Research on Clothing Color Classification Method based on Improved FCM Clustering Algorithm

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***Abstract*—In the apparel industry, apparel color is an important factor to enhance the market competitiveness of enterprise products. However, the current prediction samples of clothing fashion color styling information do not incorporate practical cutting-edge fashion information. Therefore, Self-adaptive Weighted Kernel Function (SWK) has been introduced to traditional Fuzzy C-Means (FCM) clustering algorithms. After improvement, the SWK-FCM clustering algorithm is obtained, which enhances the classification ability of fashion colors and hue. Two prediction models have been developed using the finalized data of the International Fashion Color Committee, along with the SWK-FCM clustering algorithm. The models have been tested via experiments to verify their accuracy. The experimental results show that the classification coefficients of SWK-FCM clustering algorithm are 0.9553 and 0.9258 under 5% Gaussian noise. They are higher than those of FCM (0.7063) and FLICM (0.8598). The classification entropy is lower than that of the comparison algorithm, while the same results are presented under other conditions and in the actual experiments. In addition, the overall MSE of the GM (1, 1) prediction model using the final case information is 0.00028, which is close to the order of 10-4. The MSE value of the BP neural network prediction model using the final case information ranges from 0.000529 to 0.011025. Overall, the clustering algorithm of SWK-FCM has good classification performance. Additionally, the GM (1,1) model based on SWK-FCM has better prediction results, which can be effectively applied in practical clothing color classification and popular color prediction.**

Keywords—Fuzzy clustering; SWK-FCM; fashion color scheme; Gaussian noise

I. Introduction

The development of the economy has driven changes in the overall consumption concept of the people. People's daily needs for clothing are gradually shifting towards pursuing quality and fashion [1]. Clothing color is an important element in improving the competitiveness of goods. Popular colors are the focus of attention in the clothing industry, and their effective prediction can promote the effective development of clothing enterprises [2]. Zhu D et al. constructed two neural models of perceptual data based on deep learning for the problem of popular color trends of Japanese women's clothing kawaii style [3]. In response to the difficulty of fashion designers in achieving realistic restoration of Yi clothing color images, Zhu Hai et al. proposed a Yi clothing color extraction classification and trend prediction based on the K-means algorithm [4]. Garcia C C C proposed a consumer preference data based on material culture for fashion culture prediction in response to the trend of fashion clothing color trends [5]. The current methods for predicting fashion color trends are still in the exploratory stage, resulting in low prediction accuracy, high time consumption, and high actual cost. As a clustering algorithm, FCM algorithm can effectively solve the classification time and improve the accuracy of prediction. However, traditional FCM does not perform well in actual fashion color classification prediction. At the same time, although the color quantization space method among many current methods can predict clothing color systems based on final information, it has high requirements for data extraction and low practicality. The grey model in the popular color prediction model has low requirements for dyeing sample data, but the actual prediction accuracy is not high enough. In this context, this study improves the FCM clustering algorithm and obtains an FCM clustering algorithm based on mean space constraints and adaptive weighted kernel functions (Self-adaptive Weighted Kernel Fuzzy C-Means, SWK-FCM). Based on this, the Grey Model (1,1), GM (1,1) and Back Propagation (BP) neural network prediction model are constructed. The purpose of the model is to improve the classification quality of apparel hues and achieve effective prediction of apparel fashion colors, so as to give relevant enterprises the corresponding guidance. In addition, the application of data prediction in the textile industry is still in an exploratory state, and the application of classification methods in the clothing industry is relatively shallow. Therefore, the study of using SWK-FCM clustering algorithm to classify clothing hue is innovative.

This paper is divided into five sections in total. The Section I is a summary and discussion of the current research on clothing color classification at home and abroad. Section II is the related work. Section III analyzes the clothing color classification method proposed on the basis of the improved FCM clustering algorithm. Section IV is to analyze the performance of this method. Section V concludes the paper.

II. Related Work

Fashion colors are the most important part of fashion elements, and they are pivotal in enhancing brand image and sales [6]. Therefore, achieving effective prediction of apparel fashion colors can bring higher business value to stakeholders and also promote the development of the industry. However, the prerequisite for realizing fashion color prediction for apparel is the effective classification of apparel hues [7]. Based on this, a wide range of domestic and foreign scholars have conducted in-depth research on it. Zhou Ze et al. proposed a new clothing classification method based on parallel convolutional neural networks for color tone recognition and classification. This method improved the stability and accuracy of clothing classification on the basis of effectively extracting clothing tone features in [8]. Mushtaque S et al. constructed an effective classification platform for online shopping of women's clothing in Pakistan based on the collection of top women's clothing brands in Pakistan [9]. Wu D et al. proposed a new method for apparel attribute recognition and prediction, and used it to classify apparel hues, thus improving the recognition efficiency and classification accuracy based on the constructed relational model. The accuracy of classification was improved based on the relationship model [10]. Dai Y et al. proposed five different experimental schemes to improve the accuracy of fashion color database and fashion color classification based on the collection of relevant data [11]. Han A et al. used machine learning to analyze fashion color data and determine whether fashion designers have used fashion colors proposed by relevant institutions to guide seasonal trends. This method of analyzing and classifying fashion color data effectively enhances the potential of fashion color trend analysis to guide production [12].

