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The role of colour and texture on fabric image preference

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Abstract

Colour and texture characteristics convey most of the information of an image and influence human perception as contributing factors to perceived preference. How the colour, together with the texture characteristics affects fabric image preference is not fully understood. In the present study, we firstly took texture characteristics from the perspective of image analysis techniques into consideration to evaluate the role of colour and texture in fabric image preference. The results showed that, even though colour characteristics play an important role, the addition of texture features, lead to better predictive performance in the evaluation of fabric image preference using machine learning techniques.

Introduction

Fabrics exist almost everywhere in our daily life. The preference for fabrics plays an important role in the retail market, affecting consumer satisfaction, consumer preference, and decision-making [1], and thus it has been studied from various perspectives. For example, problems of fitness, size, functionality and comfort have been considered in various studies for the preference evaluation of fabric products [2-5]. Good prediction of fabric preference contributes to the achievement of sustainability. Compared to non-appearance-related traits, visual stimuli perceived from the appearance of the fabrics have been less investigated but are attracting increased interest [6-9], suggesting the importance of the role of visual characteristics in the evaluation of fabric preference.

Colour is an essential visual stimulus which influences people's cognition, reaction and behaviour and has a profound impact on fashion design [10, 11]. Fabric colour characteristics have been assessed for their role in fashion product preference [6-9, 12-14]. As online shopping is becoming more and more popular, the dependence on product images is increasing in importance, and effort has been made in these studies on the preference evaluation using fabric images. By analysing the colours of the product shown in images, a previous study suggested an important role of colour characteristics in modelling to predict consumer preference [7]. A notable finding is that colour was the only appearance-related trait in most of these studies to evaluate the preference for a fashion product. The exceptions include a study that considered the effect of the texture of the fabrics, where the texture was represented from the perspective of the fabric physical properties [12]. In practice, the appearance of an object contains not only colour, but also other visual stimuli, such as texture. Previous studies showed that texture affects human perception when the judgement of the real products and the product images needs to be made [12, 14], and objective measurement results of the colour [15]. It is, therefore, not enough to assess the sole role of colour in preference judgement.

Fabric products are one of the most frequently purchased in our daily life. The nature of fibres and various weaving and knitting methods determine the countless appearances shown on the surface of the fabric. With the popularity of online shopping, fabric images have been used as samples in the studies of fabric colour, and the effect of texture was also evaluated in many studies. Previous studies evaluated the importance of visual systems in fabric preference, and the results showed that the presence of fabric structure affected observer preference of fabric samples [14]. Moreover, it has been found that the texture strength can decrease the visual colour difference of paired fabric images compared with that of solid colour pairs, which was evaluated by the grey scale method from the perspective of observer perception [16]. From the perspective of objective measurement, it is found that the texture affected the colour of fabric samples measured by spectrophotometer [15]. Given the nature of fabric appearance, the important role of texture in the colour study using fabric samples, and to avoid the colour measurement bias caused by texture, fabric images with simulated colours were selected in the present study to evaluate preference judgement.

To better investigate the role of texture in fabric image preference study, representation methods are required to quantify texture features. Texture analysis has been focused on classification, segmentation, and synthesis [17], and it was studied as a feature of an image rather than the feature of the object in the field of image analysis. Different texture representation methods have been studied in the image analysis field for many years, starting from the studies of statistical features of the image [17]. Grey-level co-occurrence matrix (GLCM) is a typical statistical feature of the image, reflecting a range of changes by calculating the changes between the grey levels of two pixels at a certain distance and a certain direction [18]. GLCM has been used in fabric texture analysis in many studies. It is found that using GLCM can achieve very high accuracy in inspecting the weaving density of the single colour plain weave fabrics [19], discriminating the different crossed-area states and classifying the type of weaving method, and measuring weave repeat automatically using scanned fabric samples [20, 21]. Even though the representation method regarding the grey level of the image achieves good accuracy, effort has also been made to utilise colour information in texture representation [22, 23]. The GLCM was then extended into 3D colour space to generate a colour-level co-occurrence matrix (CLCM) [24, 25]. Comparison has been made between CLCM and GLCM regarding the performance of colour texture classification, and the results showed a good improvement of CLCM over GLCM [24]. Given that less study takes texture information into consideration of fabric image preference evaluation from the perspective of image analysis, and due to the available application of utilising GLCM to analysis the fabric features, both GLCM and CLCM were adopted in the present study as the representation of texture of the image, to further investigate the role of texture in fabric image preference. The other reason why GLCM and CLCM methods were adopted is because of the easy computation and low dimension of features.

