k)$  to the new cluster center is minimised. The measure which minimises this is simply the sample mean of  $C_j(k)$ . Therefore the new cluster center is given by

$$z_j(k+1) = \frac{1}{N_j} \sum_{x \in C_j(k)} x, \quad j = 1, 2, \dots, K \quad (9)$$

where,  $N_j$  is the number of samples in  $C_j(k)$ .



**Figure 6.A.** Illustration of the image filtering process; a1) sub-image in red colour channel, a2) 3×3 median filtered image of (a1), a3) 5×5 median filtered image of (a1), b1) sub-image in green colour channel, b2) 3×3 median filtered image of (b1), b3) 5×5 median filtered image of (b1), c1) sub-image in blue colour channel, c2) 3×3 median filtered image of (c1), c3) 5×5 median filtered image of (c1). The next part (6.B) is printed on page 111.

- 4) If  $z_j(k+1)=z_j(k)$  for  $j = 1, 2, \dots, K$  then the algorithm has converged and the procedure is terminated.

Otherwise go to Step (2).

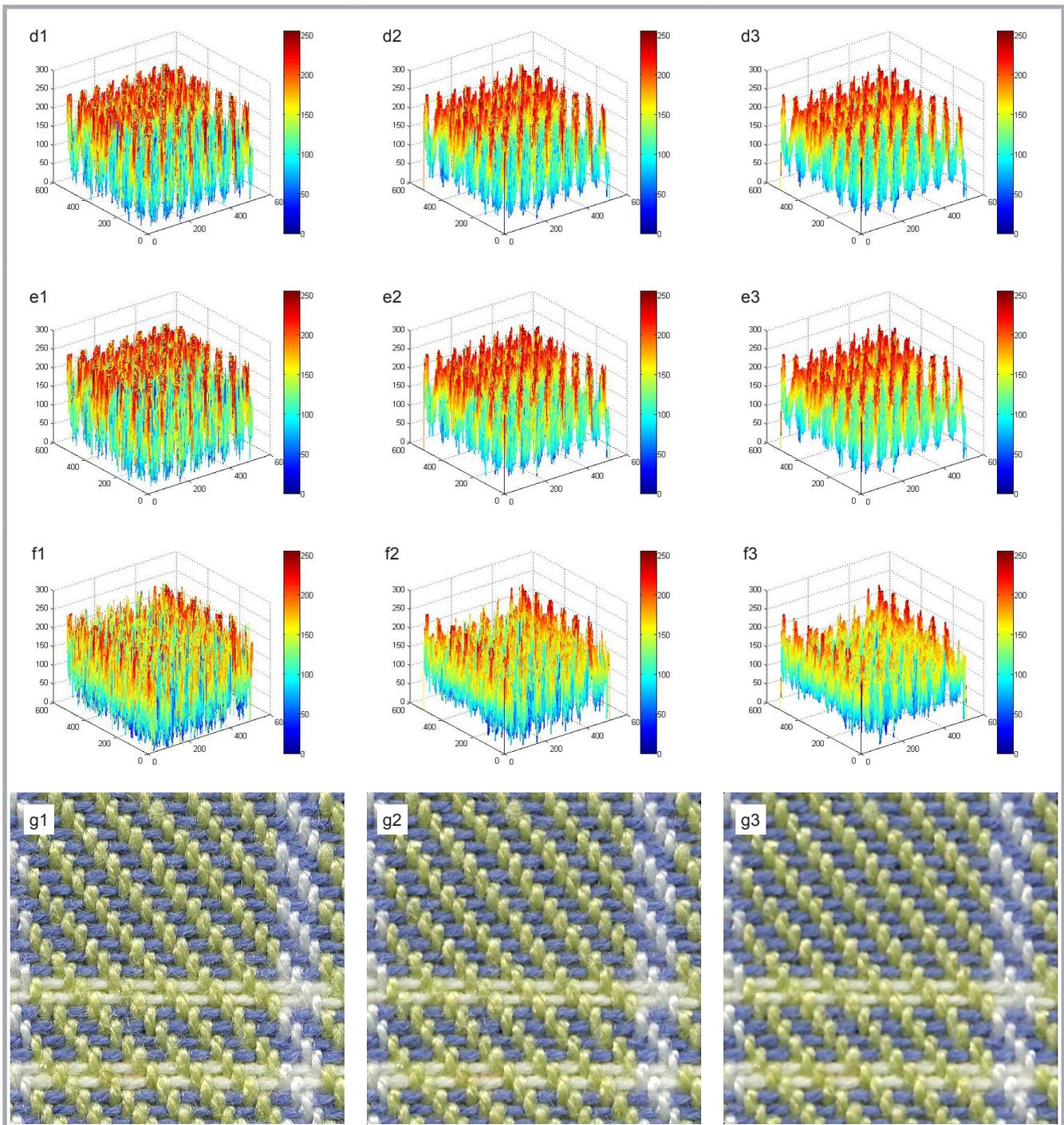
It is clear that the final clustering rely on the initial cluster centers chosen and on the value of  $K$ . Especially the value of  $K$  is of most concern since this requires some prior knowledge of the number of clusters present in the data, which is highly unlikely. Accordingly we assume that the value of  $K$  is 3 in our experiment.