In addition, Mau T N et al. effectively created an optimization method for initial clustering based on location-sensitive hashing for fuzzy clustering of categorical data, thus improving the clustering effect while reducing the dimensionality of categorical data and providing help for data trend prediction [13]. Mersch B and Buchel S et al. proposed a pricing heuristic based on machine learning for large-scale optimization of images, which improves the image coloring problem while increasing the prediction accuracy [14]. The issue of sustainable development was comprehensively analyzed through a multi-level perspective system to provide a predictive direction for the strategic transformation of the fashion industry [15-16]. Wang Wei et al. constructed a hybrid color trend prediction model based on genetic algorithm and extreme learning machine to address the issue of future color trend prediction, effectively improving prediction accuracy [17].

From the research of above scholars, the application of prediction of data in textile industry is still in the state of exploration, while the application of classification method in apparel industry is still shallow. Therefore, the research on the classification of apparel color shades using the SWK-FCM clustering algorithm possesses a certain degree of innovation, while the prediction model constructed on its basis can provide objective and scientific support to the stakeholders. In addition, it can also provide guidance for guiding consumers to form correct consumption behaviors while improving the accuracy of apparel trend prediction.

III. Analysis of Clothing Color Classification Method based on Improved FCM Clustering Algorithm

A. *Study on Clothing Color Classification based on SWK-FCM Clustering Algorithm*

There is a problem of inconsistency between current fashion color case information and actual cutting-edge fashion information. In response to this, this study combined case information and improved the Fuzzy C-Means (FCM) clustering algorithm to construct a fashion color prediction model. Traditional clustering usually refers to the process of clustering things using similarity. Cluster analysis uses mathematical methods for clustering research, using the degree of correlation between certain features of the tested object as the basis for classification, without considering other prior knowledge. Fuzzy cluster analysis is a clustering analysis method constructed on the basis of fuzzy theory. Its correlation analysis of data is performed on the basis of considering regional characteristics and classifying them [18]. In pattern recognition and image segmentation, this method can be used to describe fuzzy objects more objectively.

FCM clustering algorithm belongs to a kind of fuzzy clustering algorithm, which achieves automatic classification of sample data by optimizing each sample point and determining the class of each sample point [19]. The classification accuracy of the traditional FCM clustering algorithm is very effective in the actual clothing color classification. Therefore, the study obtained the SWK-FCM clustering algorithm by embedding the kernel function in the FCM clustering algorithm and weighting it. Compared with traditional FCM, the SWK-FCM clustering algorithm enhances inter sample features by introducing kernel functions. It effectively prevents misclassification of important details through adaptive weights, and improves the system's noise resistance by introducing spatial functions. Among them, the expression of the objective function of SWK-FCM is shown in Eq. (1).

$$\begin{aligned} T &= 2\sum_{i=1}^{a}\sum_{j=1}^{n} b_i^m \lambda_{ij}^m \left(1-K\left(x_j,u_i\right)\right) \\ &+2\gamma\sum_{i=1}^{a}\sum_{j=1}^{n} b_i^m \lambda_{ij}^m \left(1-K\left(\overline{x_j},u_i\right)\right) \end{aligned} \tag{1}$$

In equation (1), $T = 2\sum_{i=1}^{a}\sum_{j=1}^{n} b_i^m \lambda_{ij}^m \left(1-K\left(x_j,u_i\right)\right)+2\gamma\sum_{i=1}^{a}\sum_{j=1}^{n} b_i^m \lambda_{ij}^m \left(1-K\left(\overline{x_j},u_i\right)\right)$ denotes the objective function. i denotes the number of clusters, whose maximum value is a. j denotes the number of elements in the sample, whose maximum value is n. b_i denotes the dynamic weight of a class, which can express the importance of a certain class. λ denotes the affiliation degree. m denotes the fuzzy factor. $J\left(x,u\right)$ denotes the inner product kernel function. γ denotes the control parameter. On this basis, the computational expressions of the clustering center and the affiliation function can be obtained by minimizing the objective function by the Lagrange multiplier method under the corresponding constraints. Among them, the expressions of the constraints are shown in Eq. (2).

$$\begin{cases} \sum_{i=1}^{a} b_i = 1 \\ \sum_{i=1}^{a} \lambda_{ij} = 1 \end{cases} \tag{2}$$

