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Research on the way of expressing the natural concept of the painters in Qiandongnan Region under the guidance of ecological aesthetics

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SUMMARY: *The purpose of this study is to construct a computer-aided analysis framework for exploring the expression of natural concepts in the paintings of artists in southeast Guizhou under the guidance of ecological aesthetics. This method combines multi-modal image coding, graph structural relationship analysis and semantic mapping to quantify visual structures that rely on qualitative interpretation in the past. This study establishes a dataset of 1248 digitized works by 37 representative painters, and extracts relevant features around brush stroke, texture, composition and ecological imagery. Experimental results show that the proposed framework achieves 91.6% accuracy in natural concept recognition and 88.4% consistency in pen-ink expression measurement, and there is a stable coupling relationship between natural concept and pen-ink variables. The comparative analysis further finds that there are clear differences between different groups of artists in terms of ink density, line rhythm, white space organization and composition opening and closing. This study provides a computational path for interpreting regional painting language under repeatable conditions, and also provides a stable analysis reference for artistic image computing and digital humanities research.*

KEYWORDS: *Painting image analysis; Multimodal coding; Graph neural network; Natural concept recognition*

1 Introduction

1.1 Research objectives and innovation orientation

The study of regional painting under the guidance of ecological aesthetics is not only related to the accuracy of image style description, but also related to the computable expression of natural concepts in the visual system. In the continuous depiction of mountain landscape, forest and water structure, village form and national life scene, the painting group of Qiandongnan regional painters has formed a brush and ink organization mode with regional identification. Traditional interpretation is mainly based on aesthetic experience, schema comparison and case review, which can reveal the meaning of the work, but rarely puts the natural concept, formal structure and ink variables into a unified analysis framework. In the research context of technical journals, the relevant content needs to be transformed into digital objects that can be collected, coded, and compared, so as to form a research path with both artistic interpretation power and computational verifiability.

Dobbs et al. studied the discrimination mechanism of residual neural network in art authenticity recognition [1]. Frank et al. proposed a sketch analysis, attribution and

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authentication method based on convolutional neural network [2]. Hung et al. studied artistic style learning and its psychological evaluation process under the condition of artificial intelligence [3]. Lin et al. proposed a multi-selection method system for image artistic rendering [4]. Sun et al. studied the cognitive differences between artists' works and style transfer results [5]. On this basis, this study takes the ecological imagery, composition order, linear rhythm, ink color hierarchy and white space relationship in the works of painters in Qiandongnan region as the joint analysis object, and constructs a research program that combines the computational representation of natural concepts, multi-modal feature extraction, graph structure correlation analysis and expression mapping interpretation. In order to realize the quantitative identification, group comparison and semantic interpretation of the expression of ink, and provide a reproducible calculation basis for the research of regional painting numbers.

The research aims at two levels: one is to translate the natural perception, life connection and spatial ethics in ecological aesthetics into trainable visual semantic units; the other is to translate brush density, textural rubbing form, ink diffusion, boundary trend and picture opening and closure degree into structural indicators. The innovation orientation is not to replace artistic judgment, but to establish a computational analysis framework that can support cross-work measurement, cross-author clustering and cross-semantic correspondence, so that the ink and pen expression of natural concepts can obtain more stable and clear evidence support.

1.2 Research ideas on the expression of natural concepts in ink and calligraphy

The research idea of the expression of natural concept in ink and calligraphy needs to link the interpretation of ecological aesthetics with the calculation of painting images, so as to make the perception of landscape, spatial order and life meaning in the works of artists in Qiandongnan region into an analysiable technical framework. This study does not focus on the perceptual description of a single work, but converts brush shape, ink level, white space distribution, scene relationship and picture rhythm into trainable and comparable visual units.

Choi has studied the use of second-order feature statistics in arbitrary image style transfer [6]. Han et al. proposed an artistic image style transfer method based on deep extraction generative adversarial networks [7]. Liu et al. studied a coarse-to-fine structure-aware artistic style transfer mechanism [8]. Wu et al. proposed a restoration method of tomb mural fragments based on dual attention generation network [9]. Deng et al. studied the double-branch restoration model of ancient murals guided by structural information [10].

On this basis, this paper firstly conducts high-precision digital collection of representative works of painters in Qiandongnan region, and combines mountain landscape, forest and water form, village imagery and ecological scene to complete semantic annotation. Then, convolution representation, texture response, edge trend and regional co-occurrence relationship are used to extract ink and pen expression features, and graph structure is used to connect natural image units and formal organization units. Finally, mapping analysis is used to measure the differences in the expression of natural concepts among different authors, different subjects and different picture layouts, so as to form interpretable and repeatable computational correspondences among ecological semantics, ink structure and group style, and establish a stable digital analysis path for regional painting research.

The core of this idea is not to weaken artistic judgment, but to transform empirical feelings of ink into statistically significant measurement results. In the process of research, natural affinity, environmental rhythm and spatial echo in ecological aesthetics are decomposed into indicators such as scene density, contour curvature, ink diffusion range and composition opening and closing degree. For group-level comparison, the interpretation is completed by clustering results, similarity distribution and association strength. The research link formed in this way not only maintains the integrity of the connotation of the subject matter and the expression of regional culture, but also establishes a clear calculation basis for subsequent identification, classification and result analysis, so as to ensure that the corresponding relationship between technical paths and artistic objects is more stable.

2 Related work

After digital technology entered art research, the collection, recognition, comparison and interpretation of painting images gradually formed an interdisciplinary research link. Compared with general image classification tasks, regional painting research under the guidance of ecological aesthetics emphasizes the synchronous presentation of natural imagery, ink structure, and cultural semantics. Therefore, the review of related work cannot stay at the level of style recognition or work retrieval, but also needs to pay attention to the technical progress of image reconstruction, visual narrative modeling, authenticity discrimination, and semantic mapping. Kumar et al. studied the restoration method of damaged artworks based on generative adversarial networks, and maintained the texture and color continuity of the picture by reconstructing the missing areas [11]. Basu et al. proposed a survey framework of data-driven computing for digital restoration of cultural heritage, and systematically summarized image restoration, visual reconstruction and intelligent analysis paths [12]. Imran et al. studied a painting style recognition method combining deep and shallow neural networks, so that the classification of works established a more stable discriminant relationship between local texture and overall style [13]. Dobbs et al. proposed a large-scale classification method for contemporary art authentication, which combined high-dimensional visual features with work attribution recognition [14]. Amelio et al. studied the digital twin modeling of cultural heritage and the visual narrative expression of Mona Lisa, providing a new technical reference for the hierarchical representation of complex artistic objects [15].

The above studies show that artistic image computing has been extended from single recognition to multiple directions such as restoration, authentication, reconstruction and narrative expression, and the description of visual information has also developed from two-dimensional texture extraction to structural relationship organization. For the painting group of Qiandongnan regional painters, the concept of nature does not only exist in the scenery theme, but also is reflected in the overall synergy of ink intensity, line turning, space blank, scene echo and composition opening and closing. Therefore, the focus of related work should be on the computational model that can not only recognize the formal characteristics of images, but also maintain the semantic level of art.

In recent research, image generation, color reconstruction and visual inspection techniques have further promoted the refinement of art analysis. Parvathaneni et al. studied the deep learning method of digital color reconstruction of Van Gogh paintings by using the unexposed area of the frame edge, so that the color recovery of historical works can achieve higher consistency [16]. Mishra et al. proposed a research review on artificial intelligence assisted visual inspection of cultural heritage, and summarized the process of target recognition, surface damage detection and visual assessment [17]. Smith et al. studied the computer vision method of using machine learning to distinguish the authentic and imitations of Jackson Pollock, and improved the local pattern recognition ability by slice-driven strategy [18]. Zeng et al. proposed a painting authentication method based on multi-scale spatial-spectral feature fusion and convolutional neural network, so that the brush texture and color layer information can be jointly described [19]. Du et al. studied a Chinese painting style classification model based on multi-layer aggregation convolutional neural network, and achieved good adaptation effects in stroke level and screen layout recognition [20]. These results show that the current art image computing has the technical foundation from pixel restoration to style classification, from local texture to structure recognition. The contents shown in Table 1 summarize the above research paths.

