An Intelligent System for Fashion Colour Prediction Based on Fuzzy C-Means and Gray Theory

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Abstract: For design and manufacturing industries, to be able to capture the fashion trend is an essential factor that leads to winning a sale. However, colour predicting process in many organizations is not visible to the public. In order to provide colour trend to industries in advance, a predicting method is proposed in this study. In the method, the fuzzy c-means was used to separate the collected colour data, then the minimum mean-square error was used to place the similar colour clusters within different time point together and the gray model was adopted for prediction. In order to verify the prognostication of the system, four data announced by Pantone from spring 2014 to fall, 2015 were taken as the predicted samples and the colour for spring 2016 was predicted to compare with that in Pantone spring, 2016. The results show that the system has a high accuracy for predicting colour. The residual modified model constructed with the colour samples rearranged with MMSE has the best-predicted result that ranged from 83.3% to 99.4%. It indicates that the result obtained with the rearranged samples is higher than that without rearrangement. Besides, the accuracy of the gray predicted results with residual modification would be more precise than the one without residual modification. Moreover, the value of mean squared error is quite low, which was ranged from 0.000025 to 0.0277. Therefore, the current intelligent predicting system satisfies the criteria of capturing colour in trend for enterprises. Moreover, it enables industries to make decisions for selecting the colour trend. © 2016 Wiley Periodicals, Inc. Col Res Appl, 00, 000–000, 2016; Published Online 00 Month 2016 in Wiley Online Library (wileyonlinelibrary.com). DOI 10.1002/col.22057

Key words: colour science; colour predicting; fuzzy c-means; minimum mean-square error; gray theory

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INTRODUCTION

Fashion refers to imitations towards mutual interest in some novel behaviors, and the ways of thinking in everyday life. However, it is important to capture the trend to fulfill both psychological and mental needs in the society. Choi *et al*. explained the importance of an artificial fashion prediction system and the reason why industries need to have the fashion information in advance. First, the demand trend slope in fast fashion is large. Second, the variance in fast fashion of seasonal cycle is also large.[1] Therefore; fashion must be able to keep up with the contemporary trend and satisfy with customers' psychological and mental needs. Colours have been playing a significant role in fashion trend, and designers often make use of a particular colour to design clothing for specific purposes.[2] Helander and others considered visual factors, for instance, colours, value, size, in terms of customers' attraction. Furthermore, colour is an essential element of design that influences the sense of beauty and visual pleasure, which has simple, workable design features.[3,4] Designers search for design inspiration through cameras, fashion magazines, works of art, and colour samples. Regardless of design in trend or clothing, different emotional responses towards various colours will be considered as a basic element.[5] Thus, the competitive commercial environment urges customers to pay attention towards fashion in products. Zhang indicated that colour is the main factor that influences fashion design through visual stimulus and psychological response. Hence, fashion designers should think highly of the colours in each season and place importance on the customers' colour preference.[6] Koh and Lee proposed that colour is the key factor when customers are purchasing clothes. Thus, the development and implement of colour plan must be precise owing to the reason that colour influences both product design and sale volume. Therefore, knowing and predicting the fashion trend benefit both designers and manufacturers.[7] Moreover, for enterprise decision makers, if useful and valuable decision can be obtained in an early design phase via the system, a better informed decision will be generated.[8] However, Lu and others indicated that colour trend is extremely unstable and difficult to predict, and without systematic predicted method, it would be hard to obtain a precise result.[9] This is a challenging task for artificial intelligence system in the development of fashion industries. Gray theory is widely used to deal with vague and uncertainty. It has been successfully applied in different fields since 1982, for instance, predictions in crop production, climate change, calamity, and energy consumption. Gray prediction system is based on gray theory which can be constructed within only four data.[10] Therefore, this study chose gray theory to investigate fashion colour prediction with limited samples. Furthermore, institutions predicting international fashion colour such as InterColour, Pantone, Nelly Rodi and Merck do not have an openness process for colours prediction. Hence, users are not able to retrieve colours for the future trend. For people working in the related fields such as manufactures, designers and research teams, time is of the essence to obtain future colour trend because both manufacturing and marketing are time-based industries. Therefore, this study proposed a systematic prediction model, and chose the Pantone system, a famous global institution in colour development and investigation. The reason is that predicted samples need credibility and being announced regularly. Moreover, colours that are announced routinely are now becoming the standard language among various industries in colour selection and communication. Conversely, there are other predicting institutions or hybrid prediction models. For instance, colour combination with materials or languages appeared in the hybrid prediction models may results in extra factors that influence the prediction results. Those hybrid prediction models are not recognized internationally. Furthermore, in some studies investigating colour prediction, only few studies mentioned case verification or only included one brand as both trend prediction samples and underwent testifying process. Utilizing single brand as trend samples would lead to the repetition of customary colours of the brand and thus the result will not be accurate. Therefore, this study used the reference sequence that is constructed by Pantone's predicted models to verify the newly announced data of colour prediction.

This study proposed a fashion colour prediction model based on gray theory and used Fuzzy C-Means (FCM) algorithm to automatically recognize colour clusters among digital images. In order to build reference sequences that are needed in the fashion colour prediction, reference with credibility is of importance. After fashion colour predicted reference sequence was conducted, method of minimum mean-square error was used to obtain an optimal result in colour sequence. This brought a stable calculation for gray theory-based fashion colour prediction model and retrieved a precise result. Therefore, after substituting the colour sequence result into gray theory algorithm, colour prediction in the next time sequence will be obtained.

LITERATURE REVIEW

To increase saturation and value of a high quality image, maintaining elements of hue is essential. That is, being able to separate hue, saturation and value from colours benefit the particular hue study. At the same time, it should not be disturbed by saturation or value. For instance, many studies converted RGB into other colour space such as HIS, HSV and HSL in the hope of maintaining the elements of hue during the converting process.[11] There are many colour spaces used in image processing such as RGB, CIELAB and HSV, therefore, choice of colour space is an important step to be considered when processing the image. Generally speaking, both the CIELAB and HSV colour are illumination independent as the separate illuminance components from chromatic information. They are the two frequently chosen colour spaces for colour image segmentation research.[12,13] According to Schwarz *et al.*,[14] their study compared five colour models: RGB, HSV, LAB, YIQ and Opponent, and they found that HSV colour model was the most accurate to use, and it was also advocated on grounds of computational efficiency. Because colour space had a leading impact on colour image segmentation task, HSV colour space was decided for Bora and Gupta's study. The noise usually arose during the segmentation process, and the final segmented image was filtered by median filter to make the output image clearer and noise free.[15] Bora *et al.*[12] have performed a comparative analysis between $L^*a^*b^*$ and HSV colour spaces to analyse their performance with respect to colour image segmentation, and this comparative research was done considering "noise" as the main factor. For measuring their performance, MSE and PSNR were the measurement criteria for the mentioned performance analysis task. The experimental results show that HSV colour space performed better than $L^*a^*b^*$. Moreover, it was found that segmentation results obtained by using HSV were more precise as compared to the results obtained using CIELAB, because the object boundaries can be recognized more precisely and close to the human perception from the segmentation results obtained using HSV colour space. Based on these research findings above, HSV colour space is chosen for this purpose.