The present study provides a novel idea of combining colour and texture information into the fabric image preference study. The objectives of this study are: (1) to investigate the role of colour and texture characteristics on fabric image preference evaluation; (2) to include both the colour and texture information into preference modelling. To achieve these objectives, colour

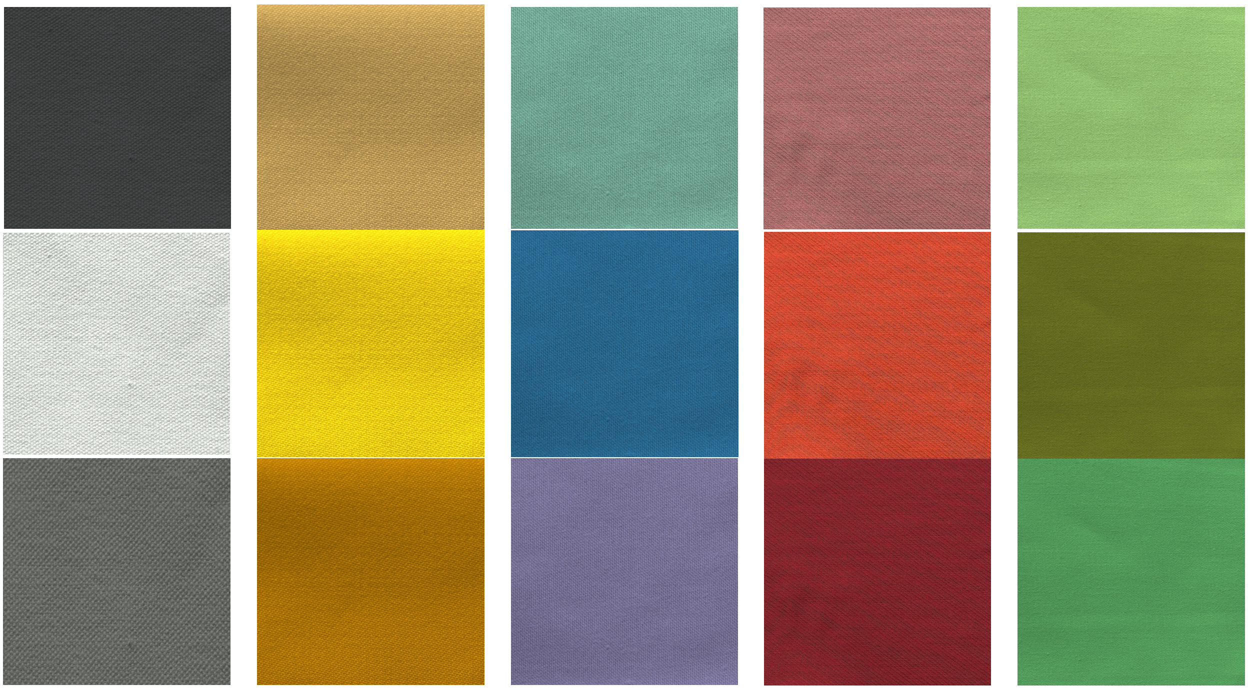


Figure 2. *Examples of original and rendered flat fabric images. Each column represents one fabric that were rendered by different colours.*

characteristics including CIE L*, a*, b*, C*, and h were pre-defined, and texture characteristics were calculated based on two texture representation methods: GLCM and CLCM. A rating study was conducted to evaluate the preference of fabric image preference.