Table 1: Artistic image computing related research paths and directions for reference in this paper

Research Literature	Main Content	Computational Method	Relevance to This Study
[11]	Damaged artwork restoration	GAN-based reconstruction	Can provide ideas for texture recovery in missing brush-and-ink regions
[12]	Review of digital restoration for cultural heritage	Data-driven computation	Can serve as a reference for a multimodal image analysis framework
[13]	Painting style recognition	Fusion of shallow and deep networks	Helps support the joint discrimination of brush-and-ink hierarchy and overall style
[14]	Contemporary art authentication	Large-scale classification	Can provide reference for attribution and difference identification among grouped works
[15]	Digital twin narrative modeling	Visual narrative representation	Can support hierarchical expression modeling of natural concepts
[16]	Painting color reconstruction	Deep learning-based reconstruction	Can assist the restoration analysis of ink hierarchy and tonal relationships
[17]	Review of visual inspection	AI-based visual inspection	Can be used for computational analysis of pictorial structure and surface details
[18]	Distinction between authentic works and imitations	Machine learning + patch-based vision	Can provide reference for fine-grained analysis of local brushstroke patterns
[19]	Painting authentication	Multi-scale spatial-spectral fusion CNN	Can be used for joint representation of brush-and-ink textures and color layers
[20]	Chinese painting style classification	Multi-layer aggregated CNN	Can directly support the task of regional painting style recognition

It can be seen that the generative model is more suitable for the repair and reconstruction tasks, the categorical model is more suitable for the style recognition and authentication tasks, and the fusion model is more conducive to connecting the visual form and semantic level. For the regional paintings in Qiandongnan discussed in this paper, the natural concept is often conveyed through mountain fluctuation, river system spreading, tree-stone relationship and blank rhythm. It is difficult to completely carry over the ecological meaning in ink organization by relying solely on color statistics or single-layer convolution features. Based on this, the function of related work in this paper is not only to provide a general algorithm reference, but more importantly to establish a computable analysis premise for the composite object of "natural concept, ink structure, and group difference". On the basis of absorbing the above research results, this paper combines multi-modal feature coding, graph structure relationship analysis and mapping measurement, and unifies the natural concept expression in the painting group works of artists in Qiandongnan region. The feature analysis stage focuses on texture intensity, edge trend, ink distribution and scene relationship simultaneously. In the result interpretation stage, the clustering structure, similarity distribution and semantic response are linked, thus forming a research path that takes into account both calculation accuracy and artistic interpretation power. This research path not only continues the focus of technical journals on models, data and indicators, but also enables regional painting research to obtain a more stable comparison scale and clearer expression boundary in the digital context, which provides a consistent reference for group comparison in subsequent results analysis.

3 Research Methods

3.1 Computational representation mechanism of ecological aesthetic semantics and natural concept

The computational representation of ecological aesthetics semantics and natural concept needs to transform mountains, rivers, trees, terraces, villages and cloud and fog blank in southeast Guizhou regional paintings into comparable visual semantic units. Single object detection is difficult to fully explain the ecological relationship between them, so the representation process cannot stay at the level of scene recognition. It is also necessary to integrate spatial order, scene dependency, and pen and ink carrying relationships into a unified semantic space. Painters in Qiandongnan often form an overall landscape order through the connection of mountains and rivers, the interdependence of forests and villages, and the mutual loan of virtual and real in the picture organization. To this end, this paper divides the screen into three types of regions: scene nodes, structure nodes and semantic nodes, and establishes a unified representation function. At the same time, semantic segmentation and manual review are combined to ensure that the mountain boundary, forest water boundary and blank range are consistent in the annotation stage. The calculation of regional ecological intensity is shown in Formula (1):

$$S_i=\alpha_1 T_i+\alpha_2 E_i+\alpha_3 C_i \tag{1}$$

where S_i represents the ecological semantic strength of the i region; T_i represents the saliency of natural subject; E_i represents the dependency, shading and transition responses within the region. C_i represents the regional culture correction term; The coefficients α_1 to α_3 are the learnable coefficients. This formula is used to upgrade the object recognition results to natural concept responses, and establish a direct relationship between the category information of the scene and the ecological significance.

There is also a hierarchical order composed of short view, medium view and long view inside the picture, so this paper further establishes the weight of regional relations. Its definition is given in equation (2):

$$R_{ij}=e^{-\|p_i-p_j\|_2^2/\sigma_p^2}\cdot e^{-\|f_i-f_j\|_2^2/\sigma_f^2}\cdot(1+\beta d_{ij}) \tag{2}$$

Here, R_{ij} represents the ecological association strength between region i and j; p_i and

p_j denote the spatial position. f_i, f_j represent the joint texture, ink, and edge features; σ_p and σ_f denote the scale parameters; d_{ij} denotes the depth of field direction consistency; Let β denote the direction weight. At the same time, this formula maintains two types of relations: space adjacency and ink similarity, which is conducive to expressing the level of landscape and the echo relationship of scenery.

In order to reflect the coordination state of the whole work in density, virtual reality, opening and closing, this paper defines the global equilibrium value, as shown in Formula (3):

$$B=\frac{1}{N}\sum_{i=1}^{N}S_i-\frac{1}{|E|}\sum_{(i,j)\in E}\left|R_{ij}-\bar{R}\right| \tag{3}$$

where, B represents the ecological equilibrium value; N denotes the number of regions; E denotes the set of relation edges; $\bar{R}$ represents the average association strength. The higher the index is, the more stable the natural semantic distribution and relationship organization are, which is suitable for subsequent natural concept classification and group comparison.

Subsequently, we project regional semantics, structure propagation results, and local pen-and-ink representations into a unified semantic space. The projection process is shown in Equation (4):

$$z_i=W_s[S_i;g_i;h_i]+b_s \tag{4}$$

where z_i stands for semantic embedding; W_s and b_s denote the projection parameters; g_i represents the structural features of the graph after propagation. h_i represents the ink feature after convolutional encoding. [ ] represents the concatenation operation. This formula ensures that works of different authors and different subjects can be compared at the same scale, and makes regional semantics, structural context and ink details enter a unified coordinate.

In the training phase, in order to enhance the aggregation of similar natural concept samples, the semantic constraint loss is set, as shown in Formula (5):

$$L_s=\sum_{(a,p,n)}\max\left(0,m+\|z_a-z_p\|_2^2-\|z_a-z_n\|_2^2\right) \tag{5}$$

Here, L_s stands for semantic constraint loss; z_a, z_p and z_n denote anchor sample, positive sample and negative sample embeddings, respectively. Let m denote the interval constant. This loss compresses the distance between close natural ideas and expands the boundary of differential expression.

After the above processing, the landscape layout, ecological connection and ink rhythm are organized as a unified computational representation link, which provides a stable calculation basis for subsequent sample database construction and mapping analysis, and facilitates cross-author comparison, and is more robust overall.

3.2 Digital collection and database construction principle of painting samples of painters in Southeast Guizhou

The digital collection and database construction of painting samples of painters in Qiandongnan region not only requires the preservation of the picture content of the works, but also requires the stable preservation of ink color hierarchy, paper texture, boundary direction and theme semantics in the collection stage. If the acquisition conditions fluctuate too much, the subsequent model is easy to misjudge the illumination difference or material reflection as the ink difference. Therefore, this paper adopts the acquisition scheme of unified illumination, fixed focal length and hierarchical color card calibration. Color correction after acquisition adopts linear mapping, whose form is shown in Formula (6):

$$I_c = A \cdot I_r + b \tag{6}$$

Here, I_c represents the corrected image vector; I_r represents the original acquisition vector. A represents the color transformation matrix; b denotes the bias vector. This formula is used to correct the hue offset at different times and different devices, so that the ink color is consistent with the white margin.