HSV colour space is defined by three elements of colour, hue, saturation and value. HSV is an intuitive colour representation; it describes colour by its colour space.

TABLE I. A comparison of the prediction models for fast fashion sales.

Refs. No.	Application domain: Fast fashion sales prediction		
	Method	Forecasting error	Features
23	• GM and EELM hybrid models • Extended extreme learning machine (EELM) • Gray method	42.2%–50.7% (MAPE)	• Achieving real time sales forecasting for fast fashion operations. • The proposed algorithm with GM and GM-EELM models can automatically and intelligently select the appropriate model
24	Evolutionary neuron network (ENN)	0.0023–0.0712 (MSE)	• It studied the ENN for sales forecasting in fashion retailing. • The proposed ENN method for forecasting is a highly automatic one.
1	• ANN • GM • Markov regime switching • GM and ANN hybrid models	45.2% 50.7% 94.4% 42.2% (MAPE)	• By employing real sales data from a fashion company, the study examines and compares with different prediction models in the domain of colour trend prediction. • The GM and ANN hybrid model is the best one for prediction sales by various colours where only few data is available.
25	• Evolutionary neuron network (ENN) • Statistic	0.208 (MSE)	• The proposed model can be completed within the given time constraint and the prediction accuracy is also optimized.
26	Extreme learning machine (ELM)	0.9962 (μ_{mse})	• The prediction is more stable by using the statistical mean value of multiple trials. • ELM outperforms several sales prediction methods that are based on backpropagation neural networks.

Binary code is adopted when analyzing images in order to maintain the original colour of the image. Therefore, HSV is better than RGB and YCbCr. Furthermore, when value is changed, colour rate remains the same, therefore, compared to RGB, HSV is more stable and precise.[16] Compared with RGB, CMY, YUV, YIQ, YPbPr, YCbCr, YCgCrm and YDbDr, HSV is a colour space that is suitable for skin and the predicted result is better than other colour notation.[17] Literature in medical field indicated that using colour correction filter in HSV to testify 319 dermoscopy images can successfully corrected most of the inappropriate colour coordination images in both hue and saturation.[18] According to the literature listed above, adopting HSV space in the studies of different fields performed well. Hence, in this study, colour trend image announced by Pantone would be transformed from RGB to HSV colour space.

Clustering is the task to group a set of similar data and the data in the same group are more similar than data in different groups. Cluster analysis used in image segmentation is to group each pixel based on colour similarity among pixels. Fuzzy C-Means (FCM) algorithm is a commonly used cluster analysis, and it can obtain optimal clustering in image colour separation.[5,19] Applying FCM to image segmentation is increasingly widespread. Effective colour clustering and substituting the data in prediction models is the main focus of this study, and hence how to retrieve optimal clustering result is of importance. Automatic colour cluster analysis is usually suitable for classifying thread images into different colours, for instance, histogram clustering, FCM and X-means algorithms.[20] FCM is a cluster analysis technology that categorizes vague degree in related elements and clusters the optimal classifying results. Up to now, it has been effectively applied to functional analysis, clustering, design categories, such as astronomy, geology and medical imaging, target identification and image separation fields.[19,21] FCM algorithm can be used to categorize similar data point on feature space through images and calculate the midpoint distance between pixels and cluster through the usage of the minimum objective function in the iteration.[22]

In recent years, many researchers have implemented different prediction models in various filed such as control loading problems, generic, advertisement, finance, network instruction, technology assessment problems, technology trend, integrated circuit output, electricity and fashion sales time series problems. There are some studies about fashion trend prediction, and a majority of them focused on fashion sales forecasting, but there are few studies in fashion colour prediction. Table I is a comparison of the prediction models for fast fashion sales, which contrasts their research methods, forecasting errors and features. No matter which method is adopted, lack of original data is the main problem in prediction. Thus, when selecting a prediction method, the main criteria is to find out a method that can be processed with a small amount of original data.

Yu and others stated that there is a scant amount of colour prediction data that can be used in marketing. However, colour trend is quantitative, and it is closely related to time factors. Therefore, the prediction model is based on time sequence.[1,26] In time sequence prediction, artificial neural network (ANN) and gray model (GM) and other methods are frequently used for prediction. According to Choi *et al.*, time sequence prediction is an essential factor in many decision support systems. There

TABLE II. A comparison of the prediction models for fashion colour trend.

Ref. No.	Prediction method	Data	Evaluation method	Findings
	Application domain: Fashion colour trend prediction			
28	A GM(1,1) model is applied to predict the trend of textile fashion colours.	The study acquires the five successive years from 1991 to 1995 for men's wear in Autumn/ Winter to predict the sixth year (1996) of colour.	The way evaluate the regression equation's ability to forecast is to compare the standard error of estimate, to the standard deviation of the response variable.	• The GM(1,1) model is more applicable to fashion color prediction than the GNNM(1,1) one. • With the assistance of a gray model, the colour trend can be traced more easily and precisely. • The result provides the suggestion ratios of the hues and the tones for variant colours.
29	The study proposes to combine extreme learning machine (ELM) with gray relational analysis (GRA) in prediction. The GRA is used prior to the ELM analysis in evaluating the relationship between input and output data series and selecting the parameters with two biggest GRA coefficients as inputs to the ELM.	• Six years' data of colour trend for men's wear in Autumn/Winter are used in this prediction analysis. • The first four years (1991-1994) of colour data are used as the historical data for training and the color of the fifth year (1995) is used as the verification data. • Models with various neurons at the hidden layer are tested and the parameters which yield the best results are chosen as the input parameters to be used for predicting for the sixth year (1996).	The Sum of Absolute Error (SAE) is used as the error metric which evaluates the prediction accuracy of each model.	With real data analysis, the results show that the ANN family models, especially for ELM with GRA, outperform the other models (GM, GNNM, ARIMA, ANN) for predicting fashion colour trend.
Present study	The minimum mean square error was used to place the similar colour clusters within different time point together automatically and the gray model was adopted for prediction.	Four data announced by Pantone from spring 2014 to fall, 2015 were taken as the predicted samples and the colour for spring 2016 was predicted to compare with that announced by Pantone in spring, 2016.	The Mean Squared Error (MSE) is used to evaluate the error between the predicted and the original colours.	• The residual modified model constructed with the colour samples rearranged with MMSE has the best-predicted result. • The accuracy of the gray prediction model with residual modification would be more precise than the one without residual modification.

are a lot of well-established and widely adopted forecasting methods, but they do not performed well when the pattern is highly volatile.[27] Table II shows the comparison between colour prediction literature in the previous studies and in the current study. References 28 and 29 compared data requirement, speed of computation, simplicity of operation and accuracy in different color prediction method. In addition, the two studies focused on predicting men's fashion in clothes. Clothing material in colour prediction was taken into consideration. However, in this study, colour was the only factor that was considered in colour selection and predictive analysis. Accuracy and stability of the predictions were the center of interests. Normally, gray theory provides a technology that transfers information from black (unknown) to white (known). The process is accomplished based on limited, but not completed data. That is, the advantage of gray theory is to employ uncertain or scattered information to deal with complicated task,[30] and this characteristic is applicable for study with limited samples. Moreover, in Hsiao's study, it is found that gray prediction model can be used efficiently to predict and evaluate image and thus is reasonable for product colour plan activities in products.[31] This study also adopted the Gray method for colour prediction and residual calculation. However, before that, minimum mean square error (MMSE) would be used to predict the order of the smallest angle on hue. In this case, a more accurate prediction would be obtained. In addition, even though each method has its own method for accuracy evaluation, the method calculating linear distance has been adopted in the previous literature and proved to be feasible. Considering that the domain of colour trend forecasting with a limited amount of historical data are needed for prediction in gray theory, and its well prediction result, the study chose this theory to explore the colour trend prediction.