Therefore, the expression of the cluster center u_i is calculated as shown in Eq. (3).

$$u_i = \frac{\sum_{j=1}^{n} \lambda_{ij}^{m} J\left(x_j, u_i\right)\left(x_j, \overline{u_j}\right)}{\left(1+\gamma\right)\sum_{j=1}^{n} \lambda_{ij}^{m} J\left(x_j, u_i\right)} \tag{3}$$

Similarly, the expression for the calculation of dynamic weights is shown in Eq. (4).

$$b_i = \frac{\sum_{j=1}^{n} \lambda_{ij}^{m} \left(1 - J\left(x_j, u_i\right)\right)^{\frac{1}{m-1}}}{\sum_{i=1}^{a} \left(\sum_{j=1}^{n} \lambda_{ij}^{m} \left(1 - J\left(x_j, u_i\right)\right)\right)^{\frac{1}{m-1}}} \tag{4}$$

Finally, the expression of the affiliation function is calculated as shown in Eq. (5).

$$\lambda_{ij} = \frac{b_i \left(1 - J\left(x_j, u_i\right) + \gamma\left(1 - J\left(\overline{x_j}, u_i\right)\right)\right)^{\frac{1}{m-1}}}{\sum_{k=1}^{a} b_k \left(1 - J\left(x_k, u_i\right) + \gamma\left(1 - J\left(\overline{x_k}, u_i\right)\right)\right)^{\frac{1}{m-1}}} \tag{5}$$

Therefore, the specific steps of the SWK-FCM clustering algorithm constructed in the study are shown in Fig. 1.

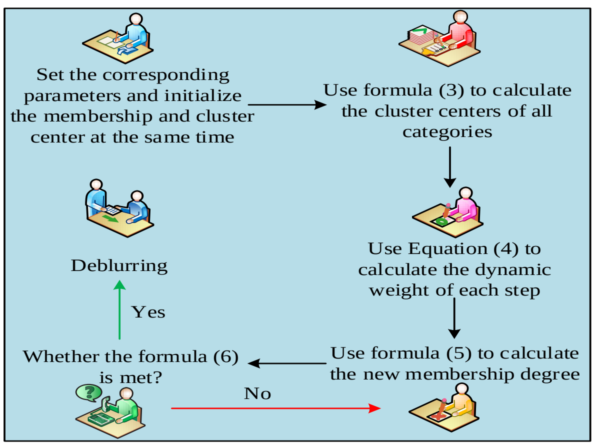


Fig. 1. Detailed steps of SWK-FCM clustering algorithm.

In Fig. 1, the SWK-FCM algorithm firstly sets the corresponding parameters and initializes the affiliation and clustering centers at the same time. Secondly, it calculates the clustering centers of all categories and the dynamic weights of each step using Eq. (3) and Eq. (4). Then it updates the affiliation and calculates the new affiliation using Eq. (5). It continuously updates the affiliation and calculates the new affiliation until it satisfies Eq. (6). The final step is defuzzification, thus completing the classification. Among them, the determination constraints embodied in the steps are shown in Eq. (6).

$$\max\left\{\left|\lambda_{ij}^{old} - \lambda_{ij}^{new}\right|\right\} < \delta \tag{6}$$

In Eq. (6), λ_{ij}^{old} denotes the old affiliation. λ_{ij}^{new} denotes the new affiliation. δ denotes the threshold value. In addition, in the final deblurring equation, the classification of each pixel point needs to be achieved based on the corresponding equation, which is expressed as shown in Eq. (7).

$$v = \arg\max x_i \left\{\lambda_{ij}, i = 1, 2, \cdots, a\right\} \tag{7}$$

In Eq. (7), v indicates the category to which it belongs. Since the color system of different popular colors itself is different, this leads to different methods of color classification. Therefore, in the actual process of popular color data processing, it is necessary to determine the popular color hue classification method. Based on Eq. (1) to (7), the proposed SWK-FCM algorithm can automatically classify the color hues of clothing fashions and gradually determine the relevant intervals of color hue values for further processing of the data. Its process in apparel color clustering is similar to Fig. 1. However, there is a slight difference in the last step. That is, according to Eq. (1), the objective function value is calculated and the minimum error value is set. Until the objective function value is less than the given minimum error value or the number of iterations exceeds the limit, the algorithm process ends. The expression of the minimum error value calculation is shown in Eq. (8).

$$\varepsilon = \frac{\left|T_t - T_{t-1}\right|}{T_t} \tag{8}$$

In Eq. (8), ε denotes the minimum error value. t denotes the number of iterations. By using the SWK-FCM clustering algorithm to cluster the hue and return to the hue center and hue affiliation matrix, the hue value interval of each color class of the garment can be obtained after the corresponding processing of the affiliation matrix. The individual unclustered hue values are automatically assigned with the hue value interval that spans the adjacent interval. At the same time, the frequency of each type of hue in different years can be obtained statistically. The corresponding formula is used to calculate the proportion. The calculation expression is shown in Eq. (9).

$$P_{i'} = \frac{f_{i'}}{F} \times 100\% \tag{9}$$

In Eq. (9), $P_{i'}$ indicates the proportion of colors in the i' category in different years. $f_{i'}$ indicates the frequency of colors in the i' category. F indicates the total number of colors announced in the fashion color scheme of a certain year.