After color correction, it is necessary to unify the image scale to avoid the interference of amplitude size and scanning resolution in feature extraction. The scale normalization process is shown in Equation (7).

$$I_n(x,y) = I_c\left(\lfloor x/s_x \rfloor, \lfloor y/s_y \rfloor\right) \tag{7}$$

where I_n represents the normalized image; s_x and s_y denote the horizontal and vertical zoom ratios. $\lfloor \cdot \rfloor$ denotes the rounding operation. This formula makes works of different sizes enter a unified resolution space, which is convenient for subsequent convolutional coding and region segmentation.

In the sample storage stage, we establish a five-layer index of "author-subject-time-scene-label-ink attribute" for each work, and calculate the sample quality score by combining local clarity, edge integrity and semantic interpretability. In addition, the samples are stored in three levels: main map, local map and texture block. The main map retains the composition relationship, the local map retains the scene connection, and the texture block highlights chapping, ink splashing and dry and wet change. The quality evaluation is shown in Equation (8):

$$Q_k = \gamma_1 L_k + \gamma_2 B_k + \gamma_3 M_k \tag{8}$$

Here, Q_k represents the quality score of the k image; L_k represents local sharpness; B_k denotes edge integrity; M_k stands for semantic interpretability; γ_1 to γ_3 are the weighting coefficients. This formula is used to filter the samples with serious out-of-focus, color cast or occlusion to ensure that the database has high analysis reliability.

Due to the unbalanced number of retained works by different authors, this paper also introduces sample weights in the training set construction stage to reduce the impact of class skew. The weights are calculated as shown in Equation (9):

$$w_k = \left(\frac{1}{n_{c(k)}}\right) \log\left(1 + \frac{N}{n_{c(k)}}\right) \tag{9}$$

where w_k denotes the training weight of sample k; $n_{c(k)}$ is the number of samples in the class to which sample k belongs. N represents the total sample size of the database. This formula can improve the participation of few-sample authors and few-sample topics in the training process, so that the group comparison results are not dominated by high-frequency categories.

According to the above process, the database is finally composed of five parts:

high-resolution original image, normalized image, local slice, semantic annotation file and attribute index table. The files are saved in lossless format, the metadata fields are uniformly encoded, and the version number and source tag are added to facilitate subsequent retrieval, batch reading and cross-model reuse. Before storage, each work undergoes two rounds of manual review and one program verification, and the semantic annotation covers mountains, water bodies, trees, villages, roads, clouds and fog, terraces and blank areas. When the database is divided, the synchronization constraint of author identity and genre is applied to avoid highly similar works by the same author from entering the training set and the test set at the same time. The sample library established in this way not only retains the content integrity of regional paintings, but also provides a stable data foundation for subsequent ink recognition, relationship modeling and mapping analysis.

3.3 Principle of multimodal coding and recognition of ink expression features

The recognition of ink and pen expression features cannot only rely on gray statistics or single path convolution results. Painters in southeast Guizhou often organize linear outline, ink color stacking, dry and wet conversion and blank rhythm into expression units when they represent rocks, trees, water vapor and villages. Therefore, this paper adopts a multi-modal scheme of joint coding of texture, edge, regional relationship and semantic label. The basic representation of the local texture response is given in Equation (10).

$$t_i=\mathrm{Conv}(X_i;W_t)+\mathrm{Pool}(X_i) \tag{10}$$

Here, t_i denotes the texture vector of the ith local patch. X_i represents the input image patch; W_t represents the convolution kernel parameters; $\mathrm{Conv}(\cdot)$ denotes convolutional extraction; $\mathrm{Pool}(\cdot)$ represents the pooling aggregation. This formula is used to extract local information such as texturing density, percolation range and texture.

The stroke direction and contour trend determine the operation mode of the screen qi pulse, so this paper further constructs the edge direction coding. Its expression is given in Equation (11):

$$d_i=\mathrm{softmax}\left(W_d[H_i^0;H_i^{45};H_i^{90};H_i^{135}]+b_d\right) \tag{11}$$

where d_i represents the directional distribution vector; H_i^0, H_i^{45}, H_i^{90} and H_i^{135} represent the gradient responses in the four directions, respectively. W_d and b_d denote the mapping parameters. This formula is used to measure whether the stroke is mainly spread horizontally, vertically, slanting in or turning, so as to capture the linear organizational characteristics.

The ink color level is not a uniform gray distribution, but a nonlinear diffusion process composed of thick, light, focal and broken states. In order to describe this process, this paper sets the ink diffusion index, as shown in Formula (12):

$$u_i=\eta_1\mathrm{Var}(G_i)+\eta_2(1-\rho_i)+\eta_3A_i \tag{12}$$

where u_i represents the ink diffusion index of the i region; $\mathrm{Var}(G_i)$ represents the grayscale variance; Let ρ_i denote the local structural coherence; A_i represents the proportion of edge blurred area; η_1 to η_3 are the weight coefficients. This formula can distinguish the different states of strong pen, wet ink halo and layer on layer.

After the texture, orientation and ink coding are completed, the cross-modal attention mechanism is used to complete the joint representation. The fusion process is shown in

Equation (13).

$$m_i=\mathrm{Attn}(Q_i,K_i,V_i)=\mathrm{softmax}\left(\frac{Q_iK_i^T}{\sqrt{d}}\right)V_i \tag{13}$$

Here, m_i represents the fused multimodal representation. Q_i, K_i and V_i are obtained by linear transformation of texture vector, direction vector and ink vector, respectively. d denotes the feature dimension. This formula can adaptively adjust the contribution ratio of each modality in different works, so that the features such as thick pen, light ink and large white space maintain reasonable weights when fused.

In the final recognition stage, the joint discriminant function is used to output the ink expression type. The classification result is shown in equation (14):

$$\hat{y}_i=\arg\max \mathrm{Softmax}\,(W_o[m_i;r_i;s_i]+b_o) \tag{14}$$

where $\hat{y}_i$ represents the category of ink expression of the region or the work; W_o and b_o denote the output layer parameters; r_i represents regional relationship features. s_i represents the semantic feature. This formula combines local ink information, structural relations and ecological semantics to complete the discrimination.

Through the above processing, the system can not only identify the arrangement of shading, the rhythm of lines and the organization of white space, but also distinguish the ways in which natural concepts are carried in different authors 'works, which makes the pen-ink analysis transform from perceptual description to computational recognition with comparable scale.

3.4 The graph structure analysis method of the relationship between the natural concept of the painting group and the organization of ink

The graph structure analysis of the relationship between the natural concept of the painting community and the ink organization does not regard each work as an isolated static image, but organizes the author, the work, the scene unit, the ink fragment and the semantic label into a heterogeneous relationship network. Painters in southeast Guizhou usually form a relatively stable expression paradigm through repetitive brushwork rhythms and spatial echoes when they express mountain layering, forest and water interweaving, village dwelling and cloud and fog blank. It is easy to cut off the connection between the natural concept and the overall organization if the interpretation is only based on the local texture of a single work. In order to maintain comparability at the group level, this paper constructs five types of nodes: author-works-scene-ink-semantics based on the sample database, and takes theme co-occurrence, composition adjacency, ink color similarity and stroke transition consistency as the main edge types. The composition of nodes is shown in Table 2.