THEORETICAL FOUNDATION

Colour System HSV

HSV colour space is a method used to describe colours visually for human beings and it accords with human visual cognition. The study adopted HSV value in colour for prediction. It can reach nondimensionalization without limited units and colours can be known from the exact angle. That is, even though the value and saturation are unknown, hue can still be obtained. The transformation equation between RGB and HSV are as followed:

$$H=\begin{cases} 60\times\dfrac{G-B}{\mathrm{MAX}-\mathrm{MIN}}+0, & \text{if } \mathrm{MAX}=R \text{ and } G\geq B \\ 60\times\dfrac{G-B}{\mathrm{MAX}-\mathrm{MIN}}+360, & \text{if } \mathrm{MAX}=R \text{ and } G<B \\ 60\times\dfrac{B-R}{\mathrm{MAX}-\mathrm{MIN}}+120, & \text{if } \mathrm{MAX}=G \\ 60\times\dfrac{R-G}{\mathrm{MAX}-\mathrm{MIN}}+240, & \text{if } \mathrm{MAX}=B \end{cases}$$
$$\mathrm{S}=\frac{\mathrm{MAX}-\mathrm{MIN}}{\mathrm{MAX}},\quad V=\mathrm{MAX} \tag{1}$$

R, G and B are the points that have been normalized, and the points were between 0 and 1. MAX and MIN referred to the largest point and smallest point in R, G, B, respectively. If the largest point equals to the smallest point, then H cannot be defined. Conversely, if the largest point is 0, then S cannot be defined. Hence, from the definition, hue points is ranged from 0° to 360° and the saturation and value points are between 0 to 1.

FCM Colour Clustering

According to membership function, FCM clustering method describes degree in different levels by using objective function minimization to achieve clustering effect. The initial clustering process begins from randomly designated cluster center. It is often incorrect, however, through iterative procedure, cluster center can be repeatedly updated and so does membership degree of the data. Therefore, cluster center gradually moves towards correct position. The definition for target function is as followed:

$$J=\sum_{j=1}^{n}\sum_{i=1}^{c}{u_{ij}}^{m}\|x_j-v_i\|^2$$
$$\text{s.t. } u_{ij}\in[0,1],\ i=1,\ 2,\ \ldots,\ c \text{ and} \tag{2}$$
$$\sum_{i=1}^{c}u_{ij}=1,\ \mathrm{j}=1,\ 2,\ \ldots,\ \mathrm{n}$$

Among all,
c: number of clusters
n: number of data
x_j: data samples
u_{ij}: the degree of membership of xj in the cluster i
v: cluster centroid
m: Fuzziness exponent that influence fuzzy clustering
$\|x_j-v_i\|$: Distance from point j to cluster centroid i

Five steps in the implementation process are as followed:

1. Before using the FCM algorithm, parameters including the target number of clusters, c, the fuzziness exponent, m, and the termination tolerance, ε, must be specified.
2. Provide initial value, v_i, in each cluster center and initialized membership grade $u_{ij,}$ and set iteration $t=1$.
3. Utilize the degree of membership to update the cluster center by using Eq. (3).

$$v_i=\sum_{j=1}^{n}{u_{ij}}^{m}\ x_j\Big/\sum_{j=1}^{n}{u_{ij}}^{m},\ i=1,2,\ldots.c. \tag{3}$$

4. Updating the cluster center with Eq. (4).

$$u_{ij}=\left[\sum_{k=1}^{c}\left(\|x_j-v_i\|/\|x_j-v_k\|\right)^{2/(m-1)}\right]^{-1},\ \text{for } 1\leq\ i\ \leq\ c,\ 1\leq\ k\ \leq n \tag{4}$$

5. Calculate objective function, J, and evaluate whether the iteration process is terminated. The convergence criteria were set as $\frac{|J_t-J_{t-1}|}{J_t}$, where J_t is the objective function of the tth iteration. If the iteration process is not converged, then return to step 3.

Minimum mean-Square Error

In order to arrange together similar colours in different time sequences, and obtain an optimal result in colour sequence, the minimum mean-square error (MMSE) method was adopted in this study. After colour predicted reference sequence was conducted, the colour samples would be transferred from RGB to HSV and retrieve hue (H) as the checking parameter. It is ranged from 0° to 360° on the hue circle. If the predicted angle is over 360°, it would be recalculated from 0°. Therefore, problems related to not being able to calculate, over 360°, will not exist. Moreover, in order to get a precise prediction, the minimum mean-square error for obtaining optimal colour sequence is given as Eq.(5).

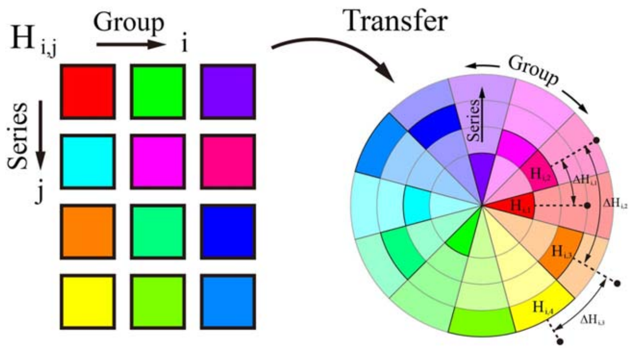

Fig. 1. Colours of minimum mean-square error angle among different time point.

$$\Delta H=\min\sum_{i=1}^{n}\sum_{j=2}^{m}\left(H_{i,j}-H_{i,j-1}\right)^{2} \tag{5}$$

Where,

ΔH is the minimum mean square error function for the hue.

H : degree of the colour located on the hue circle.

n : Sample numbers of each fashion colour data.

m : Numbers of predicted time sequence.

Before adopting this method to retrieve optimal sequence result, colours in different time sequences would be presented as Fig. 1(a). Table crosswise (axis i) refers to colours in the same time sequence; and table longitudinal (axis j) refers to substitutable sequence in gray theory. The colours were first placed on a concentric hue circle [Fig. 1(b)] ordered by the earliest data in the center, and a concentric circle was therefore retrieved. Colours that are close to the center of the circle have an earlier time point. With the minimum mean-square error method, the colour with the smallest angle difference will be explored from inside to outside. For instance, the colour nearest to colour $H_{i,1}$ is colour $H_{i,2}$ which was found with minimum mean-square error by calculating the $\Delta H_{i,1}$, and the same method was used to calculate $\Delta H_{i,2}$, $\Delta H_{i,3}$ for finding $H_{i,3}$ and $H_{i,4}$. After the process has been completed, the colour sequences in different time points can be obtained. For example, the colour sequence colours in ith time point can be expressed as Eq. (6).

$$H_i=\left\{H_{i,1},\ H_{i,2},H_{i,3,}\ldots\ldots\ldots H_{i,n}\right\} \tag{6}$$

This will be taken as the reference sequence for constructing the fashion colour prediction model by using gray theory.