## Experimental results

The image filtering processes in the three parallel channels R, G and B are shown in **Figure 6.A**. Different median filter sizes are used, incorporating a 3 × 3 template and 5 × 5 template, to process the sub-images. These filtered images are presented using three dimensional (3D) images, as exhibited in **Figure 6.B (d1 - d3, e1 - e3 and f1 - f3)**, so as to clearly demonstrate the changes after different convolutions of two kinds of filtering templates. In the end, the interlaced multi-coloured dyed yarn woven fabrics after different median filter processing are illustrated in

**Figure 6.B (g1 - g3)**. From **Figure 6.B (g3)**, it can be seen that the hairiness or fibres spreading over the fabric surface have been eliminated effectively and the colour information is also completely reserved.

With the help of the K-means algorithm based on the Lab colour space, the segmentation and classification results are shown in **Figure 7** (see page 112). It can be found that three different clusters are successfully identified as illustrated in **Figures 7.a2 - 7.a4**, although there are some isolated noise points.



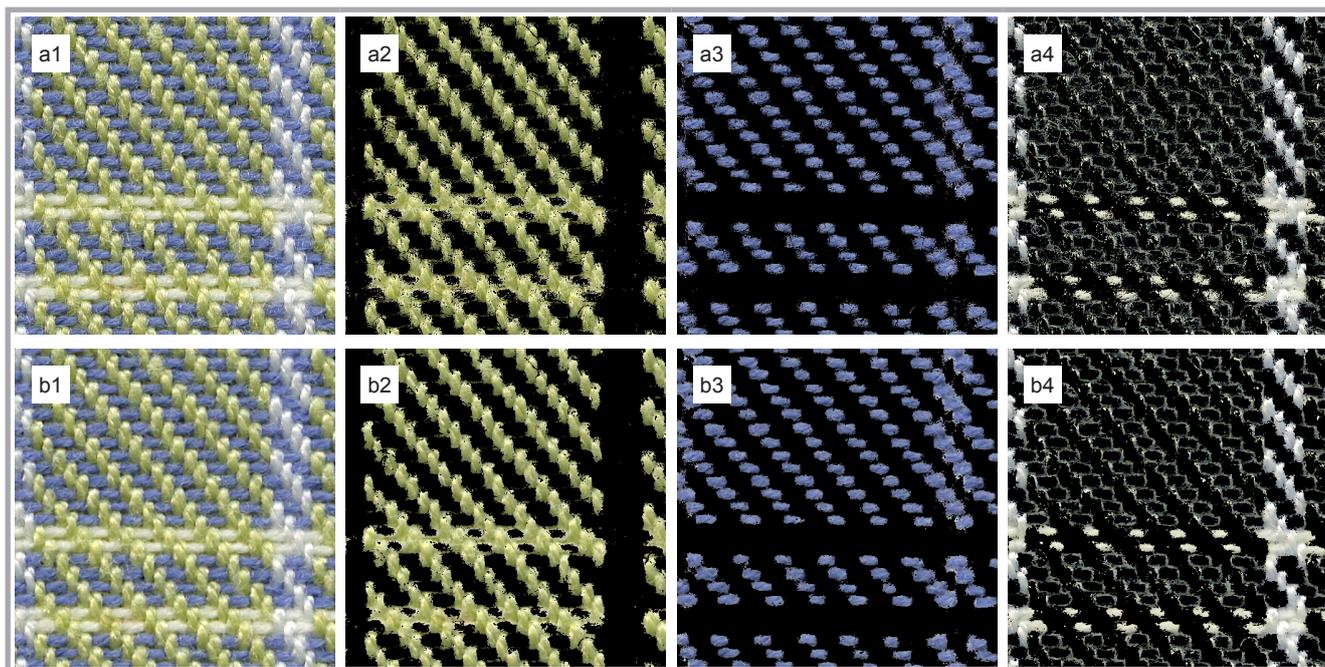
**Figure 6.B.** Illustration of the image filtering process; d1) 3D image of (a1), d2) 3D image of (a2), d3) 3D image of (a3), e1) 3D image of (b1), e2) 3D image of (b2), e3) 3D image of (b3), f1) 3D image of (c1), f2) 3D image of (c2), f3) 3D image of (c3), g1) dyed yarn woven fabric image of ID 1, g2)  $3 \times 3$  median filtered image of (g1), g3)  $5 \times 5$  median filtered image of (g1).