Method

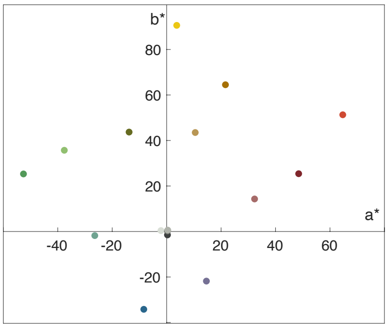
Photography and fabric image processing

Fifteen fabrics of various materials, in a single white colour, were selected. Fabrics were placed under a simulated CIE D65 lighting condition, and a Sony DSLP camera with a speed of 1/200 second, ISO 500, white balance of 6200 K was used to capture images of the flat fabrics. The distance between the camera and the fabric was set to 45 cm so that the textures on the fabrics can be presented in an appropriate way.

Sixteen colours that were set close to the CIE reference colours red, yellow, green, blue, and grey [26], giving an average distribution in the CIELAB colour space, were selected to post-process the fabric images. The distributions of the colours in the CIE a*b* and C*L* coordinates are shown in Figure 1. New fabric images were generated in the following procedures:

1. The corresponding CIE XYZ values were calculated from the CIELAB values with the CIE1931 standard observer and CIE D65 illuminant.
2. A gain-offset-gamma (GOG) model was built for a professional BenQ display which was used in the experiment, transferring the CIE XYZ to display RGB values, to ensure the colours were displayed accurately [27]. For 30 randomly selected test colour patches of a wide range of RGB values, the CIEDE 2000 colour difference between the measured and predicted CIE XYZ values through GOG model was 1.13.
3. The RGB values of the selected colours were then obtained from the GOG model. By multiplying the grey level of the original images and RGB channels respectively, fifteen fabric images were rendered initially by each of the sixteen colours separately.
4. The rendered RGB channels were then adjusted by the mean values of each channel.

Therefore, 15 × 16 = 240 images were generated for the experiment. Examples of the rendered flat fabric images are shown in Figure 2.



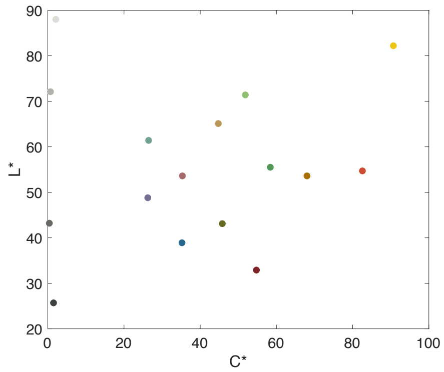


Figure 1. *The distributions of colours in the CIE a*b* and C*L* colour space.*

Assessment of preference for fabric images

A psychophysical experiment was conducted to assess the subjective judgement of the overall appearance preference of the fabric images. Twenty observers (10 females, 10 males, aging from 21 to 39, mean = 28.5), who passed the Ishihara test for colour vision deficiency, participated in the experiment.

The experiment was conducted in a dark room. The interface of the experiment is shown in Figure 3. Images were set to an appropriate size so that the fabrics in the images were seen at a similar size as seen physically. The surrounding colour of the image was set to a mid-grey (L*=50). Observers were asked to rate the 240 fabric images one by one in random order on the professional BenQ display with an sRGB colour gamut and a peak white luminance of 114 cd/m^2 which was characterised prior to the experiment. The distance between the observer and the display was set to approximately 40 cm. The 7-point Likert-type scale based on the method of categorical judgement was used in the observer judgement, where 1 refers to *completely dislike* and 7 refers to *completely like*.

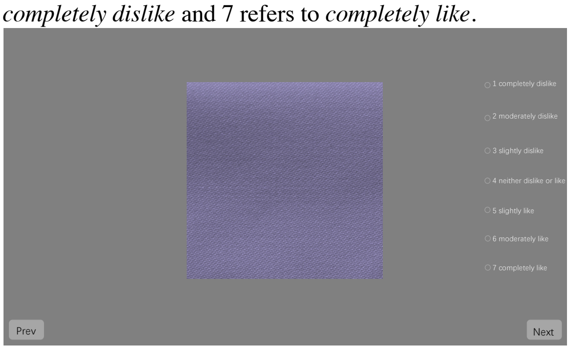


Figure 3. *The interface of the experiment.*

Analysis of colour and texture features

In total, 3 colour characteristics represented by CIE L*, a*, b* parameters, and 10 texture features from two classes of texture characteristics (GLCM and CLCM), were analysed for each of the 240 fabric images. The calculations were performed in MATLAB.