Table 2: Graph node composition and attribute description

Node Type	Node Content	Main Attributes	Analytical Role
Author node	Individual painter	Creation period, thematic preference, ink usage habit	Represents the expressive source at the group level
Work node	Individual painting work	Format, composition type, pictorial density	Represents the work-level organizational unit
Scene element node	Mountains, water, forests, villages, fields, clouds and mist	Category label, area, position, hierarchy	Represents the objects carrying natural concepts
Brush-and-ink node	Line segments, texture-stroke areas, ink masses, blank spaces	Direction, intensity, density, diffusion degree	Represents the carrier of formal expression
Semantic node	Tranquility, flow, aggregation, openness, profundity	Semantic intensity, response threshold	Represents ecological perception categories

In the process of graph structure modeling, the local ink in a single work no longer exists as an isolated texture, but returns to the overall relationship of the author group, the scenery combination and the natural concept. The establishment of edge relationship follows the principle of local first and global second: the scenes and ink fragments with spatial adjacent relationship are preferentially connected within the same work, and the cross-graph connection between different works is established based on semantic similarity and style proximity. The decision rules for edge relations are shown in Table 3.

Table 3: Edge relation determination rules

Edge Type	Connected Objects	Determination Basis	Weight Source
Thematic co-occurrence edge	Work–scene element	Co-occurrence within the same work	Co-occurrence frequency
Compositional adjacency edge	Scene element–scene element	Spatial adjacency and similar hierarchy	Distance and depth of field
Ink-tone similarity edge	Brush-and-ink–brush-and-ink	Similar grayscale distribution and diffusion pattern	Ink-feature distance
Turning consistency edge	Brush-and-ink–brush-and-ink	Similar line direction and curvature variation	Directional consistency
Semantic proximity edge	Scene element/work–semantic	Similar semantic response values	Semantic matching probability
Author inheritance edge	Author–work	Author affiliation relationship	Fixed weight

In order to make different nodes absorb both the neighboring ink information and the cross-work semantic information during the propagation process, we adopt a weighted propagation mechanism to update the node status. The node update is calculated as shown in Equation (15):

$$h_i^{(l+1)}=\sigma\left(\sum_{j\in N(i)} e_{ij}\, W_r h_j^{(l)}+W_s h_i^{(l)}\right) \tag{15}$$

where $h_j^{(l)}$ denotes the state vector of node i in layer l;N(i) is the set of neighborhoods connected to node i. Let e_{ij} denote the relationship weight of edge (i,j). W_r stands for relational transformation matrix; W_s stands for self-connected transformation matrix; Let $\sigma(\cdot)$ denote the nonlinear activation function. This formula is used to write the neighborhood propagation information and the node's own attributes into the next layer representation, so that the structure propagation can not only maintain the original semantics, but also absorb the context.

After the relationship aggregation is completed, this paper further calculates the belonging probability of nodes to the whole natural concept cluster, which is expressed as Formula (16):

$$p_{ic}=\frac{\exp\left(-\|z_i-\mu_c\|_2^2/\tau\right)}{\sum_{c'=1}^{C}\exp\left(-\|z_i-\mu_{c'}\|_2^2/\tau\right)} \tag{16}$$

Here, p_{ic} represents the probability that node i belongs to the natural concept cluster of class c. z_i denotes node embedding; μ_c denotes the center of the c cluster. C represents the total number of natural concept clusters; Let τ denote the temperature coefficient. This formula is used to measure the semantic similarity degree of different works and different scenery combinations in the group network, and provides a unified scale for subsequent author group division and expression comparison.

In the concrete implementation, the author node records the creation age, theme preference and ink habit, the work node records the style, composition type and screen density, the scene node records the mountain, water, forest, village, field, cloud and fog and other objects, and the ink node records the linear direction, tex-brush intensity, shading level and blank proportion. Semantic nodes correspond to ecological perception tags such as quiet, flow, aggregation, stretch, and deep. In order to avoid the bias of high-frequency topics on the overall network, this paper adopts degree normalization for the high-density nodes of mountains and waters, and retains higher update weights for the few sample author nodes. The network obtained in this way can not only present the internal organizational logic of a single work, but also present the expression transfer trajectory at the group level, so that the ecological meaning of regional paintings can be stably described and compared at the structural level.

3.5 Mapping analysis method between natural concept and ink expression

The mapping analysis between natural concept and ink expression does not directly convert the recognition results into aesthetic judgment, but establishes the corresponding channel between semantic variables and ink variables based on the relationship between computational representation and graph structure. When dealing with natural subjects, painters in Qiandongnan often write the heaviness of mountains, the flow of water, the growth of trees and the stability of villages into different line rhythms and ink color arrangements. In order to enable these contents to be systematically interpreted, this paper constructs a two-way mapping framework of "natural concept vector - ink expression vector" based on the above node embedding and multi-modal features. The overall mapping process is shown in Fig. 1.

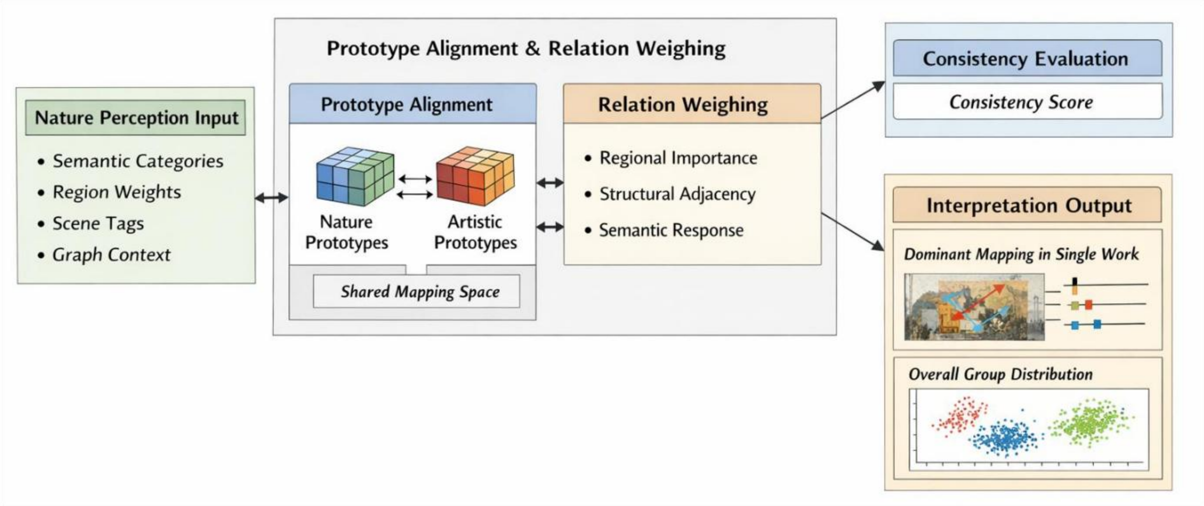

Figure 1: The flow chart of the mapping between nature concept and ink expression

In the mapping stage, the natural concept category, region weight and graph structure context are received firstly, and then prototype alignment, relationship weighting and consistency calculation are completed. Finally, two kinds of results are output: work-level interpretation and group-level interpretation. In order to measure the closeness between natural semantics and pen-and-ink forms, we define a coupling strength function. The mapping strength is calculated as shown in Equation (17).

$$M_{ab}=\exp\left(-\|u_a-v_b\|_\Sigma^2\right) \tag{17}$$

Here, M_{ab} represents the mapping strength between type a natural concept and type b ink expression. u_a represents the natural concept prototype vector; v_b represents the pen and ink representation prototype vector; Σ represents the collaborative weight matrix; $\|u_a-v_b\|_\Sigma^2=(u_a-v_b)^T\Sigma(u_a-v_b)$ denotes the weighted distance. This formula is used to measure the closeness between the concept of nature and the expression of ink in a unified weighted space, so that the semantic categories such as quiet, flow, and aggregation can be quantitatively corresponding to the formal states such as light ink disperseness, directional traction, and dense deposition.

After obtaining the mapping relationship between various types of prototypes, it is also necessary to judge whether the correspondence of different regions inside a single work is stable. To this end, this paper further sets the mapping consistency score, which is expressed as Formula (18):

$$C_k=\frac{\sum_{i=1}^{n_k}\omega_i\ M_{(y_i,\hat{y}_i)}}{\sum_{i=1}^{n_k}\omega_i} \tag{18}$$

where C_k represents the mapping consistency of the k work; $M_{(y_i,\hat{y}_i)}$ represents the mapping value between the real semantic category of the region and the predicted ink category. ω_i denotes the region importance; n_k denotes the number of regions in work k. This formula is used to integrate the corresponding situation of different local areas and measure whether the internal natural concept and ink expression of the whole work are consistent. The higher the value, the more concentrated and clear the internal expression link of the work.