Thus a  $3 \times 3$  median filter is utilised to solve the problem.

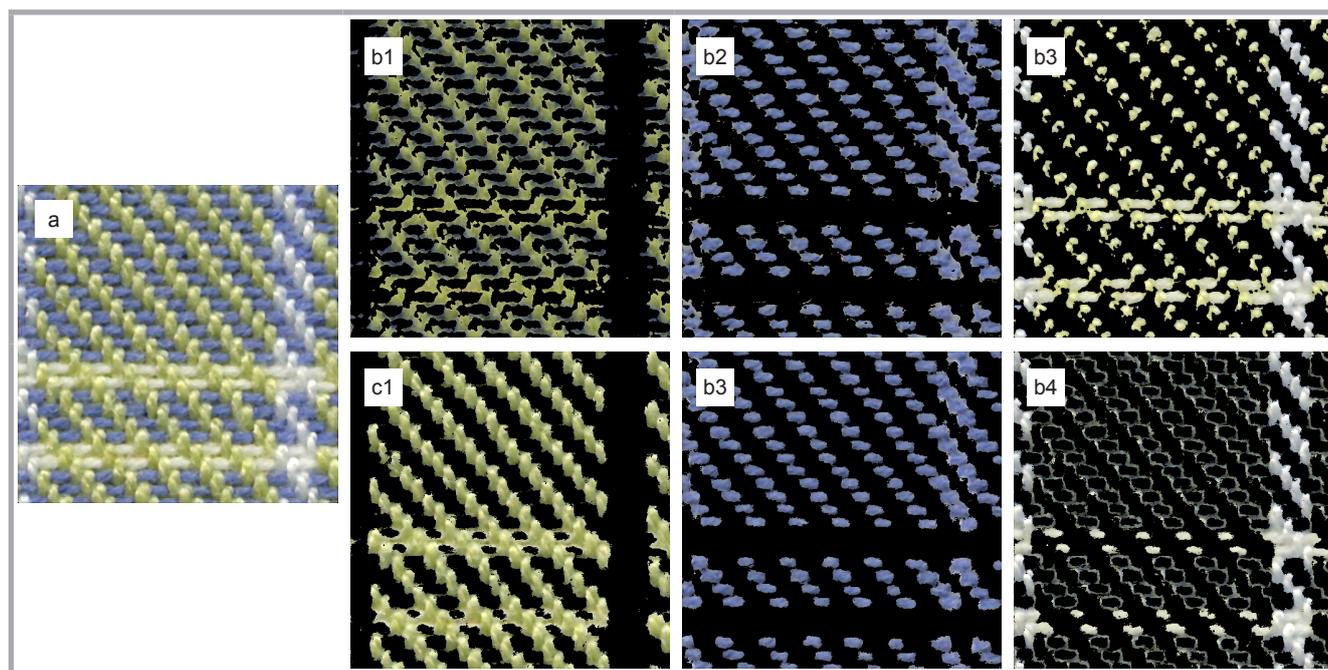
In the previous section, it was declared that the median filtered image was composed of three different colour yarns. The  $5 \times 5$  median filtered image in **Figure 8.a** (see page 112) shows better quality than the  $3 \times 3$  median filtered image. Therefore classification results based on the  $5 \times 5$  median filtered image are described in **Figures 8.b1 - 8.b3**