Grey-level co-occurrence matrix (GLCM) features

GLCM features are concerned with the spatial statistical distribution of grey levels in the image [28]. Following the procedure for calculating GLCM as shown in Figure 4, the matrix was calculated for 0°, 45°, 90°, and 135° respectively and for each of the fabric images. There were in total 14 GLCM-based features defined by a previous study [28]. In this experiment, five features, which are contrast, correlation, angular second moment (ASM, also known as energy), homogeneity, and entropy were calculated for each of the four orientations of each image [28, 29], due to their ability to recognise fabric nature [21] and analyse fabric texture [20] as shown in previous studies. The values of the five GLCM-based features were then obtained by averaging the values for the four orientations. For fabric images that in same texture but different colours, the GLCM features are different due to the variance of grey levels.

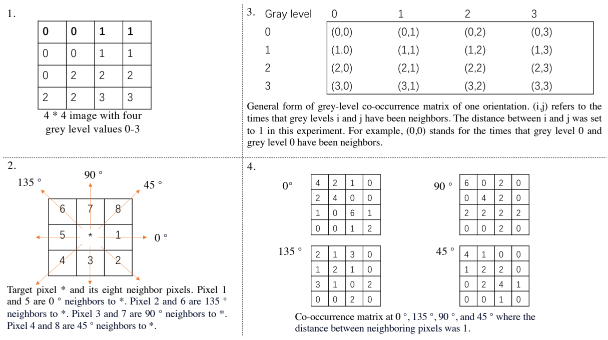
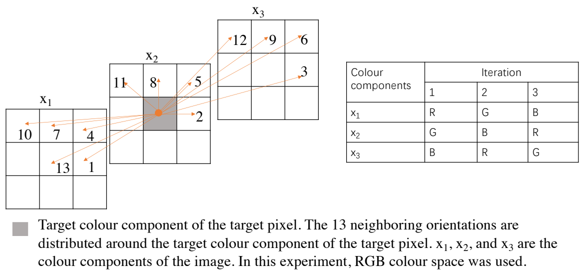


Figure 4. *Example of the procedure to calculate GLCM features, which is modified from [28].*

Colour-level co-occurrence matrix (CLCM) features

The calculation of the CLCM features adopted similar methods as the GLCM features, while the major difference is expanding the 4 orientations in GLCM to 13 orientations spread in the three colour components in CLCM, as shown in Figure 5 [24]. For a target colour component of a target pixel (e.g., the grey patch in Figure 5), the 13 orientations were distributed in the three colour components (i.e., RGB) of the image respectively. Three iterations were selected so that each colour component can be defined as the target. For example, for the first iteration in Figure 5 (i.e., x_1=R, x_2=G, x_3=B, thus G is the target component), matrix of orientation 1 would be the statistical variation between location 1 in R component and the target in G component, matrix of orientation 2 would be the statistical variation between location 2 and the target in G component, and matrix of orientation 3 would be the statistical variation between location 3 in B component and the target in G component. The 13 CLCM matrices were calculated first for each RGB component. Features including contrast, correlation, ASM, homogeneity, and entropy were then calculated for the RGB components respectively in the same way as for GLCM. The CLCM-based features were represented by averaging the corresponding values of the RGB components.



Colour components	Iteration		
	1	2	3
x_1	R	G	B
x_2	G	B	R
x_3	B	R	G

Figure 5. *Principle of calculating the 13 CLCM, which is modified from [24].*

Data analysis

Inter-observer variability was examined using Cronbach's alpha coefficient (α) [30], which is the factor ranging from 0 to 1 to analysis the reliability of scale.The internal consistency in the ratings of preference of the flat fabric images is acceptably reliable at Cronbach's α=0.73.