B. Construction of a Color Prediction Model for Fashionable Clothing Colors based on Final Case Information

After elaborating the SWK-FCM clustering algorithm, the processed data can be brought into GM (1,1) with BP neural network to achieve the prediction of clothing process color shades. Before that, it is necessary to design the process of garment process color trend prediction using the finalized information. The study uses the information of the apparel fashion color case issued by the International Color Council as the actual data source, and uses the SWK-FCM clustering algorithm to classify the color shades of apparel, so as to redefine the color intervals. GM (1,1) and BP neural network are used to perform color shade prediction, and the specific process is shown in Fig. 2.

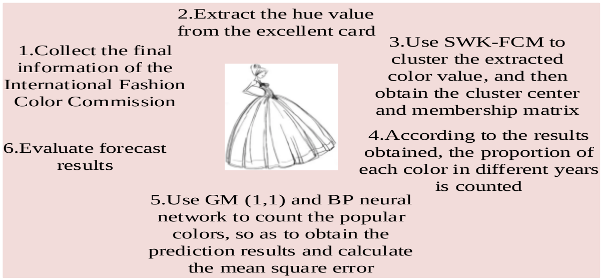


Fig. 2. Fashion color trend prediction process based on final information.

From Fig. 2, the process of predicting the trend of fashion colors using the case information is firstly to collect the historical case information of the International Color Council and extract the color phase values from the color cards. Secondly, it is to cluster the proposed color phase values by using SWK-FCM to obtain the cluster center and affiliation matrix. The next step is to count the proportion of each color in different years based on the results obtained. Then, GM(1,1) and BP neural network are taken to count the popular colors to obtain the prediction results and calculate the mean square error. Finally, evaluating the prediction results. Among them, the main steps of the prediction of the fashion color prediction model using GM (1,1) based on the final case information are shown in Fig. 3.

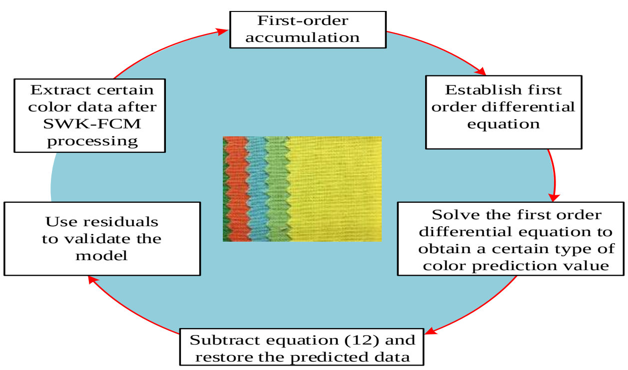


Fig. 3. Main steps of fashion color prediction based on GM (1,1).

From Fig. 3, the main steps are to first extract the original sequence of a certain type of color data after SWK-FCM processing and perform first-order accumulation to generate a first-order sequence; second, to establish a first-order differential equation and solve the first-order differential equation to obtain the predicted value of a certain type of color. Next step is to perform continuous accumulation of the equation to reduce the predicted data. Finally, the residual is used to verify the model. The expression of the original sequence and the first-order cumulative equation is shown in Eq. (10) [20-22].

$$\begin{cases} y^{(0)}(v') = y^{(0)}(1), y^{(0)}(2), \cdots y^{(0)}(v') \\ y^{(1)}(v') = \sum_{i''=1}^{v} y^{(0)}(i'') \end{cases} \tag{10}$$

In Eq. (10), $y^{(0)}(v)$ denotes the original sequence. $y^{(1)}(v)$ denotes the first-order sequence. i'' denotes the color category whose maximum value is v'. And the computational expression of the established first-order differential equation is shown in Eq. (11).

$$\frac{dy^{(1)}(v')}{dv} + cy^{(1)}(v') = h \tag{11}$$

Eq. (11), c denotes the whitening coefficient, which reflects the trend of the variable. h denotes the endogenous control gray scale. In addition, the expression of the predicted value of a certain type of color obtained by solving this first-order differential equation is shown in Eq. (12).

$$\hat{y}^{(0)}(v'+1) = \left(y^{(0)}(1) - \frac{h}{c} \right) e^{-cv'} + \frac{h}{c} \tag{12}$$