Gray Prediction

Gray system indicates that information is uncertain and incomplete which is often used in the studies with few data and uncertain information. It is based on the Gray causality construction to obtain sequence of data that is already known and come up with the regularity. Therefore, referenced information can be accessed. In gray system theory, it is based on Series, that is,

Let X as Series, $x(k)$ as kth element in x (data)

$$\begin{gathered}X=((x(1),\ x(2),\ \ldots,\ x(n))\\ x(k)\in X,\ \ k\in K=\{1,\ 2,\ldots,n\}\end{gathered} \tag{7}$$

Through accumulation, layers in reference are changed and from the results, potential regulations of the data exist. Among all, Accumulated Generating Operation (AGO) is one of the common methods. That is,

Let $x^{(0)}$ be the original sequence,

$$x^{(0)}=\left(x^{(0)}(1),\ x^{(0)}(2),\ \ldots,x^{(0)}(n)\right),n\geq 2 \tag{8}$$

Let $x^{(1)}$ as $x^{(0)}$ under T sequence transformation

$$x^{(1)}=\left(x^{(1)}(1),\ x^{(1)}(2),\ \ldots,x^{(1)}(n)\right) \tag{9}$$

If $x^{(1)}$ satisfies

$$x^{(1)}(k)=\sum_{m=1}^{k}x^{(0)}(m), \tag{10}$$

then $x^{(1)}$ is called as the first AGO of $x^{(0)}$. Next, in order to make the accumulated sequence meaningful, gray constructed method can be adopted to build up models with partial differential equation. The gray partial differential equation for the GM(1,1) model is given as follow.

$$x^{(0)}(k)+aZ^{(1)}(k)=b \tag{11}$$

where $Z^{(1)}(k)$ is the white background value for deriving the partial differential Eq. (11), which can be expressed as Eq. (12), whereas a and b are constants.

$$Z^{(1)}(k)=0.5x^{(1)}(k)+0.5x^{(1)}(k-1) \tag{12}$$

Substitute $k=2,3\ldots$, n to Eq. (11) and get,

$$\begin{gathered}x^{(0)}(2)+aZ^{(1)}(2)=b\\ x^{(0)}(3)+aZ^{(1)}(3)=b\\ \vdots\\ x^{(0)}(n)+aZ^{(1)}(n)=b\end{gathered} \tag{13}$$

In matrix form, Eq. (13) can be represented as,

$$\mathbf{y}_N=\mathbf{B}\cdot\mathbf{P} \tag{14}$$

where,

$$\mathbf{y}_N=\left[x^{(0)}(2),\ x^{(0)}(3),\ \ldots,\ x^{(0)}(n)\right]^T$$

$$\mathbf{B}=\begin{bmatrix}-z^{(1)}(2) & 1\\ \ldots & \\ -z^{(1)}(n) & 1\end{bmatrix},\mathbf{y}_N=\begin{bmatrix}x^{(0)}(2)\\ \vdots\\ x^{(0)}(n)\end{bmatrix}$$

$$\mathbf{P}=\begin{bmatrix} a \\ b \end{bmatrix}$$

After the constants a and b are obtained by Eq. (15),

$$\mathbf{P}=\begin{bmatrix} a \\ b \end{bmatrix}=\left(\mathbf{B}^T\mathbf{B}\right)^{-1}\mathbf{B}^T\mathbf{y}_N \tag{15}$$

the GM(1,1) model can be built as

$$\hat{x}^{(1)}(k+1)=\left(x^{(0)}(1)-\frac{b}{a}\right)e^{-ak}+\frac{b}{a} \tag{16}$$

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k) \tag{17}$$

Substitute the equation above into Eq. (16), and get

$$\hat{x}^{(0)}(k+1)=(-a)\left(x^{(0)}(1)-\frac{b}{a}\right)e^{-ak} \tag{18}$$

Conversely, on the precision of testifying model, the following equation can be adopted to calculate the relative residuals,

$$e(k)=\frac{x^{(0)}(k)-\hat{x}^{(0)}(k)}{x^{(0)}(k)}\times 100\% \tag{19}$$

in order to evaluate the precision of the prediction.

To gain a more precise predicted result, relative residuals correction can be implemented; equation for residual is listed below,

$$\varepsilon^{(0)}(k)=x^{(0)}(k)-\hat{x}^{(0)}(k) \tag{20}$$

where $x^{(0)}(k)$ is the original data, while $\hat{x}^{(0)}(k)$ is the predicted value.

Hence, the residual sequence can be retrieved.

$$\varepsilon^{(0)}=\left(\varepsilon^{(0)}(1'),\ \varepsilon^{(0)}(2'),\ \ldots,\varepsilon^{(0)}(n')\right) \tag{21}$$

After the residual sequences were calculated and the first AGO of $\varepsilon^{(1)}$ was obtained, the GM (1,1) model for the residual sequence can be built as Eq. (22).

$$\hat{\varepsilon}^{(1)}(k+1)=\left(\varepsilon^{(0)}(1)-\frac{b_\varepsilon}{a_\varepsilon}\right)e^{-a_\varepsilon k}+\frac{b_\varepsilon}{a_\varepsilon} \tag{22}$$

and get,

$$\hat{\varepsilon}^{(0)}(k+1)=\hat{\varepsilon}^{(1)}(k+1)-\hat{\varepsilon}^{(1)}(k) \tag{23}$$

After combining Eqs. (18) and (23), a residual modified gray prediction model can be obtained as shown in Eq. (24).

$$\hat{x}_{rm}^{(0)}(k)=\hat{x}^{(0)}(k)+\hat{\varepsilon}^{(0)}(k) \tag{24}$$

Where, $\hat{x}_{rm}^{(0)}(k)$ is the residual modified predicted value. Through the procedure of residual modification, a more accurate gray prediction will be obtained.

Mean Squared Error

The Mean Squared Error (MSE) can be calculated in one of many ways to quantify the difference between values implied by an estimate and the true quality being certificated.[32] In this study, MSE is the cumulative squared error between the original and predicted colours. This is to verify if the predicted result of the system is similar to the colour report for Pantone spring, 2016. Moreover, the study not only computes the accuracy of predicted result, and MSE is also taken as the tool for this comparative process. The formula for calculating MSE is shown in Eq. (25):

$$\mathrm{MSE}=\frac{1}{3}\left[\left(\frac{H}{360}-\frac{H'}{360}\right)^2+(S-S')^2+(V-V')^2\right] \tag{25}$$

Where, H, S, V and H', S', V' are the degree of hue, saturation and value of the actual and predicted colours, respectively.