The observed ratings were averaged across all observers to create a score for each fabric image. All the predictors were then z-standardised prior to correlation analysis and modelling of colour and texture characteristics. The Pearson Correlation Coefficient (two-tailed) was used to assess the relationships between various colour and texture characteristics and the preference ratings. To further investigate the role of colour and texture characteristics in predicting the preference of fabric images, techniques from machine learning were implemented in the modelling process.

Separate models were built for colour characteristics only, texture characteristics only, and the combination of colour and texture characteristics. The modelling process was carried out using the caret package in R [31]. During the modelling process, repeated 5-fold cross-validations were used to evaluate the predictive power of colour and texture characteristics. The data (preference ratings, colour characteristics, and texture characteristics) was randomly split into a training dataset and a testing dataset. The training dataset was then used for model training using a Support Vector Machine (SVM) technique with a radial basis function (RBF) kernel which performed very high accuracy in texture classification [24, 32, 33]. The RBF kernel can handle the nonlinear relationship between the predictors and dependent variables and has only two hyperparameters (C, γ) which influence the complexity of model selection [34]. In the training process, 5-fold cross-validation (repeated 50 times) was implemented to tune the hyperparameters until a combination of C and γ with minimum RMSE (root mean square error) was generated for the model. The above process was repeated 50 times with different random splits of the data. The model's overall predictive performance was assessed by the mean RMSE and R^2 over all the 50 splits fit with the optimal C and γ. RMSE is a factor to represent the difference between predicted values and the original values, and R^2 explained the fitness of the model. By using cross-validation in the data split and hyperparameter tuning, the problem of overfitting will not affect the model significantly as the model is tested using the new testing data.

Results

Zero-order correlations between each colour and texture characteristics and fabric image preference ratings

The Pearson Correlation Coefficient (two-tailed) was used to identify the correlations between each colour and texture characteristic and preference rated by the observers. The results are shown in Figure 6. The preference for fabric images significantly correlated with 9 of 13 colour and texture characteristics. It negatively correlated with GLCM ASM feature ($p<0.001$), and CLCM homogeneity feature ($p<0.05$), while no significant correlations were shown on CIE redness-greenness, a*, GLCM homogeneity feature, CLCM correlation and energy features. According to Figure 6, fabrics in darker colour and bluish colour would be preferred, which is consistent with the studies using pure colour patches to evaluate preference [35, 36]. It is noted that most texture representation methods were used as a tool to achieve high classification accuracy, segmentation, and so on [17], and it still remains unknown the relationship between the texture representation features and the perceptual texture.

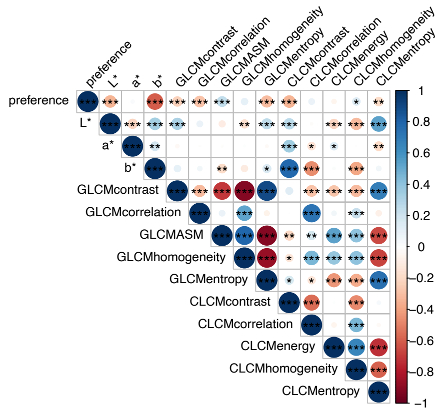
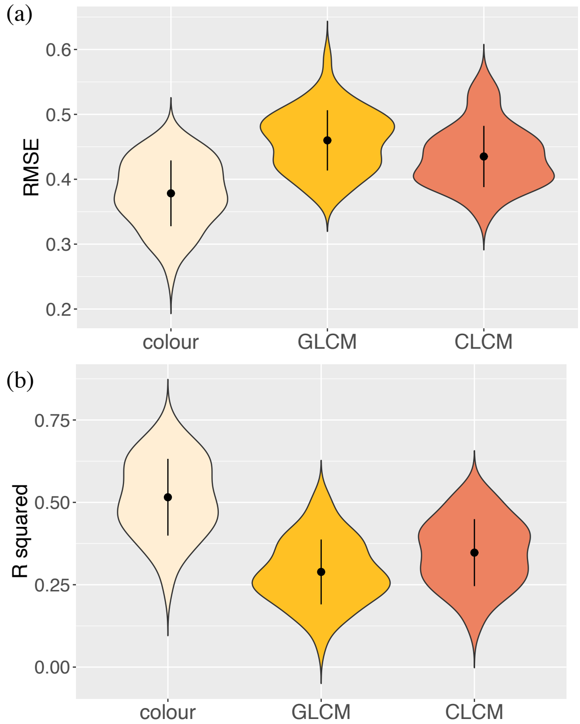