In Eq. (12), e denotes the natural constant. Therefore, based on the stepwise representation of the GM (1,1) model, Eq. (12) is cumulated. The predicted data expression obtained by this reduction is shown in Eq.(13).

$$\hat{y}^{(0)}(v'+1) = \hat{y}^{(1)}(v'+1) - \hat{y}^{(1)}(v') \tag{13}$$

Finally, the model is validated using the nibbling formula, and the expression of the residual formula is calculated as shown in Eq. (14).

$$\eta(v') = \frac{y^{(0)}(v') - \hat{y}^{(0)}(v')}{y^{(0)}(v')} \tag{14}$$

In Eq. (14), $\eta(v')$ denotes the relative error. The model is considered to meet the requirement when the relative error meets the corresponding condition, which is expressed in Eq. (15).

$$\begin{cases} |\eta(v')| < 0.1 \\ |\eta(v')| < 0.2 \end{cases} \tag{15}$$

In Eq. (15), when the relative error satisfies the first row of the equation, it means that the GM model achieves good accuracy. When the relative error satisfies the second row of the equation, it means that the GM model achieves general requirements. In addition to the GM model, the apparel popular color hue prediction model constructed by using the final case information also contains the BP neural network prediction model. BP neural network is a one-way propagation multilayer feedforward network, which is trained repeatedly by the samples of the network. Therefore, the weights and thresholds of the network can be gradually reduced on the negative gradient and achieve the expected results to a certain extent [23]. Because there is little color information of popular colors, and after analyzing the prediction results of current popular colors according to different network structures, the study chose a BP neural network for prediction. Its network topology is schematically shown in Fig. 4.

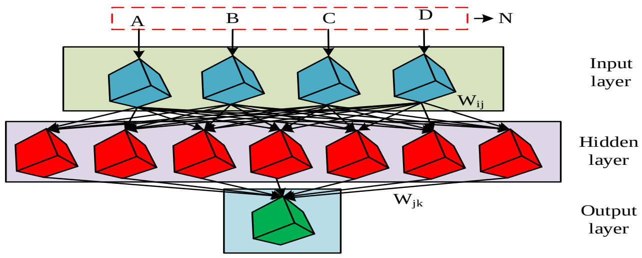


Fig. 4. Topological structure diagram of fashion colors based on BP neural network.

In Fig. 4, N denotes the color data related to a certain type of clothing color for the previous N years. O denotes the target value. W_{ij} denotes the weight value of the i-th neuron in the input layer relative to the j-th neuron in the hidden layer. W_{jk} denotes the weight value of the j-th neuron in the hidden layer relative to the k-th neuron in the output layer. From the figure, the topology of clothing fashion color using BP neural network contains the same three-layer structure. However, in the process of predictive modeling, the data related to each type of color needs to be trained separately. Firstly, the number of nodes in the input layer, output layer and should that layer needs to be set. The study sets the number of nodes in the input layer to 4, which are represented by A, B, C and D respectively. The number of nodes in the implicit layer is 7, and the number of nodes in the output layer is 1. Next, parameters such as excitation function, minimum learning rate, and maximum number of iterations are set. When the error associated with the training exceeds the expected value, it enters the backward propagation of the error, and then the gradient decreasing method is used to gradually correct the hidden layer weights to obtain the expected result. Finally, the completed training model is used to predict the color correlation data for the next year.

IV. Performance Analysis of the Prediction Model Constructed Based on SWK-FCM Clustering Algorithm

To verify the effectiveness of the garment fashion color shade prediction model constructed in the study, the study analyzed it using experiments. This study first evaluated the quality of clothing color classification using the SWK-FCM clustering algorithm. Then, the fuzzy local information c-means (FLICM) clustering algorithm was introduced and compared with SWK-FCM clustering algorithm and traditional FCM clustering algorithm [24]. Before the experiment, the threshold value is set to 0.00001, the fuzzy factor is 2, the control parameter is 3.8, and the Gaussian kernel parameter is 110. In addition, based on the information of the international spring and summer women's fashion color definitions released by the International Color Council from 2017 to 2022, the study collects and organizes nearly 300 colors and uses the SWK-FCM clustering algorithm to find ten clustering centers. After data processing, the classification results and the contents of the classification intervals are shown in Table I.

TABLE I. Ten Clustering Centers and Hue Intervals of Hue Values in PANTONE Color Space

Hue classification	Name	Cluster center	Chromatic value range
1	Green	2	[1, 4].
2	Greenish yellow	6	[5, 8].
3	Yellow	10	[9, 11].
4	Yellow-red	13	[12, 15].
5	Red	17	[16, 21]
6	Red-purple	26	[22, 30]
7	Purple	39	[31, 40].
8	Purplish blue	44	[41, 48]
9	Blue	53	[49, 57].
10	Turquoise	61	[58, 64].