IMPLEMENTATION PROCESS

To provide users a concrete colour prediction method, the study combined different theoretical methods and applied JAVA language to construct a colour prediction system based on gray theory. The research procedure is shown in Fig. 2, and the interface for the colour prediction system built by this study is shown in Fig. 3. The interface is divided into two sections. Region I will show the grouped image data automatically clustered by using FCM. Region II will show the colour sequence for the colours in different time points arranged by using the minimum mean-square error, and the fashion colours for the next required time predicted by using residual gray prediction model. Based on the implementation procedure, the user should input some fashion colours from different points of time. To satisfy the requirement for gray prediction theory, at least four samples in time sequence should be selected. Considering large numbers of the colour data in digital image pictures, or complex colour combination, FCM algorithm is applied to recognize colour clusters in image automatically. Thus, colourful images can be clustered efficiently. The content in region I includes inputting data [Fig. 3(a)], controlling the number of clusters manually [Fig. 3(b)], automatic colour clustering [Fig. 3(c)], clustering result saving [Fig. 3(e)], and parameter setting [Fig. 3(f)].

After colour clusters in different time points are built, the method of minimum mean-square error is adopted to rearrange these colour clusters before undergoes colour prediction. Thus, colour sequence in various time points have the least angle sum of square. This method arranges similar colours together in different time sequence, and obtains an optimal result in colour sequence. Finally, the optimal colour sequence can be substituted in the colour prediction system based on gray theory, and colour data in different time sequence (H) can be plug into gray prediction model for calculation. Thus, degrees on the hue circle will be obtained and followed by calculating the difference between predicted hue (H) degree and original hue (H) degree as the predicted number sequence. Thus,

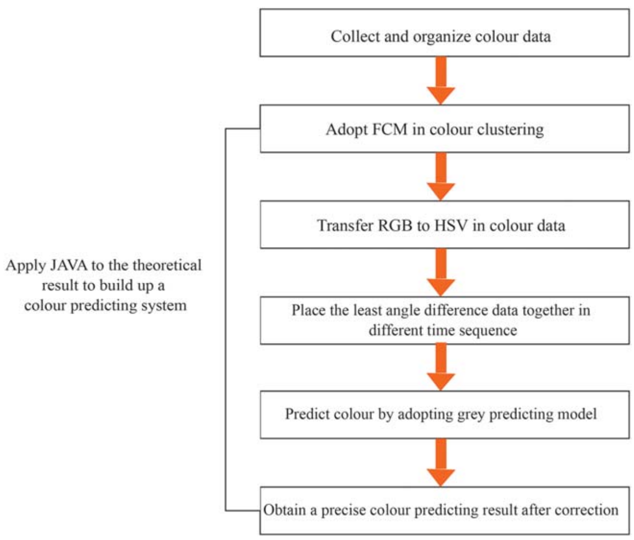

Fig. 2. Implementation procedures for this study. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

predicted error is accessed. Finally, the colour prediction along with residual modification in the next time sequence will be retrieved by recalculating error and original degree. That is, every sequence can be calculated in the next time point of possible fashion colour. This is called predicted colour clusters. The procedures mentioned above is shown in region II of Fig. 3, including the functions of inputting colour data [Fig. 3(g)], file saving [Fig. 3(h)], manual inputting colour data [Fig. 3(i)], dropper colour picking [Fig. 3(j)], the least angle difference calculating [Fig. 3(k)], and prediction producing [Fig. 3(*l*)].

CASE STUDY

This study applied the fashion colour prediction model based on FCM and gray theory to the case study for colour prediction in spring, 2016. The fashion colour prediction report announced by Pantone top 10 women's colours in spring 2014 to fall 2015 was first collected. In total there were four reports for different seasons with 10 different colours in each season as shown in Fig. 4,[33–36] including the colour reports for spring and fall of 2014 and 2015. Fuzzy C-means was used to cluster these colour images in various time sequences. Ten colours were announce in each season, and hue (H) is ranged from 0° to 360°. Thus, the target number c was set as 10 and every 36° from 0° was temporarily set as the initial clustering center which was then updated with Eq. (3) by taking the weighting index m as 2. Moreover, Eq. (4) was used to updating the membership function matrix. Finally, a more stable colour clustering result would be gained after the iteration process was converged. Figure 5 is an example of the 10 colours announced by Pantone in fall, 2014. By using FCM method, 10 chromatic colours were automatically generated and the colour ratio in the images can also be known from the results.

After the colour clusters in different time points were confirmed, the minimum mean-square error method specified in Theoretical Foundation section was used to arrange similar colours together from different points of time. Figure 6(a) shows the sequence result before rearranging, while Fig. 6(b) shows the result that rearranged with the minimum mean-square method.

The colour sequences with the smallest colour difference obtained with the minimum square error method for fashion colours announced from spring 2014 to fall 2015 were taken as the reference series for generating the GM(1,1) gray prediction model by using Eqs. (12)–(24). The accuracy of the constructed residual modified gray prediction model can be defined by Eq. (26).

$$\text{Accuracy}=1-\left|\frac{\text{predicted value}-\text{actual value}}{\text{actual value}}\right| \quad (26)$$

In this study, the HSV colour system was used, thus the hue(H) of the colour can be taken to evaluate the predicted accuracy for the fashion colour one needs in the required time by using Eq. (27).

$$\text{Accuracy}=1-\left|\frac{\text{predicted hue degree}-\text{actual hue degree}}{\text{actual hue degree}}\right| \quad (27)$$

The result for this study is shown in Fig. 7. In which, the colour sets 1–4 represent the fashion colours announced by Pantone from spring 2014 to fall 2015, colour set 5 represents the fashion colour announced in spring 2016 and Colour Set Gray Forecaster is the prediction generated by this system.

To check the accuracy of the residual modified gray prediction model with minimum mean-square error proposed by this study, a comparison between the predicted result generated from this study and the fashion colour announced by Pantone in spring, 2016 is presented in Table III. It shows that the residual modified model constructed with the colour samples rearranged with MMSE has the best predicted result that ranged from 83.3% to 99.4%. All the colours except no.9 (83.3%) and no.10 (89.5%) have the precision rate higher than 90.5%,

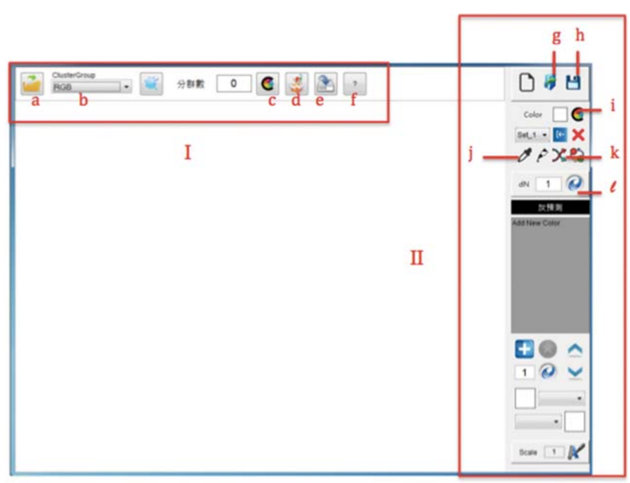

Fig. 3. Interface of the prediction system.