Figure 6. *The Pearson Correlation Coefficient between each colour and texture characteristic and fabric image preference. Asterisks indicate the statistical significance: *p<0.05, **p<0.01, ***p<0.001.*

Models by colour and texture characteristics

To further investigate the role of colour and texture characteristics in predicting the preference of fabric images, techniques from machine learning were implemented. Cross-validated SVM regression models (5-fold with 50 repeats) were built for colour and texture characteristics to evaluate the predictive power. The predictive performance was assessed by the mean RMSE and R^2 overall splits, as shown in Figure 7.



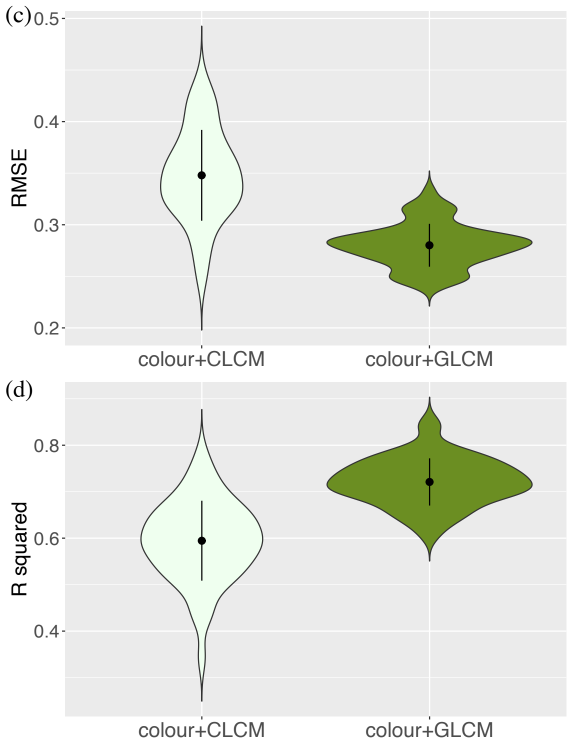


Figure 7. *The model performance of colour and texture characteristics in predicting fabric image preference. (a) (b): models built by colour characteristics only and by texture characteristics only. (c) (d): models built by the combination of colour and texture characteristics. Black dots and the lines indicate the mean RMSE or R^2 and standard deviation from repeated k-fold cross-validation. The width of the outline curve represents the frequency of data points.*

In general, for models built by only one class of characteristics, Figure 7 (a) and (b), models of colour characteristics showed better performance than models of texture characteristics. Models of colour showed the best predictive accuracy ($Mean_{RMSE}$=0.37, SD_{RMSE}=0.05, $Mean_{R^2}$=0.52, SD_{R^2}=0.12), followed by models of CLCM ($Mean_{RMSE}$=0.44, SD_{RMSE}=0.05, $Mean_{R^2}$=0.35, SD_{R^2}=0.10).

For models built by the combinations of colour and texture characteristics, Figure 7 (c) and (d), the predictive performance was improved compared with models built by only one class of characteristics. The model of combining colour and GLCM features showed the best performance ($Mean_{RMSE}$=0.28, SD_{RMSE}=0.02, $Mean_{R^2}$=0.72, SD_{R^2}=0.05), which means it can predict the fabric image preference within 0.28 points on a 7-point scale, and 72% of preference ratings can be explained by the SVM model.

The performance of models built by colour and texture characteristics was summarised and compared in Table 1, where RMSE represents root mean square error and SD represents standard deviation.