After completing the initial alignment of the natural concept prototype and the pen-and-ink expression prototype, the system continues to enter the mapping refinement process, whose specific process is shown in Fig. 2. The process consists of five steps: regional feature input, local mapping calculation, weight correction, works-level summary and group-level output. The region feature input layer receives information such as scene semantics, stroke direction, ink level and white space ratio. The local mapping calculation layer generates the initial mapping value. The weight correction layer adjusted the results by combining the region area, structure position and semantic response strength. The works-level aggregation layer forms the consistency score and dominant expression path of a single work. The group-level output layer counts the mapping center, discrete distribution and relationship feature information values of different authors and subjects.

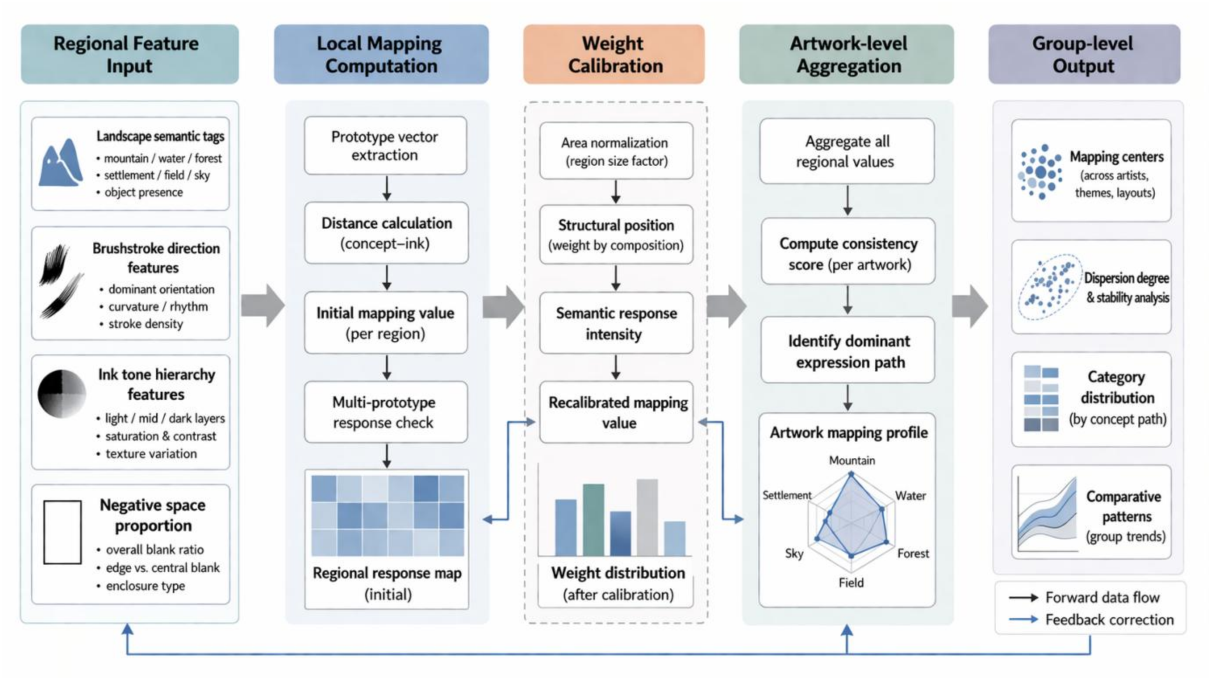

Figure 2: Flowchart of hierarchical summary of mapping results between natural concepts and pen-and-ink expression

In the specific analysis, the system outputs both the local interpretation within a single work and the overall comparison between groups of authors. For a single work, the dominant correspondence is extracted according to the regional mapping matrix, and the natural concept is mainly carried by which ink features. For the author group, we systematically compare the common trends and different paths of different authors in the expression of landscape, forest, cloud and village according to the mapping center and dispersion degree. In order to avoid a single high-response region dominating the judgment of the whole work, this paper adds a local balance constraint in the mapping summary, and uses a soft label writing method for the fuzzy boundary region. In this way, the occasional changes of the local scene will not interfere too much with the overall mapping results, and the real differences in the expression habits of the author groups can be more clearly revealed. This path not only maintains the stability of the model output, but also retains the sense of hierarchy and continuity of artistic semantics in the interpretation stage, so that the group comparison in the subsequent result analysis has a more consistent reference.

4 Results and analysis

4.1 Experimental sample setting and evaluation index analysis

In order to ensure the comparability of the natural concept recognition and ink expression analysis results of regional painter groups, the sample source, image specification, annotation method and evaluation scale are uniformly set in the experimental stage. In the experiment, 1248 paintings by 37 representative painters in southeast Guizhou are selected, and the samples cover major natural images such as mountains, rivers, trees, villages, terraces, clouds and fog, and three common types of paintings such as manual pages, vertical axes and banners are retained. After high-precision digital acquisition, all images are uniformly converted to 2048×2048 resolution, and verified one by one according to the theme label, composition level and ink structure.

Then, according to the principle of author independence, the samples were divided into training set, validation set and test set, including 872 images in training set, 188 images in validation set and 188 images in test set, so as to avoid similar works by the same author entering different data subsets at the same time. During the experiment, the scene semantics, line direction, ink level, whitespace ratio and region adjacency are recorded synchronously, and the local slice and the whole image label are written into the index library.

Three types of core indicators are set in the evaluation stage. The first is the recognition accuracy of natural concept, which measures the model's ability to distinguish ecological semantic categories such as quiet, flow, aggregation, stretch and secluding. The second is the consistency of pen and ink expression, which measures the degree of overlap between the system output and the manual annotation in stroke rhythm, shading configuration, and composition opening and closing. The third is the mapping stability coefficient, which is used to measure the correspondence stability between natural concepts and ink features in cross-work comparisons. In addition to the above indicators, the experiment also counted the region-level recall value, class equilibrium value and group distribution deviation, which were used to assist in analyzing the force direction of different author samples in the recognition process.

All the tests are completed in a unified computing environment, and the training end uses Python 3.11 and PyTorch 2.2. The graph structure analysis and mapping interpretation module runs three times under the same batch of parameters, and the average result is used as the basis for subsequent comparison. At the same time, the missing boundaries and low contrast regions are manually checked to ensure that the evaluation results are not disturbed by abnormal samples and the output is stable.

4.2 Identification of natural concepts of regional painters and measurement results of ink expression

In the test sample, the system completed two tasks: natural concept recognition and ink expression measurement. The overall results show that the distribution of all kinds of samples in the unified mapping space is relatively stable, and the five types of natural concepts show clear boundary characteristics in most works. Line rhythm, ink level, white space organization and composition opening and closing also show good distinguishing effects, which indicates that the multi-modal coding, graph structure propagation and mapping analysis paths constructed in the previous section can better carry on the ecological semantic and formal information in the works of painters in southeast Guizhou region. Different authors, different subjects and different style books maintain a relatively stable output state in the test stage, which shows that the model has a relatively stable recognition and analysis ability under the condition of cross-sample measurement.

As shown in Fig. 3, the main diagonal recognition responses of the five types of natural concepts in the test set remain above 0.90, and the recognition accuracy of quiet class is 93.2%, flowing class is 90.8%, aggregation class is 91.1%, expansive class is 92.4%, and deep class is 90.5%. There was 4.1% cross response between quiet class and expansive class, 5.3% adjacent confusion between deep class and aggregate class, and the misjudgment ratio of other classes was controlled within 3.0%.

