International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 2982-2996

https://doi.org/10.70517/ijhsa464248

Optimization Methods for Color Coordination and Spatial Perception in Environmental Art Design Empowered by Intelligent Algorithms

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Abstract This paper innovatively solves the quantification problem of the colour wheel being connected at both ends in the HSL colour space by constructing a colour preference feature extraction model. It generates a library of 57 test schemes covering the entire colour gamut using a non-uniform sampling grid. Based on eye-tracking experiments, visual aesthetic parameters are quantified. Furthermore, by integrating the Pix2Pix image translation model with the SE-Inception V3 aesthetic scoring network, an intelligent colour matching algorithm is proposed. At the spatial perception level, four core elements (interface, path, node, and focus) are identified, and optimisation is conducted using seven regions in Area A as a case study. In terms of colour extraction, the SSIM reaches 0.676, an improvement of 8.1% to 8.8% over MCM/K-Means/OM, and the PSNR is 22.16 dB, an improvement of 7.1% to 18.3%. In terms of colour coordination, the normalised colour difference mean was 0.264, outperforming professional designers at 0.227, with a subjective score of 4.69/5.0. The entropy-weighted TOPSIS model showed spatial perception polarisation, with Zone C's comprehensive index at 0.8685 and Zone G at 0.1492. IPA behavioural analysis revealed cultural experience-oriented spaces achieved a cultural-driven behavioural satisfaction score of 4.34. The study indicates that intelligent algorithms, by quantifying artistic elements and spatial perception metrics, can significantly enhance the scientific rigor and experiential quality of environmental art design.

Index Terms environmental art design, colour preference characteristics, eye-tracking, visual aesthetics, image translation model, spatial perception

I. Introduction

Contemporary urban development is evolving rapidly, and environmental art design has increasingly become a key tool for enhancing urban quality and shaping spatial characteristics [1]. Colour, as a core element of environmental art design, holds unique value in spatial identification, cultural heritage, and psychological guidance [2], [3]. Research indicates that environmental colours significantly influence both physiological and psychological aspects of human beings. Appropriate colour combinations can improve spatial perception, enhance environmental comfort, and create a positive user experience [4]-[6]. Additionally, environmental colours serve as an important medium for preserving regional culture and highlighting contemporary characteristics [7]. In recent years, the development of emerging digital technologies has opened up new possibilities for colour innovation in environmental art design, driving environmental colour planning into a new phase of development [8]-[10].

The application of digital technology has opened up unprecedented possibilities for colour design. Digital technology has driven innovations in colour planning methods, with technologies such as 3D modelling and virtual reality enabling the visualisation and validation of colour schemes. Reference [11] utilises 3dsMax software and Quest3D environmental colour conversion technology to coordinate colour spaces in environmental art design, with the designed three-dimensional model solutions effectively meeting the practical needs of current environmental art design. Reference [12] combines modern technology with traditional art to express the increasingly diverse nature of environmental art design, breaking through the limitations of traditional display modes by adopting 3D virtual reality technology, thereby providing new insights for design practices in environmental art, particularly in terms of colour. Literature [13] proposes an environmental art design method based on computer 3D animation technology. By introducing RGB decomposition technology and colour template space projection algorithms to process and integrate animation images in environmental art design methods, it achieves strong three-dimensional visual presentation capabilities. Literature [14] explores the relationship between computer colour vision and human perception in virtual reality environments. It applies colour models to measure the smooth transitions of colour tones in environmental art design and evaluates the degree of colour perception based on human physiological responses, providing objective criteria for environmental art design. Literature [15] explores the theory framework of object-based rendering (ABR), designing visual mappings for different colour data to achieve more expressive and appealing three-dimensional visualisation effects tailored to aesthetic styles, demonstrating high practicality in artistic design.