and **Figures 8.c1 - 8.c3** (see page 112). As a contrast, it can be seen that the classification results in the Lab colour space exhibit better performance than those in the RGB colour space. Obviously when the yarn colours have similar intensity but with different hue values, such as the green colour yarn and white yarn colour, the colours cannot be segmented well in the RGB space. However, they can be distinctly segmented in the Lab colour space.

Three separated clusters are classified and defined as cluster 1, cluster 2 and cluster 3 respectively. Histograms of the three clusters along axes R, G and B are described in **Figure 9** (see page 113). Using similar methods based on the Lab colour space, colour segmentation and classification results for the other three interlaced multi-coloured dyed yarn woven fabrics are illustrated in **Figure 10** (see page 114).



**Figure 7.** Classification results of ID 1 in Lab colour space; a1) Dyed yarn woven fabric image of ID 1, a2) Cluster 1 of (a1), a3) Cluster 2 of (a1), a4) Cluster 3 of (a1), b1) 3×3 median filtered image of (a1), b2) Cluster 1 of (b1), b3) Cluster 2 of (b1), b4) Cluster 3 of (b1).



**Figure 8.** Classification results with K-means algorithm for interlaced multi-coloured yarn dyed woven fabric: (b1-b3) classification results in the RGB colour space ( $k=3$ ); (c1-c3) classification results in the Lab colour space ( $k=3$ ); a) 5×5 median filtered image of ID 1, b1) Cluster 1, b2) Cluster 2, b3) Cluster 3, c1) Cluster 1, c2) Cluster 2, c3) Cluster 3.