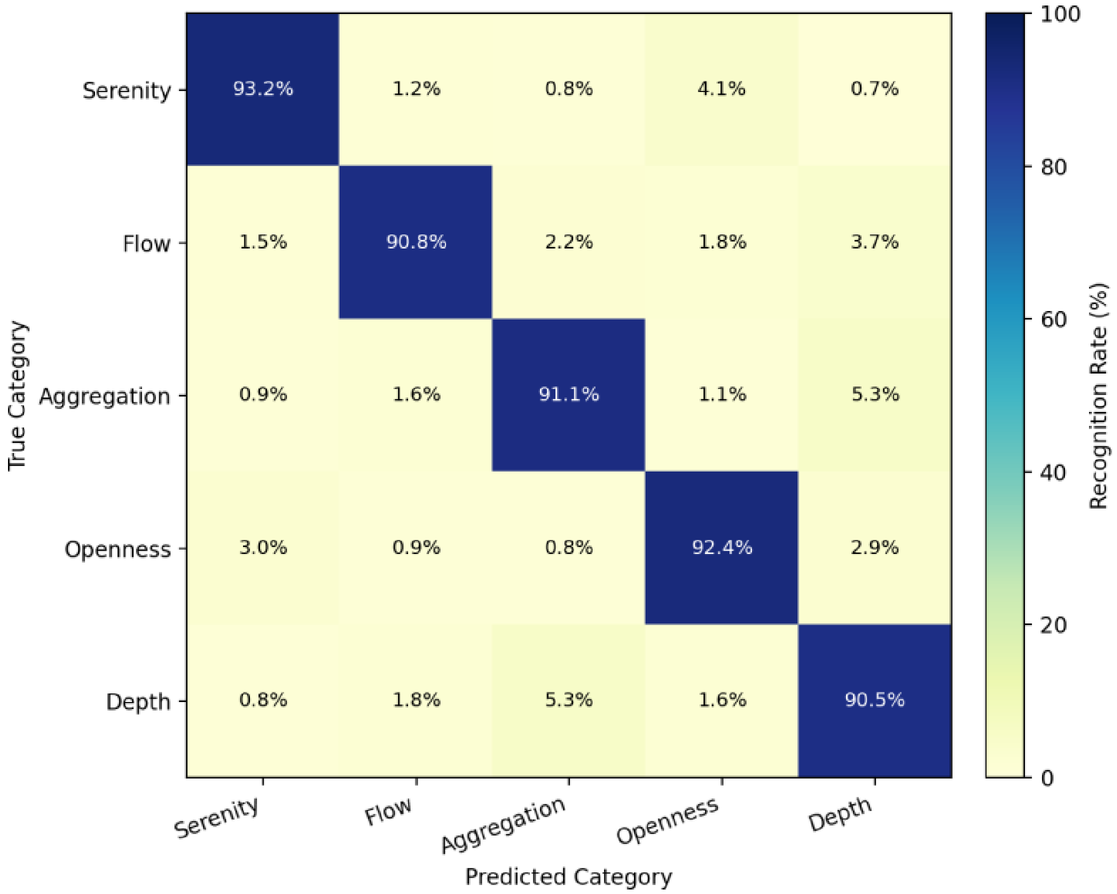

Figure 3: Confusion heatmap for natural concept category recognition

The distribution shows that there are still local overlaps between samples with similar screen opening and closing degree or similar ink layer, but the overall discrimination of ecological semantic differences has been relatively stable, especially in the compound scene of mountains, trees and villages, the category responses maintain high consistency.

As shown in Fig. 4, the pen-ink expression features form a clearer cluster boundary in the embedding space. The accuracy of shading configuration recognition is 89.1%, the accuracy of line direction recognition is 87.9%, the accuracy of white space organization recognition is 88.6%, and the consistency of ink expression is 88.4%. The average distance of the samples within the class was 0.18, and the center distance between the classes was 0.43. The quiet class was mainly distributed in the high blank and low diffusion area, the aggregation class was concentrated in the high density and high level area, the flow class was spread along the continuous strip area with strong direction traction, and the stretch class fell more in the outer edge area with high opening and closing degree of the composition.

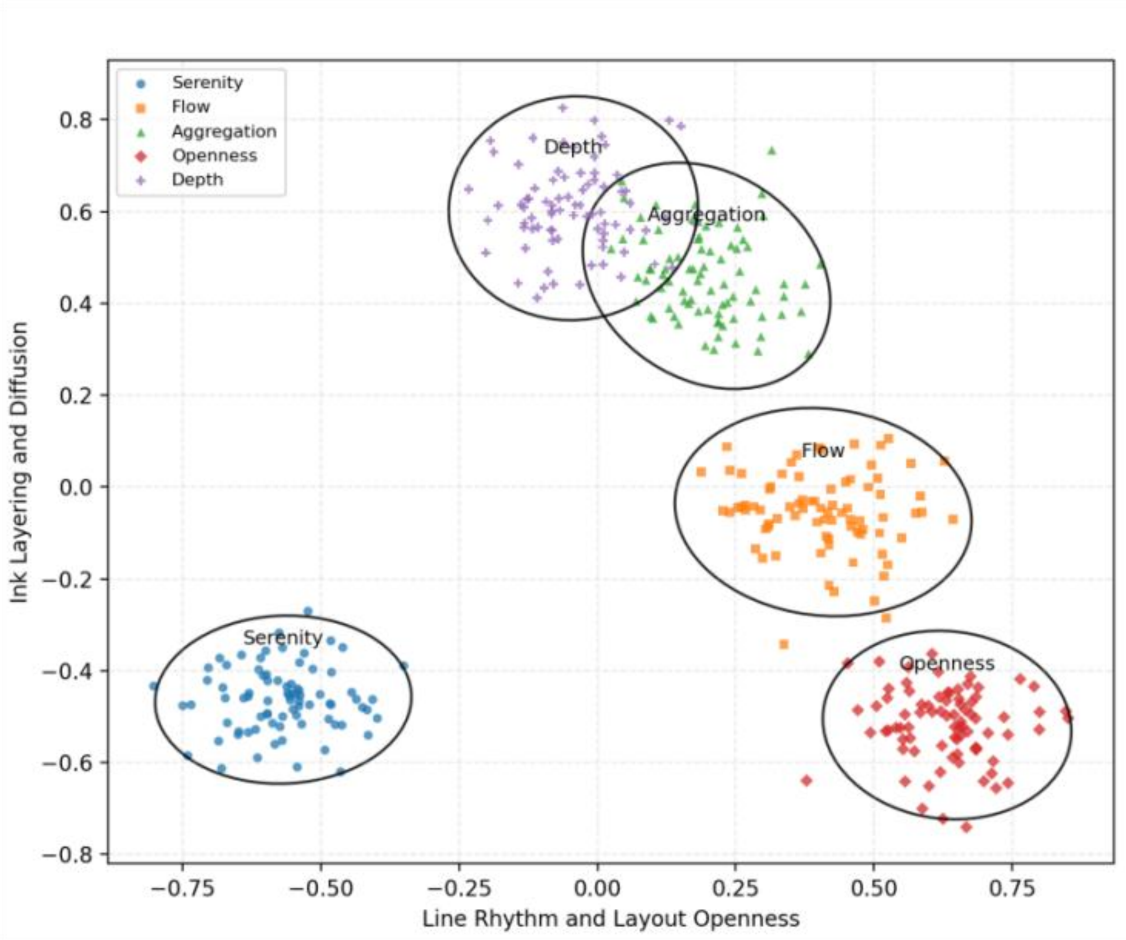

Figure 4: Spatial distribution map of pen-ink expression feature embedding

The results show that when painters in Qiandongnan deal with natural themes, the organization of ink and brush is not a random combination of discrete distribution, but a computable spatial aggregation relationship formed around a relatively stable expression paradigm. Although there are differences in local brush stroke density among different author samples, there is no obvious drift in the overall cluster center.