(a) 2014 Spring (b) 2014 Fall

(c) 2015 Spring (d) 2015 Fall

Fig. 4. Fashion colour announced by Pantone from spring, 2014 to fall, 2015.

indicating that the technology proposed in this study has a high precision rate for colour prediction. The precision rate for the predicted results obtained with the residual modified model constructed with the colour samples not rearranged was ranged from 2.2% to 98.3%. The nonresidual modified model constructed with nonrearranged colour samples produces the worst predicted results that ranged from 0.5% to 97.7%. It is claimed that the predicted result obtained with the rearranged colour samples is significantly higher than that obtained with nonrearranged colour samples. Moreover, the residual modified model with rearranged colour samples can also increase the accuracy. Table IV shows a comparison MSE and accuracy of the predicted fashion colours for Pantone spring, 2016 with residual modified prediction model. According to the experiment results, the MSE value is quite low, which was ranged from 0.000025 to 0.0277. It indicates that the predicted results by this system performs well, besides, this system has a better accuracy outcome in fashion colour prediction.

RESULT AND DISCUSSION

This study proposed a systematic colour prediction model and used JAVA to construct an automatic prediction system to effectively simplify data in fashion colour

Fig. 5. Colour clustering result by Fuzzy C-means.

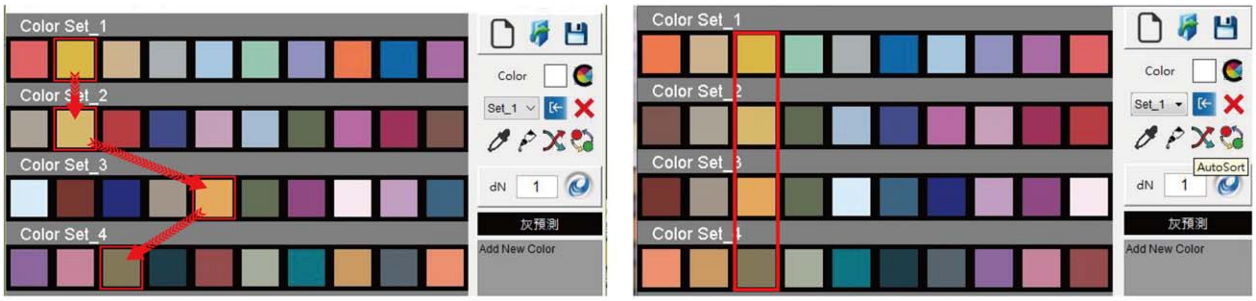

Fig. 6. A comparison of the colour sequences between the results of before and after the matching procedure—(a) colour sequence before matching procedure; (b) colour sequence after matching proce.

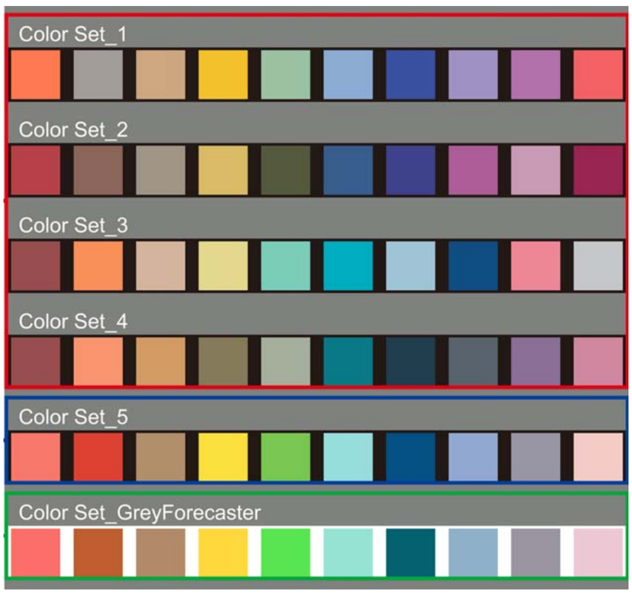

Fig. 7. Fashion colour for spring 2016 predicted by this system. The first four rows (boxed in red) show the Pantone selections from Spring 2014 through fall 2015. The fifth row (boxed in blue) show the Pantone Spring 2015 collection. The bottom row (boxed in green) show the system preditions for Spring 2015.

collection, analysis and prediction. In the case study, 4 fashion colours from spring, 2014 to fall, 2015 were taken as the reference samples for constructing a residual modified fashion colour prediction model. The comparison between fashion colour in Pantone spring, 2016 and that generated by this study was made. Large amount of data is not needed in gray system, and this feature accords with the need in the colour prediction study. The outcome in the experimental study was satisfied. There were two factors that enabled the high precision result. First, the least angle error among colour cluster was calculated, and similar colours in time sequence were placed together. Hence, the predicted accuracy obtained with the constructed model with rearranged colour samples was significantly higher than that with non-rearranged colour samples. Second, the gray prediction result with residual modification was another factor that made the outcome more accurate. The advantage of gray prediction model was that by accumulating the original data, the irregular data became clearer. The simple increasing trend could be used as a prediction model. In this model, different equations can be used to obtain answer and become an exponential function. Since few reference data were needed in this kind of prediction model, an accurate prediction model could be obtained when applying the concept to predict fashion colour in the with only a few fashion colour samples from the previous seasons. The prediction model is a general solution of the differential equation given in Eq. (11). Meanwhile, angle difference of the colour in original data and prediction data were substituted into residual modifications. Through residual

TABLE III. A comparison of the precision rates for different prediction models.

	Pantone Spring, 2016 Original Hue	Rearrange (MMSE)				Non-Rearrange(Non-MMSE)			
		Without residual modification		With residual modification		Without residual modification		With residual modification	
		Hue	Accuracy	Hue	Accuracy	Hue	Accuracy (%)	Hue	Accuracy (%)
1	4	0	97.7%	3	99.4%	0	97.7	1	98.3
2	4	17	92.7%	17	92.7%	21	90.5	18	92.2
3	30	25	97.2%	25	97.2%	292	45.5	292	45.5
4	52	49	98.3%	49	98.3%	0	71.1	2	72.2
5	101	118	90.5%	118	90.5%	357	42.2	357	42.2
6	181	168	92.7%	169	93.3%	0	0.5	5	2.2
7	205	188	90.5%	188	90.5%	147	67.7	146	67.2
8	219	205	92.2%	205	92.2%	103	35.5	110	39.4
9	251	281	83.3%	281	83.3%	123	28.8	124	29.4
10	360	341	89.5%	341	89.5%	316	75.5	314	74.5

TABLE IV. Comparing MSE and accuracy of the predicted fashion colours for Pantone spring, 2016 with residual modified prediction model.