Additionally, artificial intelligence technology assists in optimising colour planning, and big data analysis can provide scientific basis for colour decisions. Reference [16] designed and implemented a hierarchical environmental art design system, utilising a series of image processing techniques and fuzzy C-means clustering methods to perform high-precision analysis of colour images in environmental art, thereby maximising the aesthetic and practical functions of colour planning. Literature [17] considers the sustainable development of environmental artworks and proposes an environmental art design model based on fuzzy algorithms. Through fuzzy variable entropy analysis, it identifies influential directions for environmental art design, with the most outstanding performance in colour planning. Literature [18] establishes a colour optimal matching model for environmental art design practice, using Bayesian conditional theory as the decision theorem for colour image segmentation in art design, effectively enhancing the visual effects of colour transitions in the design process. Literature [19] explores the complex relationship between colour and human psychological needs in urban environmental art design, using an interactive genetic algorithm to construct a decision-making model integrating environmental, human psychological, and colour theory, aiming to design urban environmental colour patterns that enhance spatial quality and human well-being. Literature [20] introduced eye-tracking technology to study management and planning methods for urban environments and colours. By analysing the visual perception impact of iconic urban environmental landscapes on people, it helps designers create colour expression patterns that align with local characteristics, thereby further promoting the sustainability of urban environments. Literature [21] addresses issues such as the inability to extract feature invariants of pattern colours and low colour matching accuracy by proposing the establishment of an intelligent colour matching model based on Markov models. This model can effectively improve the efficiency and level of colour matching, thereby enhancing the aesthetic appeal and value of artistic design. Literature [22] indicates that enhancing the visual appeal and practicality of an area is the primary function of environmental art design. It proposes introducing generative adversarial networks and computer-aided design methods to improve the flexibility and effectiveness of environmental art design, thereby strengthening aesthetic features such as colour balance, spatial layout, and visual balance in design outcomes. Literature [23] employs the semantic difference method (SD) to assess people's perception of colour space in landscape design. The established colour matching model can guide the design of spatial colour backgrounds and the establishment of relationships between space and emotion, thereby enhancing the artistic and aesthetic qualities of landscape design.

However, in contemporary environmental art design, while the application of digital technology has improved design quality and efficiency, it has also exposed some issues [24], [25]. Among these, the improper use of colour is a common problem. Traditional colour theory is not fully adaptable to digital environmental design, and designers sometimes overly rely on software-preset colour schemes, neglecting the influence of colour psychology and environmental factors on colour perception [26]-[28]. For example, some designs overly prioritise visual impact while neglecting the potential emotional effects of colour, resulting in spaces that evoke discomfort [29], [30]. Additionally, inappropriate colour combinations can lead to unclear information transmission, impairing the understanding and use of spatial functions [31], [32]. Therefore, the application of new technologies should be grounded in actual needs, avoiding blind pursuit of technical effects. Technological innovation must also be deeply integrated with environmental design concepts, enhancing colour expressiveness while ensuring the overall coherence and harmony of the environment [33]-[36]. This requires more precise colour matching and spatial perception optimisation tools to help designers accurately preview and adjust colour combinations in design schemes, ensuring they align with users' visual needs and aesthetic preferences [37].

The core methodology of this paper lies in quantifying and modelling complex artistic design elements, and utilising machine learning, computer vision, and other technological means for intelligent analysis and generation. First, a colour preference feature extraction model is constructed, which delves into the quantitative representation methods of colour schemes in the HSL colour space. Specifically, a correction formula is proposed to address the characteristic of the colour wheel being closed-loop, ensuring the comparability of colour contrast intensity across different colour schemes. Detailed principles for sampling schemes are established for evaluating user preference features. Based on the obtained user preference data, visual aesthetics are innovatively quantified, and normalised visual aesthetics parameters are constructed using eye-tracking experiment data. Subsequently, the image translation model Pix2Pix was introduced as the backbone network. The core breakthrough lies in the proposed intelligent colour matching model that integrates visual aesthetics. A palette visual aesthetics scoring model was trained using the SE-Inception V3 network, and this score was integrated into the total loss function of Pix2Pix as an aesthetic loss function. The perspective is expanded from colour to the spatial perception level, identifying four key spatial components that influence the viewing experience, and attempting to establish an ‘material space-psychological perception’ association system. Subsequently, spatial depth perception is clearly selected as the core subjective perception element for study, exploring the significant influence of the environmental background on it.