Table 1: Comparison of model performance

	Predictive performance	
	Mean RMSE (±SD)	Mean R^2 (±SD)
Colour characteristics model	0.37±0.05	0.52±0.12
GLCM features model	0.46±0.05	0.29±0.10
CLCM features model	0.44±0.05	0.35±0.10
Colour+GLCM features model	0.28±0.02	0.72±0.05
Colour+CLCM features model	0.35±0.04	0.59±0.09

Discussion

240 flat fabric images with simulated colours and natural textures were used in the present study. The results showed the importance of combining colour and texture characteristics in determining fabric image preference.

Earlier studies evaluating fabric preference focused mainly on one appearance-related cue such as colour, and it is commonly agreed that colour played a significant role in judging the preference [6-9, 13, 14, 35]. The present study showed the similar importance of colour in determining fabric image preference. Models of colour characteristics showed better performance than models of texture characteristics but not to a great degree. When predicting fabric image preference, it is beneficial to consider colour together with texture characteristics to get better predictive performance. Considering the importance of fabric image preference in the fashion market, the present study attempted to provide a robust idea to assess the role of a wide range of visual stimuli characteristics on the preference of fabric images.

GLCM and CLCM were used as the texture representations of the fabric images in the present study from the perspective of statistical texture features. Very little studies evaluated GLCM and CLCM regarding the subject's perceptual aspects. Features such as contrast and homogeneity used in the present study cannot represent the finer or rougher appearance perceived by subjects. As shown in Figure 2, the fabrics in the same column vary only in colours, remaining the texture the same, but the results of texture characteristics calculated from GLCM and CLCM were different. As outlined in the introduction, by using techniques in image analysis, texture was studied as a feature of image rather than the feature of the object. Given the countless fabric products that can be presented in the image, this study provides a useful method to assess the texture features using the techniques in image analysis in the evaluation of fabric preference.

The basic principles in GLCM and CLCM are to calculate the statistical variations of grey level or colour level at a certain distance and a certain direction. It is, therefore, clear that the colour characteristics and texture characteristics are not fully independent traits here. Compared to GLCM, it can be the fact that CLCM features contain colour information as well. It is, therefore, reasonable that model of CLCM achieved better predictive performance than the model of GLCM. However, it is surprising that model combining colour and GLCM outperformed the model combining colour and CLCM. As the colour characteristics has been included directly, it is possible that the underlying colour information contained in CLCM features made the model redundant, and thus decreased the predictive performance.

As shown in Figure 6, significant correlations between colour characteristics and texture characteristics still exist. The results show that the combination of colour and GLCM features played an important role in preference modelling for fabric images, but it is still unknown the separate role of colour and texture in the predictive power, and the independence of colour and texture characteristics was not identified in the present study. Other categories of texture representation methods have been studied and the sensitivity to grey-scale variation was taken into consideration. Li et al. [32] developed a novel scheme, Median Robust Extended Local Binary Pattern (MRELBP) which almost 100% accurately classifies images with grey-scale and rotation variants using three texture datasets. Future studies would benefit from using texture representation methods which are independent of the colour characteristics to identify the most important appearance characteristics for fabric image preference.

Conclusion

The present study evaluates the role of colour and texture characteristics in predicting fabric image preference. An improvement has been achieved in preference modelling using both colour and texture characteristics obtained from the images, which firstly takes not only colour but other visual stimuli into consideration in the modelling process in fabric image preference evaluation. Fabric products are very common in daily life, and the present study provides a practical method to predict the preference for fabrics shown in the image, and such results can help the study of consumer preference by analysing the characteristics of more visual stimuli. Texture analysis using image analysis techniques was adopted in the human preference evaluation and the results showed the important role it plays. Further texture representation methods will be investigated for preference modelling.

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Author Biography

Qinyuan Li is a third year PhD student in University of Leeds. Her work forcused on predicting the visual-tactile properties of fabric from images, building fabric database which will include images, videos, and multiple physical measurements to further investigate the perception of tactile properties without using physical fabrics.