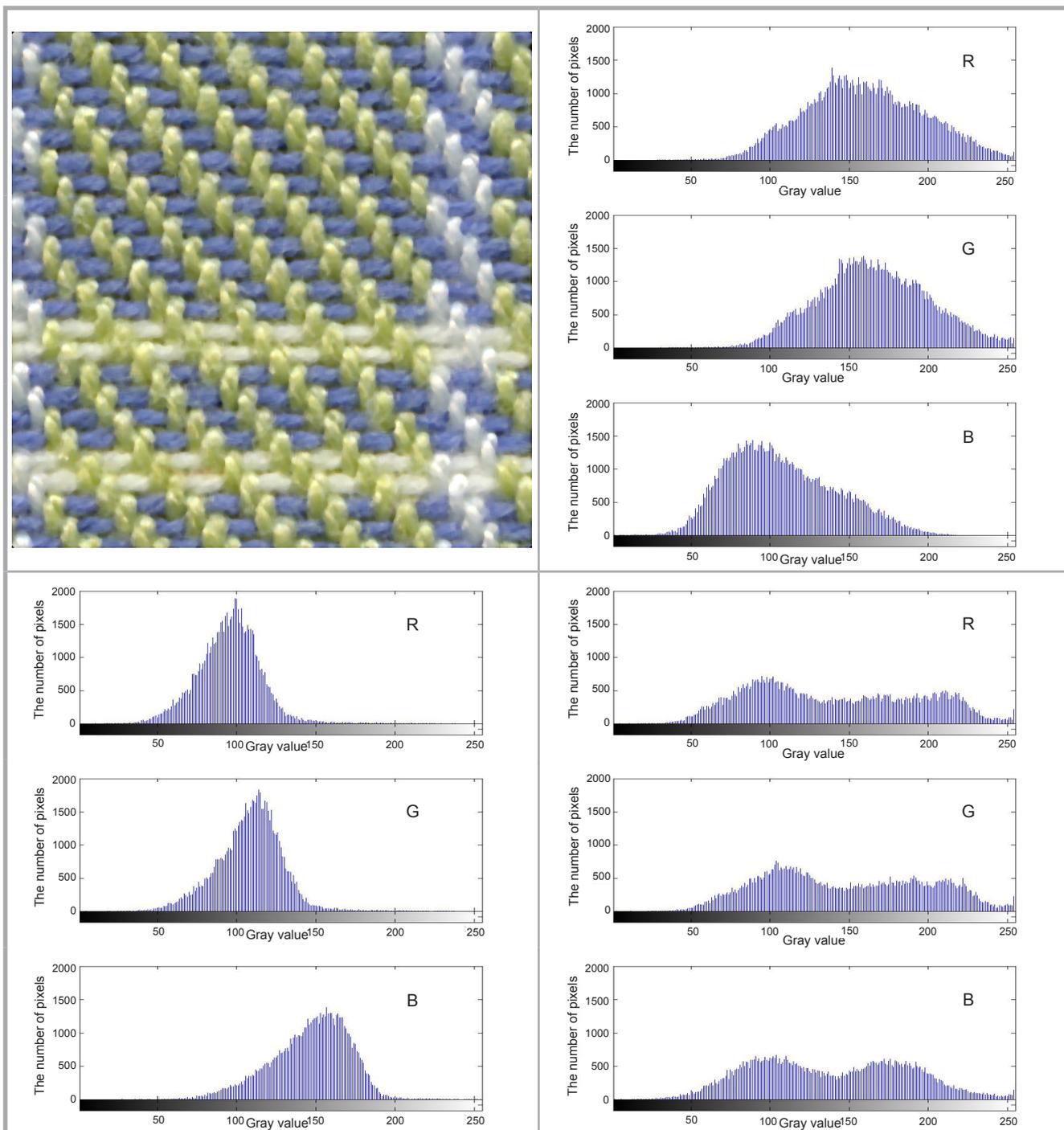
## ■ Discussion and conclusions

In this study, a novel colour clustering method for interlaced multi-coloured dyed yarn woven fabrics has been proposed. The fabric image, captured by a 1200dpi flat scanner, is decomposed into three sub-images in red, green and blue channels separately. After median filtering, the three sub-images can be

reconstructed into one filtered image in an RGB colour space. By means of conversion from the RGB colour space to a Lab colour space, the fabric image can be segmented and classified into three different clusters with the improved K-means algorithm.

Our experiment results prove that the method proposed can automatically and

correctly recognise different colour yarns for interlaced multi-coloured dyed yarn woven fabrics. The number of colour yarns and exact colour sorts could ultimately be determined. Theoretically the RGB colour space, which leads to misclassification for the colour yarns in our contrast test, has a linear correlation between the three components (red, green and blue). It is only suitable for yarn



**Figure 9.** Demonstration of colour clustering results of ID 1. Three separated clusters are listed in the upper right, bottom left and bottom right directions in sequence. The first row is the histogram along axis R, the center row - that along axis G, and the bottom row that along axis B.