In Table I, a total of ten cluster centers were obtained in this study. The corresponding colors are mainly green, yellow, red, purple, blue, and five intersecting colors. On this basis, the classification quality assessment criteria are selected as classification coefficient (E) and classification entropy (F). The experimental clothing images are selected as 5% Gaussian noise and 10% pretzel noise. The comparison results of the performance parameters of the three algorithms classification criteria simulation are shown in Fig. 5.

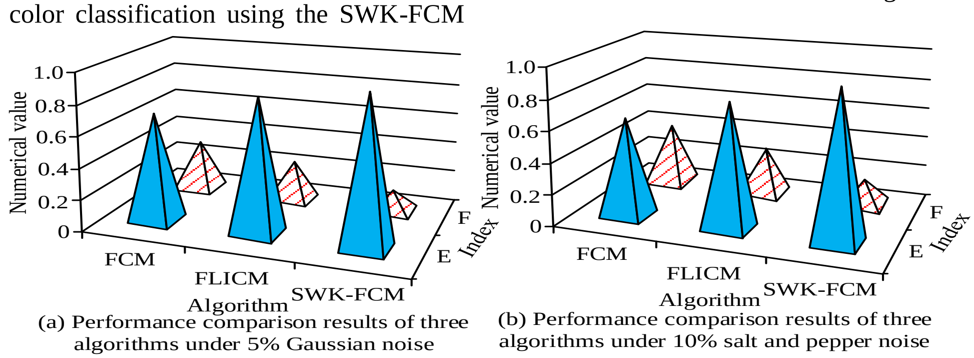
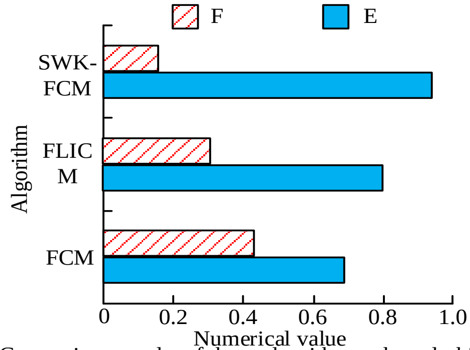
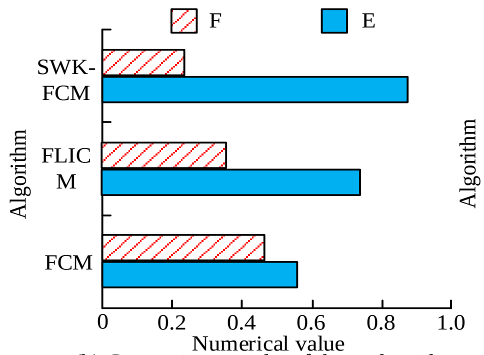


Fig. 5. Comparison results of performance parameters of clothing color hue tested by three algorithm classification standards.

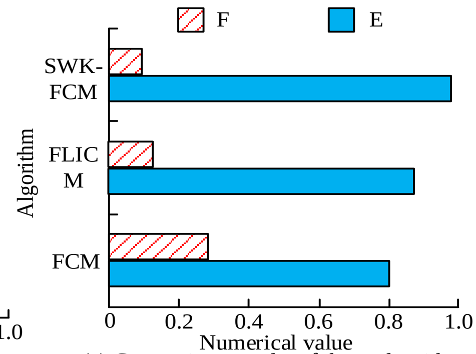
Fig. 5(a) shows the comparison results of the algorithms under 5% Gaussian noise. Fig. 5(b) shows the comparison results of the algorithms under 10% pretzel noise. From Fig. 5(a), the classification coefficient of SWK-FCM clustering algorithm is 0.9553, which is higher than 0.7063 of FCM and 0.8598 of FLICM. Meanwhile, the classification entropy of SWK-FCM clustering algorithm is 0.1380, which is lower than 0.3324 of FCM and 0.2623 of FLICM. At the same time, the classification entropy of SWK-FCM clustering algorithm is 0.1837, which is lower than that of FCM (0.3598) and FLICM (0.3157). This indicates that the SWK-FCM clustering algorithm has better classification quality and more robustness. To further verify the result, the study applies it to the actual apparel color classification, in which three colors, green, yellow-red and purple, are randomly selected under ten clustering centers. The three colors are used as the clothing classification images for the experiment. The comparison results are shown in Fig. 6.