Colour number	1	2	3	4	5	6	7	8	9	10
Pantone Spring, 2016	$R=247$ $G=119$ $B=106$ $H=4$	$R=220$ $G=65$ $B=49$ $H=4$	$R=177$ $G=143$ $B=107$ $H=30$	$R=250$ $G=224$ $B=61$ $H=52$	$R=120$ $G=199$ $B=83$ $H=101$	$R=151$ $G=221$ $B=222$ $H=181$	$R=4$ $G=79$ $B=132$ $H=205$	$R=145$ $G=168$ $B=208$ $H=219$	$R=152$ $G=149$ $B=164$ $H=251$	$R=247$ $G=201$ $B=201$ $H=360$
Residual modified model with rearranged colour samples	$R=252$ $G=112$ $B=104$ $H=3$	$R=191$ $G=92$ $B=48$ $H=17$	$R=179$ $G=138$ $B=105$ $H=25$	$R=255$ $G=217$ $B=59$ $H=49$	$R=87$ $G=230$ $B=82$ $H=118$	$R=150$ $G=227$ $B=212$ $H=169$	$R=3$ $G=97$ $B=112$ $H=188$	$R=143$ $G=176$ $B=201$ $H=205$	$R=156$ $G=148$ $B=158$ $H=281$	$R=237$ $G=199$ $B=211$ $H=341$
MSE	0.000025	0.0052	0.0007	0.0002	0.0089	0.0044	0.0090	0.0059	0.0277	0.0110
Accuracy (%)	99.4	92.7	97.2	98.3	90.5	93.3	90.5	92.2	83.3	89.5

modifications, a more precise result could be obtained. Take the first straight line for instance, the prediction shows that the accuracy was 98.2%. However, the accuracy rate was raised to 99.2% after the residual modifications. Related value changed in the calculation process was shown in Table V.

In the proposed methodology, rearranging the colour samples with MMSE and using the residual modification to improve the model has the direct influence towards the precision in the predicted result. It is easy to find out that the Hue value of prediction by this system is similar to the Hue value of the report for Pantone spring, 2016 according to Fig. 8. To prove that this model can generate accurate prediction results, the study also analysed colour data released by Pantone. Colour data in spring, 2015, fall, 2015 and spring, 2016 from Pantone were used for the prediction (Table VI). For example, in spring, 2015, 4 data were used (spring, 2013 to fall, 2014) to predict colours in spring, 2015. Accuracy rate of the prediction generated by our prediction model has increased from 87.2% to 97.7%. The range of MSE has been improved from 0.0136 to 0.0004. Moreover, high accuracy rate could be observed in fall, 2015, which was 85% to 98.8%. The colour prediction from the three different time periods indicated that the prediction model is stable and with accurate predicted ability. Although the colour predictions

TABLE V. A comparison of the prediction accuracy for the models with/without residual modification.

	Original hue degree	Predicted results for no residual modified model			Predicted results for residual modified model		
		Predicted value	Residual	Accuracy	Predicted value	Residual	Accuracy
2014 Spring	17	17	0	100%	17	0	100%
2014 Fall	359	311.3	47	73.5%	313	2.5	74.9%
2015 Spring	2	43.5	−41	76.9%	45.8	2.2	75.6%
2015 Fall	2	6.0	−4	97.7%	8.1	2.0	96.5%
2016 Spring		0.8		98.2%	2.6	1.8	99.2%

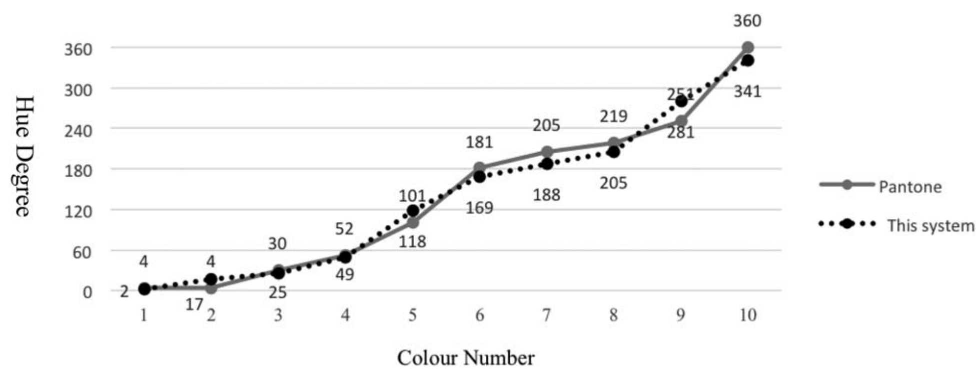

Fig. 8. A comparison of the hues between the predicted and the Pantone poposed fashion colours in spring 2016.

TABLE VI. Comparing MSE and accuracy of the predicted fashion colours for Pantone spring 2015, fall 2015, and spring 2016 with residual modified prediction model.

Colour number	1	2	3	4	5	6	7	s	9	10
Pantone spring, 2015	R=150 G=79 B=76 H=2	R=248 G=143 B=88 H=19	R=210 G=180 B=156 H=26	R=229 G=214 B=142 H=49	R=122 G=204 B=184 H=165	R=0 G=171 B=192 H=186	R=157 G=195 B=212 H=198	R=15 G=76 B=129 H −208	R=231 G=139 B=144 H=355	R=197 G=198 B=199 H=210
Residual modified model with rearranged colour samples	R=125 G=93 B=74 H=23	R=255 G=128 B=87 H=14	R=212 G=176 B=156 H=22	R=242 G=199 B=140 H=35	R=120 G=196 B=147 H=142	R=0 G=161 B=255 H=202	R=156 G=178 B=235 H=223	R=12 G=45 B=122 H=222	R=191 G=138 B=160 H=335	R=196 G=198 B=199 H=200
MSE (Mean Squared Error)	0.0136	0.0007	0.0004	0.0060	0.0163	0.0077	0.0190	0.0060	0.0125	0.0030
	88.3	97.2	97.7	92.2	87.2	91.2	86.2	92.2	88.8	94.5
Pantone Fall, 2015	R=150 G=79 B=76 H=2	R=249 G=148 B 113 H=14	R=207 G=156 B=99 H=31	R=132 G=122 B=89 H=47	R=167 G=174 B158 H=85	R=9 G=121 B=136 H=187	R=32 G=62 B=74 H=197	R=88 G=100 B 109 H=206	R=146 G=106 B 166 H=281	R=206 G=135 B 159 H=341
Residual modified model with rearranged colour samples	R=150 G=74 B=74 H=0	R=255 G=135 B=112 H=9	R=212 G=150 B=97 H=27	R=130 G=122 B=87 H=50	R=161 G=171 B=155 H=99	R=8 G=128 B=125 H=179	R=31 G=61 B=71 H=193	R=87 G=94 B=112 H=219	R=181 G=105 B=175 H=304	R=196 G=141 B=133 H=8
MSE (Mean Squared Error)	0.0001	0.0007	0.0004	0.0002	0.0059	0.0019	0.0004	0.0052	0.0163	0.0225
Accuracy (%)	98.8	97.2	97.7	98.3	92.2	95.5	97.7	92.7	87.2	85
Pantone spring, 2016	R=247 G=119 B=106 H=4	R=220 G=65 B=49 H=4	R=177 G=143 B=107 H=30	R=250 G=224 B=61 H=52	R=120 G=199 B=83 H=101	R=151 G=221 B=222 H=181	R=4 G=79 B=132 H=205	R=145 G=168 B=208 H=219	R=152 G=149 B=164 H=251	R=247 G=201 B=201 H=360
Residual modified model with rearranged colour samples	R=252 G=112 B=104 H=3	R=191 G=92 B=48 H=17	R=179 G=138 B=105 H=25	R=255 G=217 B=59 H=49	R=87 G=230 B=82 H=118	R=150 G=227 B=212 H=169	R=3 G=97 B=112 H=188	R=143 G=176 B=201 H=205	R=156 G=148 B=158 H=281	R=237 G=199 B=211 H=341
MSE (Mean Squared Error)	0.000025	0.0052	0.0007	0.0002	0.0089	0.0044	0.0090	0.0059	0.0277	0.0110
Accuracy (%)	99.4	92.7	97.2	98.3	90.5	93.3	90.5	92.2	83.3	89.5

obtained from the model were effective with accurate predicted ability, there are limitations. For example, some predicted colours still have a little visual difference. Maybe it could be improved by using other colour space such as CIELAB colour space. This will be checked, with further work in our laboratory.