As shown in Fig. 5, the natural concept categories and the pen-ink variables show a relatively stable correspondence. The average mapping strength is 0.89 for quiet class, 0.86 for fluid class, 0.91 for aggregate class, 0.88 for stretch class, and 0.82 for deep class. The high response area of the main diagonal accounted for 72.4% of the total matrix area, and the high response area of the non-main diagonal mainly appeared between the deep class and the aggregation class. In terms of local areas, the average confidence of mountain outline, forest junction and village boundary are 0.92, 0.88 and 0.90, respectively, and the average confidence of water blank and cloud fog transition area is 0.85.

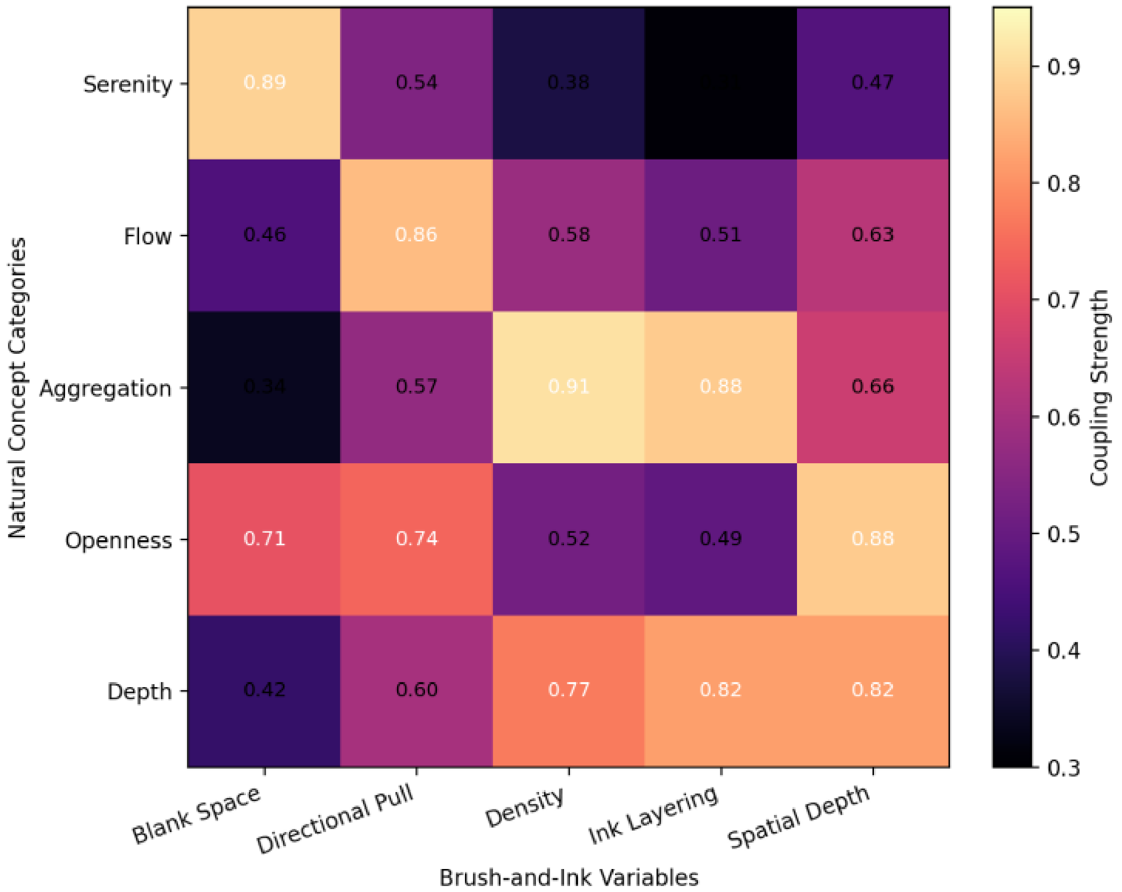

Figure 5: Coupling matrix diagram of natural concept and pen-ink variables

Combined with the above data, it can be seen that the concept of nature does not stay at the level of theme labels, but is stably written into the picture structure through lines, inks, whitespace and composition order, which provides a consistent data basis for subsequent group difference statistics.

4.3 Statistical analysis of ink characteristic indicators and group differences

In this paper, we conduct statistical analysis of ink and pen feature indicators under the unified computing framework, and use the method of feature distribution modeling and correlation calculation to quantitatively evaluate the differences in ink and pen expression driven by the natural concept of different regional painter groups. The statistical analysis includes calculating the mean, variance and correlation coefficient of line density, ink layering index, white space ratio and composition tension, so as to test the effectiveness and stability of the model in group discrimination and expression characterization.

Fig. 6 shows the distribution status of painter groups in different regions in the two-dimensional embedding space. It can be seen that all kinds of samples form a relatively clear clustering structure in the mapping space, and the boundaries between groups are relatively clear. The statistical results showed that the mean density of lines was distributed between 0.43 and 0.68, and the difference between different groups was obvious, and the overall density of the samples emphasizing freehand expression was higher. The ink layering index was concentrated in the range of 0.52 to 0.73, and some groups showed richer hierarchical changes. The proportion of white space mainly distributed between 0.20 and 0.35, and the spatial organization difference was relatively stable. Composition tension fluctuates between 0.48 and 0.65, showing higher values in the landscape genre. The data in the Fig. show that the expression of different natural concepts at the level of pen and ink can form a stable distinction through numerical characteristics, and the model has a good ability to represent the group expression structure.

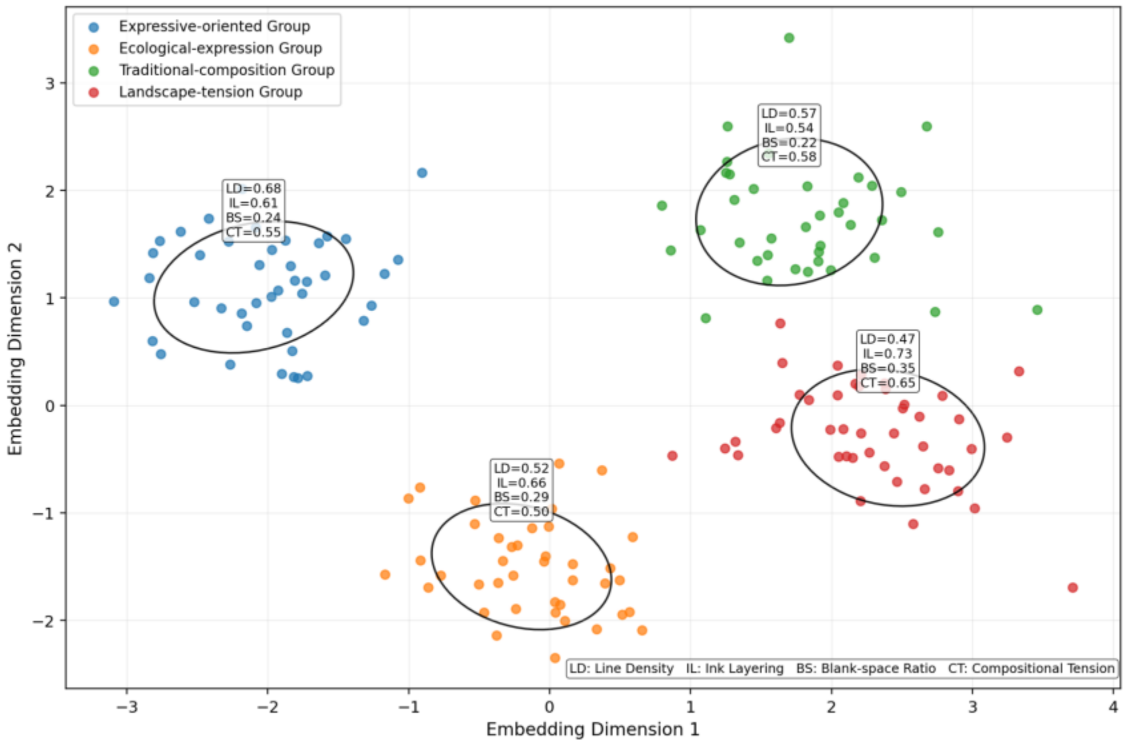

Figure 6: Spatial distribution map of pen and ink features

Fig. 7 shows the correlation matrix between each ink feature index. It can be seen that there is a strong positive correlation between line density and composition tension, and the correlation coefficient reaches 0.76, indicating that line organization has a direct impact on the overall structural tension. There is a negative correlation between the ink layering index and the ratio of white space, and the correlation coefficient is about -0.62, which reflects the trend of the relative contraction of the space space when the ink level is rich. After further analysis of different groups, it was found that the samples with natural concept favoring ecological expression formed a relatively balanced relationship between ink color and white space, and the fluctuation of the correlation coefficient was controlled within the range of ±0.10. However, the samples with traditional composition tendency show higher concentration of lines in local regions. The above results show that the ink features not only have stable statistical relationships, but also can reflect the structural differences of different natural concepts.