(a) Comparison results of three algorithms when clothing color is green



(b) Comparison results of three algorithms when clothing color is Yellow-red

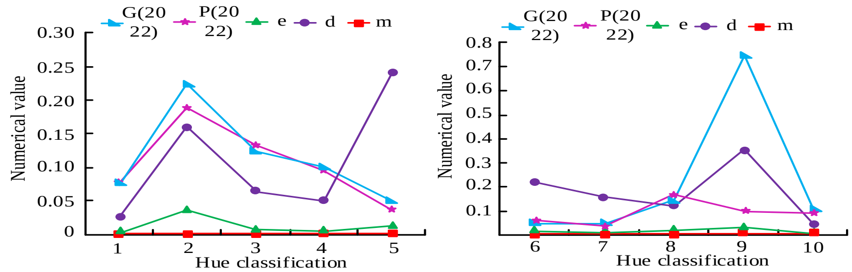


(c) Comparison results of three algorithms when clothing color is Purple

Fig. 6. Performance comparison results of three algorithms for clothing classification images.

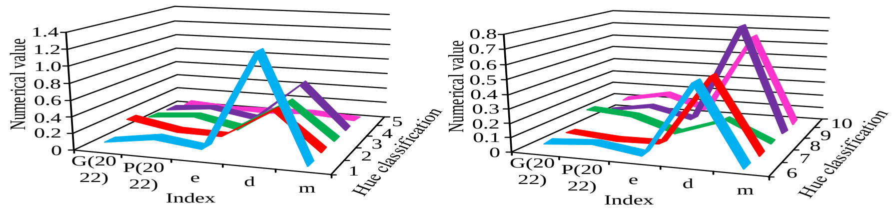
Fig. 6(a) shows the comparison results of the three algorithms when the garment hue is green. Fig. 6(b) shows the comparison results of the three algorithms when the garment hue is yellow-red. Fig. 6(c) shows the comparison results of the three algorithms when the garment hue is purple. From Fig. 6(a), the classification coefficient of SWK-FCM clustering algorithm is 0.9388, which is much higher than that of the comparison algorithm. The classification entropy is 0.1540, which is significantly lower than that of the comparison algorithm. From Fig. 6(b), the classification coefficient of SWK-FCM clustering algorithm is 0.8967, which is higher than the comparison algorithm. The classification entropy is 0.2637, which is lower than the comparison algorithm. In Fig. 6(c), the classification coefficient of SWK-FCM clustering algorithm is 0.9778, which is also higher than that of the comparison algorithm. The classification entropy is 0.0946, which is lower than that of the comparison algorithm. Therefore, the SWK-FCM clustering algorithm is less susceptible to interference from noise and has higher classification accuracy in the actual clothing color classification. Therefore, the two prediction models constructed on the basis of SWK-FCM are studied to possess better performance in theory. To verify the performance of the GM (1, 1) prediction model and the BP neural network prediction model, the study analyzes the prediction results of both of them separately. In the experiments, the study compares the absolute error, relative error, and Mean Square Error (MSE), which are denoted by e, d, and m, respectively. The results are shown in Fig. 7.

In Fig. 7, G (2022) denotes the original value in 2022. P (2022) denotes the predicted value in 2022. e denotes the absolute error; d denotes the relative error. m denotes the mean square error. Comprehensive Fig. 7 shows that the MSE values of the GM (1, 1) model color prediction using the final case information are very low, at 0.000004~0.001296. Its MSE can be as small as 10^{-6} magnitudes, and the overall MSE is 0.00028, which is close to the magnitude of 10^{-4}. This indicates that the GM (1, 1) model has higher prediction ability and higher accuracy rate. Meanwhile, based on the comparison between the prediction and the real curve in 2022, the average relative error of the popular colors in 2022 is 14.51%, which is very close to the actual value, except for the relatively large relative error of individual colors. This indicates that the GM (1,1) model using the final case information has a stronger trend inference ability. In addition, using the constructed BP neural network prediction model to determine case information, a time series is created for four consecutive years of raw color data from 2019 to 2022. It serves as the input feature vectors a, B, C, and D., The predicted results obtained through continuous training are shown in Fig. 8.



(a) Forecast results of the first five categories (b) Forecast results of the last five categories

Fig. 7. Prediction results of SWK-FCM and GM (1,1) based on final information.



(a) Forecast results of the first five categories (b) Forecast results of the last five categories

Fig. 8. BP neural network prediction results based on final information.

Comprehensive Fig. 8 shows that the MSE value of the BP neural network prediction model with 4-7-1 network structure for the popular color hues is between 0.000529 and 0.011025. While the MSE of the four colors, red, yellow-green, green, green-blue, and purple is of the order of 10^{-4}, and the overall MSE is 0.0036, which is about the order of magnitude of 10^{-2}. In summary, the prediction model using SEW-FCM and BP neural network is not as accurate as the GM (1,1) prediction model. But it can improve the prediction accuracy in comparison with other models. On this basis, to more comprehensively analyze the high accuracy of the prediction model of clothing fashion color built on the basis of SWK-FCM clustering algorithm, the study compares the two models built using the final case information with the prediction models built on the basis of traditional classification methods. The four models are represented by GM (1,1) (F), BP(F), GM and BP. Among them, the BP neural network uses relu as the excitation function, with a maximum number of iterations of 1000, 4 input feature vectors, 4 input layer nodes, 1 hidden node, and 1 output layer node. The minimum error of Xunyu is less than 10-4. The results are shown in Fig. 9.