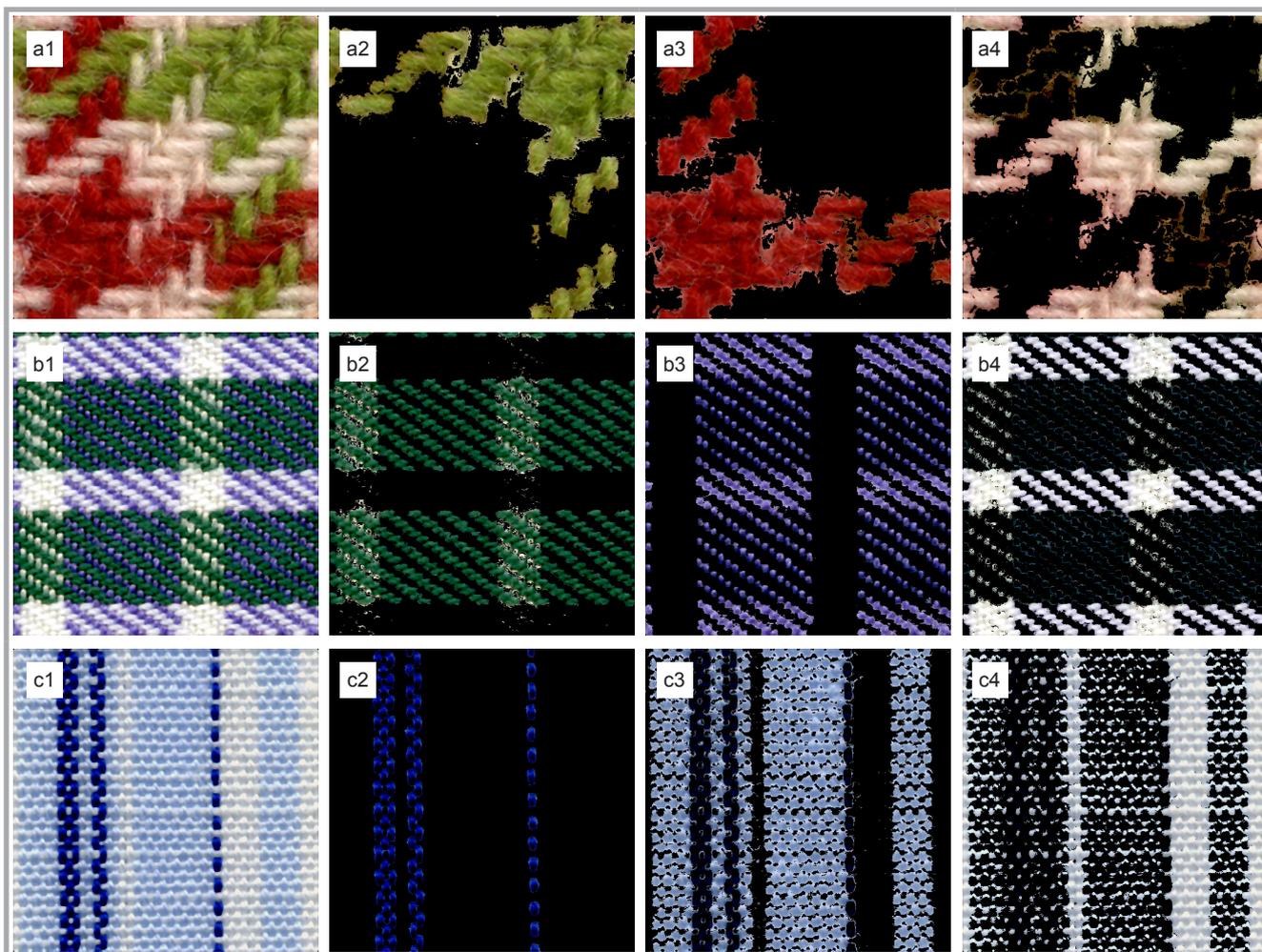
dyed fabric, which expresses more differences in the intensity. Nevertheless the Lab colour space is appropriate for most dyed yarn fabrics, even those showing an analogous hue and lightness value, but with different saturation values.

One of the confines of our work is that the accuracy of the colour clustering method relies on the colour blend's influence. The captured yarn's reflective light may be not only affected by the original

yarn itself, but also by the diffuse reflection light generated by adjacent yarns. The establishment of a colour blended model and diffuse reflection model will be the focus of our future research.

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**Figure 10.** Filtered images and colour clustering results; a1)  $5 \times 5$  median filtered image of ID 2, a2) cluster 1 of (a1) average value:  $L = 13.2$ ;  $a = -4.7$ ;  $b = 11.3$ , a3) cluster 2 of (a1) average value:  $L = 9.5$ ;  $a = 13.5$ ;  $b = 11.2$ , a4) cluster 3 of (a1) average value:  $L = 21.8$ ;  $a = 1.7$ ;  $b = 5.6$ , b1)  $5 \times 5$  median filtered image of ID 3, b2) cluster 1 of (b1) average value:  $L = 10.6$ ;  $a = -9.8$ ;  $b = 3.9$ , b3) cluster 2 of (b1) average value:  $L = 9.0$ ;  $a = 4.5$ ;  $b = -10.3$ , b4) cluster 3 of (b1) average value:  $L = 23.7$ ;  $a = -2.2$ ;  $b = -3.0$ , c1)  $5 \times 5$  median filtered image of ID 4, c2) cluster 1 of (c1) average value:  $L = 1.0$ ;  $a = 2.5$ ;  $b = -4.4$ , c3) cluster 2 of (c1) average value:  $L = 28.7$ ;  $a = -1.2$ ;  $b = -13.4$ , c4) cluster 3 of (c1) average value:  $L = 33.7$ ;  $a = -3.5$ ;  $b = -4.6$ .

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