II. Intelligent algorithm-driven environmental art colour and spatial perception optimisation methods

II. A. Colour preference feature extraction model structure

II. A. 1) Principles of Colour Relationships

The span of the three colour elements in a colour combination sequence not only determines the coverage of the colour scheme on the colour solid, but also determines the contrast intensity of each colour. The larger the span of a colour element axis, the stronger the contrast of that element in the colour scheme. In this method, the span of a colour element is calculated based on the total coverage width of the colour sequence following the principle of gradient uniform distribution, i.e., the total span of the colour element values of the first and last colours.

However, the hue axis parameters on the colour solid are connected at both ends, which results in inconsistencies with linear purity or brightness axes in calculations. According to our predefined hue span rule, the strongest colour contrast occurs when the hue span is maximum, but when the hue span is actually maximum, the first and last colours on the hue ring overlap. According to colour harmony theory, the strongest colour contrast should be complementary colours. For multiple colours, the strongest contrast occurs when hues are evenly distributed on the hue circle. Additionally, as the number of colour sets changes, the span between the first and last colours also changes accordingly. To address this issue, we employ a corrected calculation formula:

$$S = S'\frac{n-1}{n}\left(0 < S' \le 360\right) \tag{1}$$

In this context, S represents the hue span of the colour scheme, S' denotes the proxy value for the hue span, and n signifies the number of colour sets. By incorporating the hue span proxy value, we can calculate hue span parameters that better align with computational requirements (adding half a step size to each end colour). When the hue span proxy value reaches its maximum of $\left(360^{\circ}\right)$, the hue parameters are evenly distributed on the hue circle, and the colour contrast of the scheme reaches its strongest full-circle complementary state. Through this correction method, schemes with different numbers of colour sets can achieve similar colour contrast effects using the same hue span value.

II. A. 2) Sampling principles for user preference feature evaluation schemes

Obtaining users' preference characteristics is a prerequisite for generating colour scheme designs. To obtain users' preference characteristics, it is necessary to conduct reasonable user testing. Our method involves sampling according to certain rules to generate a colour scheme library that uniformly covers all colour space regions and contrast characteristics, which is then used for user testing. Based on these testing materials, we conduct evaluations of users' preference characteristics. To ensure the objectivity of the testing, the sampling scheme must not only cover all regions of the colour space but also be distributed as uniformly as possible. Otherwise, the accuracy of the test results will be affected by the uneven distribution of the scheme database. Similarly, we must also ensure that the colour element span and average value in the HSL colour space of the sampling scheme follow the principle of uniformity. This is necessary to generate a reasonably balanced colour preference testing scheme library.

We categorise the factors influencing the uniformity of sampling scheme distribution into two types: the sampling density grid within the HSL colour space and the contrast variation rules at each grid point. Among these, grid density refers to the sampling density of colour element averages, while the contrast variation rules of colour elements at each grid point determine the sampling density of contrast spans at each grid point. These two factors collectively constitute the distribution density and uniformity of the entire sampling scheme database. Theoretically, the higher the sampling grid density, the greater the number of samples, and the more comprehensive the coverage of the colour space. However, doubling the sampling density would result in an exponential increase in the number of sampling schemes. An excessive number of sampling schemes can become a burden for user surveys. Users may lack the patience to review all schemes, and an overabundance of contrast selection tasks can diminish user interest and visual acuity, thereby affecting the accuracy of evaluations.

The hue mean sampling principle is shown in Figure 1. To balance sampling density and user tolerance as much as possible, we divided the hue ring dimension into six equal segments, each spanning 60°. However, on the saturation axis, an evenly divided distribution does not create a visually uniform distribution, and the two ends of the brightness axis are also unsuitable for equal-density sampling due to being too pale or too dark. After multiple adjustments based on intuitive evaluation experiments, the sampling grid's saturation axis sampling points were finally set to 0 (neutral grey), 0.27, 0.53, and 0.79 (calculated by extrapolating from the maximum value), while the brightness axis sampling points were set to 0.25, 0.50, and 0.75. In Figure 1, the horizontal dimension represents saturation, and the vertical dimension represents brightness. Each intersection marked with a black dot represents a mean sampling point for a colour element. The far-left column corresponds to different brightness sampling points on the neutral grey axis, aligning with the central axis of the HSL colour space. The entire sampling grid structure consists of 57 grid intersections.