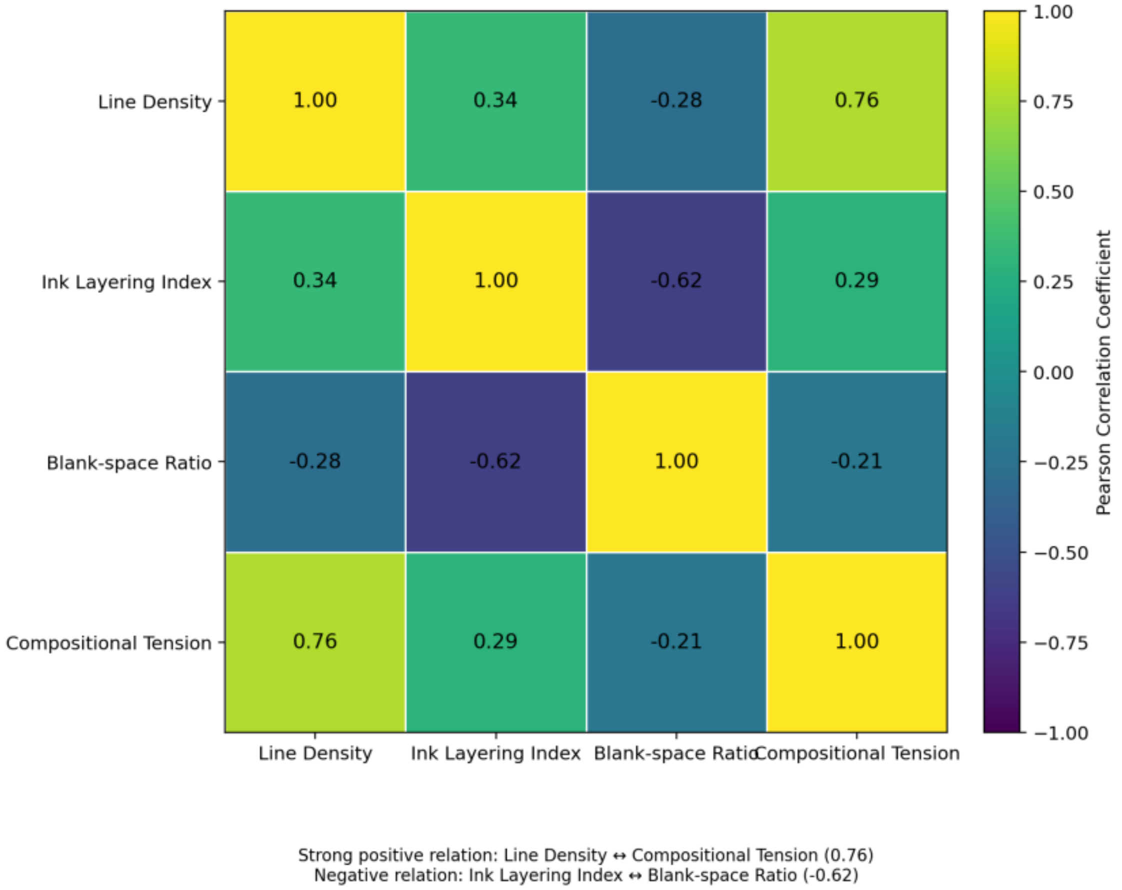

Figure 7: pen-ink feature correlation matrix diagram

In order to further evaluate the influence of each computing module on the overall analysis performance, an ablation experiment was constructed and compared. By gradually removing the multimodal coding module, the graph structure analysis module and the mapping mechanism, the changes of various indicators are observed, and the results are shown in Table 4.

Table 4: Results of ablation experiments for pen-ink feature analysis model

Model Structure	Line Density Recognition Accuracy	Ink Layering Consistency	Blank-Space Ratio Error	Compositional Tension Stability
Full model	0.92	0.89	0.05	0.90
Without graph structure module	0.87	0.83	0.08	0.84
Without multimodal encoding	0.81	0.78	0.11	0.79
Retaining only basic features	0.74	0.71	0.14	0.73

From Table 4, we can see that the full model maintains a high level in all indicators, indicating that multimodal encoding and graph structure analysis have a significant role in pen-and-ink expression modeling. After removing the graph structure module, the consistency of ink layerings decreases to 0.83, and the stability of composition tension decreases to 0.84, indicating that the structural relationship modeling has an important impact on the overall expression analysis. After further removing the multi-modal coding, the line density recognition accuracy decreases to 0.81, and the margin ratio error increases to 0.11, indicating that a single feature is difficult to fully express complex ink information. When only the basic features are retained, all the indicators are significantly reduced, and the system's ability to depict group differences is significantly weakened.

Combined with the above results, it can be seen that different regional painter groups form a stable structure of ink and pen expression pattern driven by the concept of nature, and all kinds of features show good separability and correlation in the unified computational space. Multi-modal encoding and graph structure propagation mechanism can effectively integrate formal features and semantic information, so that the model can maintain high consistency and stability in the process of group difference identification and expression analysis. The overall results show that the proposed method can achieve an effective correspondence between natural concepts and ink expression at the computational level, which provides a reliable basis for subsequent painting group analysis and style modeling.

5 Conclusion

This paper focuses on the ink and pen expression of natural concepts of painters in Qiandongnan region under the guidance of ecological aesthetics, constructs a computational research path combining multi-modal coding, graph structure analysis and semantic mapping, and completes identification, measurement and statistical analysis on the basis of a unified sample library. The measurement results show that the recognition accuracy of natural concepts reaches 91.6%, and the consistency of ink expression reaches 88.4%, which indicates that the stable relationship between ecological semantics, formal structure and group style in regional paintings can be established through a computable way. The joint analysis of line rhythm, ink level, white space organization and composition opening and closing shows that different groups of authors do not stay at the surface image differences in the processing of natural subjects, but form clear expression boundaries and structural distribution. The introduction of graph structure propagation and mapping analysis enables the alignment of scene relations, ink organization and semantic categories in the same space, thus improving the stability and interpretation strength of group comparison. Ablation results further show that the multi-modal coding, relation propagation and mapping mechanisms all have a direct support effect on the overall performance. Without any link, the recognition accuracy, structural consistency and index stability will decrease. It can be seen that the concept of nature in regional paintings can not only be illustrated through artistic interpretation, but also a clearer chain of evidence can be obtained through digital modeling. This method provides a repeatable and transferable technical framework for the research of regional paintings in Qiandongnan, and also provides a new realization path for the cross research of artistic image computing, style analysis and digital humanities. At the same time, the group center distance and local response distribution in the unified mapping space remain stable, indicating that the model still has good adaptability and discrimination under the condition of cross-author and cross-subject. Further work can be carried out in terms of expanding the sample scope, refining the subject level, and enhancing the ability of cross-media adaptation, so as to further enhance the model's ability to depict complex ink semantics.

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