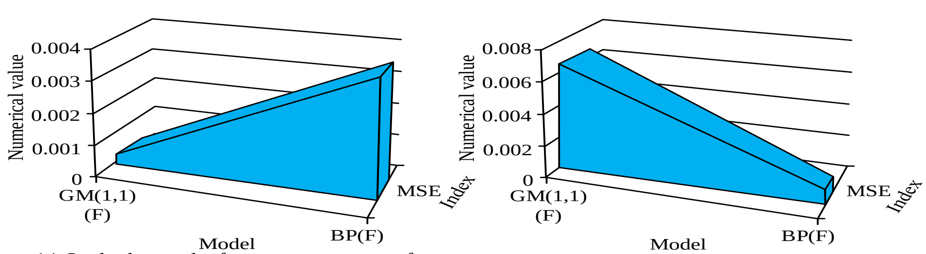
The MSE value of the GM (1, 1) prediction model using the final case information is 0.00028, while the MSE value of the BP neural network prediction model using the final case information is 0.0036. Both of them are much lower than the 0.0071 of the GM model. The GM (1, 1) prediction model is ideal, indicating that it can better predict the trend of popular colors.

Finally, to further validate the performance of the proposed SWK-FCM algorithm, a clustering algorithm using graph theory (a), a fuzzy kohlen clustering network algorithm (b), and a fuzzy covariance learning vector quantization algorithm (c) are introduced and compared with FCN (d) and SWK-FCM (e). Among them, the comparison indicators include accuracy, accuracy, recall, F1 value, and area under the curve, represented by 1-5. The results are shown in Table II.

From Table II, the algorithm proposed in the study has values of 98.95%, 98.65%, 99.01%, 99.63%, and 98.73% on indicators 1-5, respectively, which are higher than the comparative algorithms. This indicates the effectiveness and high performance of the algorithm in actual classification.

TABLE II. COMPARISON RESULTS OF DIFFERENT ALGORITHMS AND INDICATORS

-	A	B	C	D	E
1	92.41%	90.91%	95.45%	90.91%	98.95%
2	88.45%	92.34%	96.45%	89.65%	98.65%
3	90.21%	95.45%	97.11%	90.01%	99.01%
4	89.00%	93.16%	98.21%	89.51%	99.63%
5	82.06%	91.51%	94.63%	79.41%	98.73%



(a) Study the result of mean square error of fashion color prediction based on the model (b) Mean square error result of popular color prediction of contrast model

Fig. 9. Comparison results of popular color hue prediction based on final information with other models.

V. Conclusion

To achieve the prediction of the actual cutting-edge fashion information of current fashion colors, the study obtained the SWK-FCM clustering algorithm by improving the traditional FCM clustering algorithm. Meanwhile, the prediction model of GM (1, 1) and BP neural network was constructed on the basis of this clustering algorithm combined with the final case information. The performance of SWK-FCM clustering algorithm and the effect of the two prediction models were analyzed by experiments. The experimental results showed that the classification coefficients of SWK-FCM clustering algorithm under different conditions were 0.9553 and 0.9258, and the classification entropies were 0.1380 and 0.1837, respectively. The same results were presented in the actual clothing color classification. In the GM (1, 1) prediction model experiments, the MSE of the GM (1, 1) model color prediction using definite case information was in the range of 0.000004 to 0.001296, and its MSE could be as small as 10^{-6} magnitudes. In the experiments of the BP neural network prediction model, the MSE values ranged from 0.000529 to 0.011025 for the prediction of popular color shades, and the overall MSE was 0.0036, which reaches the magnitude of 10^{-2}. Among the four models compared, the mean square error value of the GM (1, 1) prediction model using the final case information was 0.00028, which is lower than the other compared models.

Overall, the SWK-FCM clustering algorithm has better classification quality, is less susceptible to noise interference in actual color classification, and can automatically classify color phases. In theory, it can also be applied to other color spaces. Among the prediction models constructed on its basis, GM (1,1) has a better prediction effect, and both can provide corresponding guidance and assistance to stakeholders in the clothing ecosystem. However, the amount of popular color finalization information selected for the study is too small, which increases the difficulty of the study. Therefore, it is necessary to increase the amount of data in the future. At the same time, the study only analyzed the hue among the three attributes of color. In the future, a comprehensive prediction of popular colors should be made based on the saturation and purity of colors.

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