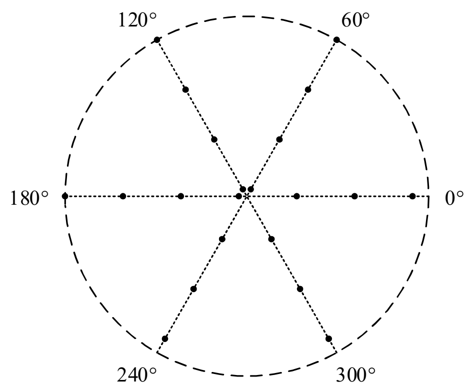

Figure 1: Color hue mean sampling principle

II. B.Design of colour matching algorithms that integrate visual aesthetics

Based on the user data obtained from the colour preference feature evaluation scheme library constructed above, this section further explores how to combine user preferences with deeper visual aesthetic principles to construct an intelligent colour matching generation algorithm.

II. B. 1) Visual Aesthetics

Since the human eye is naturally drawn to objects with greater visual appeal, quantifying visual aesthetics using eye-tracking metrics is a crucial technical approach in this field. In the process of quantifying visual aesthetics using eye-tracking metrics, the three most important eye-tracking metrics are average fixation duration, average number of fixations, and first fixation time. These metrics respectively reflect the visual comfort, visual appeal, and visual impact of the test image or video. Taking average fixation duration as an example, its calculation formula in eye-tracking experiments is shown in Equation (2).

$$T=\frac{\sum_{i=1}^{n}T\left(AOI\right)}{n} \tag{2}$$

In the formula:

n ——Number of test images or videos;

$T\left(AOI\right)$ ——Test time for dividing regions of interest in the eye-tracking experiment.

In visual search, targets with visual aesthetic appeal typically receive more attention, and corresponding eye-tracking behaviour metrics include average fixation time, average number of fixations, and first fixation time.

Using eye-tracking behaviour metrics to construct a visual aesthetic data stream, the aforementioned three eye-tracking behaviour metrics are normalised through pre-processing. Among these, average fixation duration and average number of fixation points are positively correlated with visual aesthetic preference. Taking average fixation duration as an example, the processing method is defined as follows:

$$h'=\frac{h-h_{\min}}{h_{\max}-h_{\min}} \tag{3}$$

In the formula:

h ——is the data that needs to be normalised before processing;

$h\_\min$, $h\_\max$ ——represent the minimum and maximum values of the average gaze time, respectively.

The first gaze time measurement index is negatively correlated with visual aesthetic preference in interactive tasks, and its processing process is defined as follows:

$$j' = 1 - \frac{j - j_{\min}}{j_{\max} - j_{\min}} \tag{4}$$

In the formula:
j ——is the data that needs to be normalised before processing;
$j\_\min$, $j\_\max$ ——represent the minimum and maximum values of the first gaze time, respectively.
Visual aesthetic parameter W is shown in Equation (5):

$$W = (\alpha h' + \beta i' + \gamma j') \times 10 \tag{5}$$

In the formula:
W ——Visual aesthetic parameter that integrates three different types of eye movement behaviour data, with values ranging from $[0,10]$;
α, β, γ ——Weights of three different types of eye movement behaviour data.
Among them, the three weights are also different according to different visual tasks. This chapter uses $\alpha = \beta = \gamma = 1/3$ to calculate the visual aesthetic score W.

II. B. 2) Image Translation Model

The image translation model (Pix2Pix) is a specific application of conditional generative adversarial networks (GANs) in image translation tasks. The image translation model is a conditional GAN where the generator is a U-Net and the discriminator is a Markov discriminator (Patch GAN). The generator takes a real sample image x as input and outputs a generated image $G(x)$; Since the discriminator needs to determine the authenticity of the generator's output image, the discriminator's input consists of paired images formed by the generated image $G(x)$ and the real image. The network model of Pix2Pix is shown in Figure 2.