CONCLUSION

This study integrated FCM and gray theory to construct a fashion colour prediction model and deduced the theory to the result. Java language was used to construct an automatic system that result could be used to obtain predicted colour rapidly. Because factors that influenced the fashion colour trend were complex, this study applied the gray model technique for fashion colour prediction and a residual modified model was also proposed to increase the accuracy of the prediction result. Thus, this system has a high accuracy outcome in prediction, which can give information to designers and manufacturers for making decisions about fashion trends. The proposed methodology and the system built by this study can be applied widely among different fields in colour prediction. By conducting further experiments, it is believed that a more general prediction model can be constructed.

1. Choi TM, Hui CL, Ng SF, Yu Y. Color trend forecasting of fashionable products with very few historical data. IEEE Trans Syst Man Cybern C Appl Rev 2012;42:1003–1010.
2. Best J. Colour Design Theories and Application. UK: Woodhead Publishing; 2012.
3. Helander MG, Khalid HM, Lim TY, Peng H, Yang X. Emotional needs of car buyers and emotional intent of car designers. Theor Issues Ergon Sci 2013;14:455–474.
4. Crilly N, Moultrie J, Clarkson PJ. Shaping things: Intended consumer response and the other determinants of product form. Des Stud 2009;30:224–254.
5. Zheng D. A novel method for fabric color transfer. Color Res Appl 2015;40:304–310.
6. Zhang JF. The application of color psychological effect on fashion design. Adv Mater Res 2013;796:474–478.
7. Koh L, Lee J. A study of color differences in women's ready-to-wear collections from world fashion cities: Intensive study of the fall/winter

2010 collections from New York, London, Milan, and Paris. Color Res Appl 2012;38:463–468.
8. Lei N, Moon SK. A decision support system for market-driven product positioning and design. Decis Support Syst 2015;69:82–91.
9. Choi TM, Hui CL, Yu Y. Intelligent Fashion Forecasting Systems: Models and Applications. In: Yu Y, Ng SF, Hui CL, Liu N, Choi TM, editors. Intelligent Fashion Colour Trend Forecasting Schemes: A Comparative Study. New York: Springer; 2013. p 147–160.
10. Lee YS, Tong LI. Forecasting energy consumption using a gray model improved by incorporating genetic programming. Energy Convers Manage 2011;52:147–152.
11. Chien CL, Tseng DC. Color image enhancement with exact HSI color model. Int J Innov Comput Inf Control 2011;7:6691–6710.
12. Bora DJ, Gupta AK, Khan FA. Comparing the performance of L*A*B* and HSV color spaces with respect to color image segmentation. Int J Emerg Technol Adv Eng 2015;5:192–203.
13. Narkhede PR, Gokhale AV. Color image segmentation using edge detection and seeded region growing approach for CIELAB and HSV color spaces. In: 2015 Interntional Conference on Industrial Instrumentation and Control; 2015. p 28–30.
14. Schwarz MW, Cowan WB, Beatty JC. An experimental comparison of RGB, YIQ, LAB, HSV and opponent color models. ACM Graph 1987; 6:123–158.
15. Bora DJ, Gupta AK. A new approach towards clustering based color image segmentation. Int J Comput Appl 2014;107:23–30.
16. Ali NM, Rashid NKAM, Mustafah YM. Performance comparison between RGB and HSV color segmentations for road signs detection. Appl Mech Mater 2013;393:550–555.
17. Jose MCG, Miguel AVR, Juan AGP. Detecting skin in face recognition systems: A colour spaces study. Digit Signal Process 2010;20:806–823.
18. Iyatomi H, Celebi ME, Schaefer G, Tanaka M. Automated color calibration method for dermoscopy images. Comput Med Imaging Graph 2011;35:89–98.
19. Bezdek J. Pattern Recognition with Fuzzy Objective Function Algorithm. New York: Plenum Press; 1981.
20. Zhang J, Pan R, Gao W, Zhu D. Automatic detection of layout of color yarns of yarn-dyed fabric. Part 1: Single-system-melange color fabrics. Color Res Appl 2015;40:626–636.
21. Cai W, Chen S, Zhang D. Fast and robust fuzzy c-means clustering algorithms incorporating local information for image segmentation. Pattern Recognit 2007;40:825–838.
22. Wang XY, Zhang XJ, Yang YH, Bu J. A pixel-based color image segmentation using support vector machine and fuzzy C-means. Neural Netw 2012;33:148–159.
23. Choi TM, Hui CL, Liu N, Ng SF, Yu Y. Fast fashion sales forecasting with limited data and time. Decis Support Syst 2014;59:84–92.
24. Au KF, Choi TM, Yu Y. Fashion retail forecasting by evolutionary neural networks. Int J Prod Econ 2008;114:615–630.
25. Yu Y, Choi TM, Hui CL. An intelligent fast sales forecasting model for fashion products. Expert Syst Appl 2011;38:7373–7379.
26. Sun ZL, Choi TM, Au KF, Yu Y. Sales forecasting using extreme learning machine with applications in fashion retailing. Decis Support Syst 2008;46:411–419.
27. Choi TM, Yu Y, Au KF. A hybrid SARIMA wavelet transform method for sales forecasting. Decis Support Syst 2011;51:130–140.
28. Lin JJ, Sun PT, Chen JJR, Kuo HC, Kuo WG. Applying gray model to predicting trend of textile fashion colors. J Text Inst 2010;101:360–368.
29. Yu Y, Hui CL, Choi TM. An empirical study of intelligent expert systems of forecasting of fashion color trend. Expert Syst Appl 2012;39:4383–4389.
30. Tsai HC, Hsiao SW, Hung FK. An image evaluation approach for parameter-based product form and color design. Comput Aided Des 2006;38:157–171.
31. Hsiao SH, Tsai HC. Use of gray system theory in product-color planning. Color Res Appl 2004;29:222–231.
32. Kaushik P, Sharma Y. Comparison of different image enhancement techniques based upon Psnr & Mse. Int J Appl Eng Res 2012;7:2010–2014.
33. Pantone. Pantone Fashion Color Report Spring 2014. Available at: http://www.pantone.com/pages/fcr/?season=spring&year=2014&from=topNav (accessed on September 2014)
34. Pantone. Pantone Fashion Color Report Fall 2014. Available at: http://www.pantone.com/pages/fcr/?season=fall&year=2014&pid=3 (accessed on February 2014)
35. Pantone. Pantone Fashion Color Report Spring 2015. Available at: http://www.pantone.com/pages/fcr/?season=spring&year=2015&from=topnav (accessed on September 2014)
36. Pantone. Pantone Fashion Color Report Fall 2015. Available at: http://www.pantone.com/pages/fcr/?season=fall&year=2015&from=topnav (accessed on February 2015)