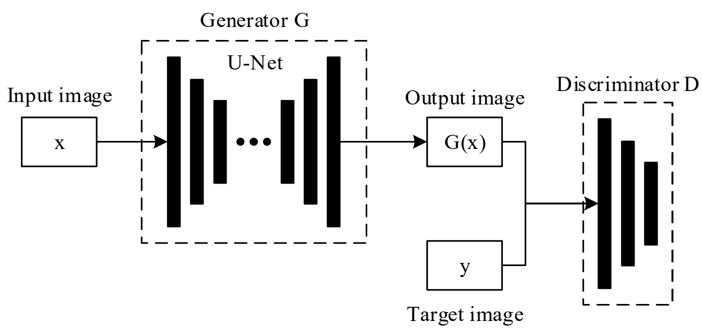

Figure 2: Pix2Pix network structure

In addition, the Pix2Pix network model introduces L_1 $Loss$ pairs of images for global judgement based on CGAN, as shown in Equation (6).

$$G^* = \arg\min_G \max_D L_{cGAN}(G,D) + \lambda L_{L_1}(G) \tag{6}$$

In the formula:
G, D —— represent the generator and discriminator, respectively;
$L_{L_1}(G)$, λ —— represent the weights of L_1 $Loss$ and L_1 $Loss$, respectively;
where L_1 $Loss$ is defined as follows:

$$L_{L_1}(G) = E_{x,y,z\sim p_{data}}\left[\|y - G(x,z)\|_1\right] \tag{7}$$

In the formula:
G ——generator;
x, y, z ——represent real samples, conditional probability, and random noise, respectively.
The loss function of Pix2Pix is shown in formula (8):

$$L(G_{\min}, D_{\max}) = E_{x\sim p_{data}(x)}[\log D(x \mid y)] + E_{z\sim p_z(z)}\left[\log(1 - D(G(z \mid y)))\right] + \lambda L_{L_1}(G) \tag{8}$$

II. B. 3) Intelligent colour matching model integrating visual aesthetics

A visual aesthetic evaluation model is constructed using visual aesthetic parameters and the primary colour palette of the corresponding image. This evaluation model is used to score the input colour palette, and the resulting score is then used to optimise the loss function of the Pix2Pix backbone network. The evaluation model adopts the SE-Inception V3 network model, which compresses image features through global average pooling and scores the probability distribution of image aesthetic quality scores. The model is trained using the true visual aesthetic parameters of the palette as labels for the corresponding palette.

The aesthetic loss function $S(G)$ and the total loss function of the intelligent colour matching algorithm established in this chapter are shown in Equations (9) and (10), respectively:

$$S(G) = 10 - Score \tag{9}$$

$$L(G_{\min}, D_{\max}) = E_{x\sim p_{data}(x)}[\log D(x \mid y)] + E_{z\sim p_z(z)}\left[\log(1 - D(G(z \mid y)))\right] + \lambda L_{L_1}(G) + \gamma S(G) \tag{10}$$

In the formula:

$Score$, 10 —— represent the score of the colour palette visual aesthetics evaluation model and the full score of the aesthetic evaluation, respectively;

γ —— $S(G)$ represents the weight.

The technical process of the intelligent colour matching algorithm that integrates visual aesthetics proposed in this section is shown in Figure 3.

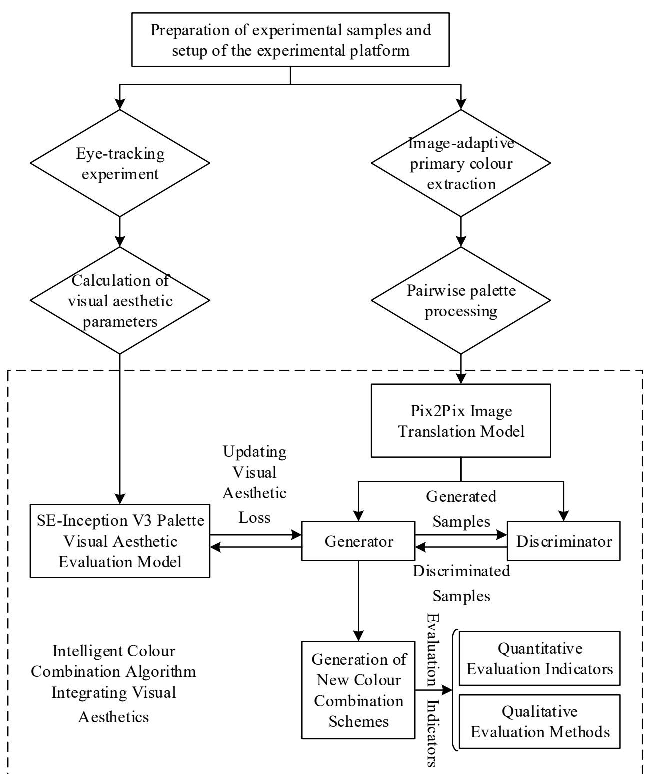

Figure 3: Framework of color matching methods incorporated visual aesthetics

II. C.Extraction of spatial constituent elements and selection of subjective perception elements

The aforementioned colour matching algorithm, which integrates visual aesthetics, provides an optimised visual foundation (colour scheme) for the environment. However, to fully optimise the user's spatial experience, it is necessary to gain a deeper understanding of how the constituent elements of space influence core subjective perceptions. This section shifts the focus of our research to the relationship between spatial structure and subjective perception.

II. C. 1) Extraction of spatial constituent elements

Based on a summary and synthesis of existing research, four types of spatial components closely related to sightseeing space design have been identified, namely spatial interfaces, spatial paths, spatial nodes, and visual focal points. Through literature research and review, the attributes of spatial components that influence the three manifestations of sightseeing experience have been clarified, and the characteristics of the coupling relationship between material spatial components and psychological perception components have been sorted out. An attempt has been made to establish a system of influencing factors for ‘material space-psychological perception’ and to explore effective architectural sightseeing space design strategies.

II. C. 2) Selection of subjective perception factors

This paper selects spatial depth (distance) perception as the environmental perception variable. The depth perception discussed in this paper refers to self-centred distance perception, i.e., the observer's subjective perception of the distance to the target object. Visual depth perception, as a fundamental parameter for judging spatial scale, plays a significant role in environmental cognition and is closely related to directional and temporal perception. The uncertainty and variability of depth perception in classical Chinese gardens enable viewers to experience a rich garden experience while perceiving the garden space as larger than its actual scale. This study will integrate subjective evaluations with objective physiological data to conduct an in-depth exploration of the interrelationships between the use of scenic frames, landscape viewing patterns, and spatial depth perception, aiming to provide a more comprehensive understanding of the experiential characteristics of environmental art design.

Previous studies have shown that depth perception is influenced by environmental context. In different environmental contexts, such as halls, corridors, and open lawn environments, as well as indoor and outdoor environments, people's judgments of depth values exhibit significant differences. Additionally, with the development of panoramic visual technology, panoramic images provide a broader range of environmental visual information compared to traditional photographs. Inagami et al. investigated the correlation between different fields of view—from a limited frontal view to a 360° panoramic view—and a sense of oppression. The results showed that a sense of oppression is most strongly correlated with the field of view and the highest correlation with panoramic vision. Building on existing research, this paper discusses the potential influence of peripheral visual information forming the frame at the viewpoint on depth perception.

III. Research on colour extraction and matching technology optimisation

Based on the colour preference feature extraction model and intelligent colour matching algorithm that combines visual aesthetics constructed above, Chapter 3 will further verify the model's effectiveness through experiments. By comparing traditional algorithms such as MCM and K-Means, and combining objective indicators such as SSIM and PSNR with eye-tracking data, the proposed method will be systematically evaluated for its breakthroughs in colour extraction accuracy and aesthetic matching.

III. A. Colour extraction evaluation research

To validate the effectiveness and superiority of the colour preference feature extraction model proposed in this study, 100 images covering complex natural landscapes, animals, and people were carefully selected and collected manually as experimental samples. The median cut method (MCM), K-means clustering algorithm, and octree algorithm (OM) were selected as comparison algorithms and tested together with the colour matching model combining visual aesthetics constructed in this study.

III. A. 1) Comparison Algorithm

MCM is a colour quantification technique that can divide colours into two subspaces based on the median of one dimension of colour, and then continue to divide the subspaces.

The K-Means clustering algorithm iteratively adjusts the cluster centres to minimise the objective function M, so that the sum of the squares of the distances from each pixel to its nearest cluster centre is minimised.

OM is a recursive image segmentation technique that organises and quantifies colours by constructing an octree structure.

III. A. 2) Evaluation Indicators

For colour extraction evaluation, an objective evaluation method is employed, utilizing two metrics: Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR). The objective evaluation process is as follows: first, the original image is converted from RGB colour mode to Lab colour mode. The Lab colour mode accounts for the uniformity of human visual perception, providing more consistent and predictable colour comparisons. Next, each pixel in the image is examined individually, and the Lab colour values of the examination results are recorded. Next, the colour difference between the Lab colour value of each pixel and all extracted target colours is calculated, and the target primary colour with the smallest colour difference is selected to update the colour value of that pixel. Finally, a new image with the extracted colours replaced is generated and output, and the SSIM and PSNR between the original image and the new image are calculated.

III. A. 3) Evaluation results of colour extraction using different algorithms

In general tasks, five colours provide sufficient flexibility to capture the essence of an image without being overly complex. Therefore, for the sake of fair comparison and consistency analysis, all four contrast methods were set to extract five colours in the experiment. Among 100 image samples, the extracted colours were evaluated using the evaluation system proposed in this study. The comparison results of structural similarity (SSIM) and peak signal-to-noise ratio (PSNR) are shown in Figures 4 and 5, respectively.

As shown in the SSIM comparison results in Figure 4, the average SSIM values for the MCM algorithm, K-Means clustering algorithm, and OM algorithm were 0.621, 0.624, and 0.625, respectively, while the average SSIM value for the proposed colour preference extraction model reached 0.676, exceeding that of the three comparison algorithms.

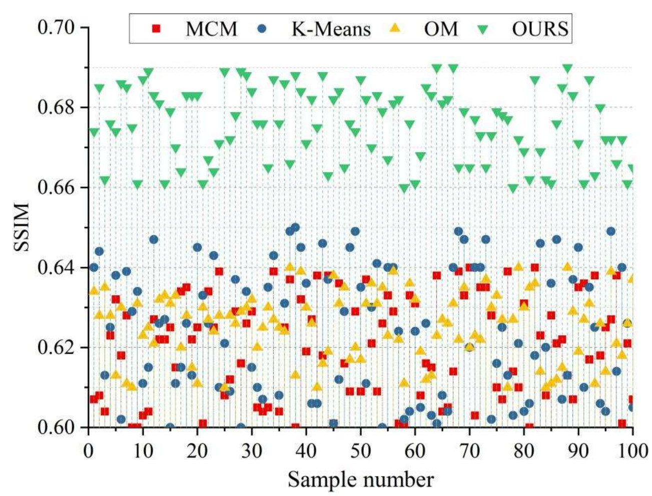

Figure 4: Structural Similarity Index Measure (SSIM) comparison results

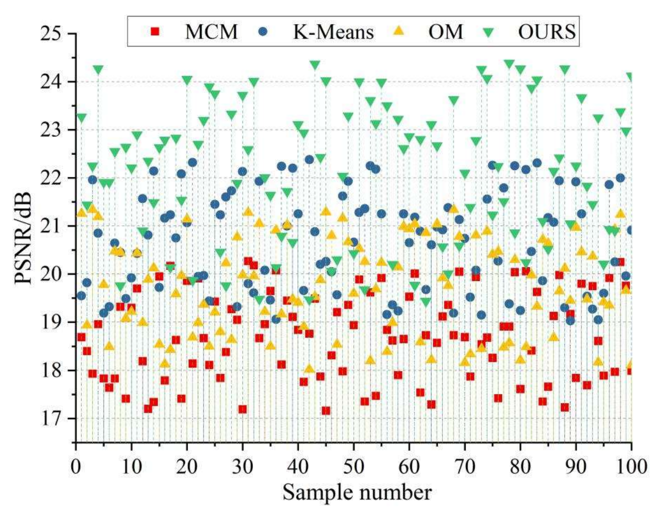

Figure 5: Peak Signal-to-Noise Ratio (PSNR) comparison results

As shown in the PSNR comparison results in Figure 5, the overall PSNR of the proposed colour preference extraction model is higher than that of the three comparison algorithms. Specifically, the MCM algorithm achieves a maximum PSNR of 20.27 dB, a minimum of 17.16 dB, and an average of 18.72 dB. The PSNR of the K-Means clustering algorithm fluctuates between 19 dB and 22 dB, with an average of 20.68 dB. The average PSNR of the OM algorithm was 19.75 dB. The colour preference extraction model achieved a maximum PSNR of 24.39 dB, with an average of 22.16 dB, representing improvements of 18.33%, 7.10%, and 12.13% compared to the three comparison algorithms, respectively. This indicates that the colour preference extraction model offers superior colour visual perception performance.

III. B. Colour matching algorithm performance experiments and analysis

To validate the effectiveness and superiority of the colour matching algorithm proposed in this study, 3,000 sets of colour palette images were collected and randomly divided into 600 colour combinations containing five images each, forming a set of visual stimuli.

III. B. 1) Visual behaviour data and visual aesthetic parameters

The study recruited 100 students with normal visual function and no colour recognition disorders as volunteers to wear eye-tracking devices for the experiment. The average eye movement response for each area was calculated, and visual aesthetic parameters were calculated based on visual behaviour data. The visual behaviour data and visual aesthetic parameters for some colour combinations are shown in Table 1.

Table 1: Visual behavioral data and visual aesthetic parameters

Color palette combination	Average fixation time/ms	First fixation time/ms	Average number of fixation points	Visual aesthetics parameters
1	644	149	3.44	6.71
2	793	191	3.07	8.49
3	609	217	3.30	8.58
4	777	204	2.78	8.02
5	676	126	2.05	7.36
6	770	154	2.64	6.02
7	848	179	2.09	6.91
8	666	126	3.21	7.68
9	628	151	2.20	7.74
10	620	218	2.63	7.99
…	…	…	…	…
Average	703	172	2.74	7.55

As shown in Table 1, among the 10 combinations, the highest visual aesthetic parameter was 8.58, the lowest was 6.02, and the average was 7.55. The average fixation time varied widely, ranging from 609 to 848 ms. The average fixation time for the 600 colour combinations was 703 ms, the average first fixation time was 172 ms, and the average number of fixation points was 2.74. In summary, the colour combinations developed under the colour matching model constructed in this paper combine moderate visual complexity with strong visual impact, and the overall colour scheme demonstrates excellent aesthetic performance.

III. B. 2) Objective evaluation of colour schemes

Train the image translation model in the colour matching algorithm that integrates visual aesthetics using 600 colour schemes as the training set, with 500 training iterations.

To further evaluate the system's colour matching performance, colour difference was used as an evaluation metric. Colour difference detection involves analysing colour differences after extracting image colour feature values. Colour difference detection was conducted on actual colour matching samples and model-generated colour matching samples for the red, green, and blue colour families. The results of the colour difference detection are shown in Table 2.

Table 2: The color difference test results of the red, green and blue color systems

Color blending combination	Actual ratio			Model output ratio			Color difference
	Red	Green	Blue	Red	Green	Blue	
1	110	99	90	109	98	88	0.993
2	91	80	69	88	79	68	0.985
3	107	96	85	105	94	82	0.891
4	96	84	74	94	81	72	0.911
5	96	85	74	94	84	71	0.883
6	110	100	90	107	99	89	1.086
7	99	91	79	98	88	78	0.965
8	103	93	80	97	90	79	1.143
9	91	79	67	90	76	65	1.046
10	95	83	73	93	81	70	0.931
…	…	…	…	…	…	…	…
Average	…	…	…	…	…	…	0.983

As shown in Table 2, the error between the actual colour ratio samples and the predicted colour ratio samples R, G, and B is all $\Delta E < 1.2$, with an average colour difference of 0.983. This proves that the colour difference is related to human visual perception, indicating that the colour ratio samples produced have virtually no colour difference and achieve the expected effect.

The study selected an image translation model without eye-tracking technology and paired it with a professional design team as a comparison algorithm to test the proposed colour matching algorithm.

Next, the normalised minimum colour difference average was used as an objective evaluation metric. Twenty colour combinations were randomly selected, and the objective evaluation results under the three schemes are shown in Figure 6.

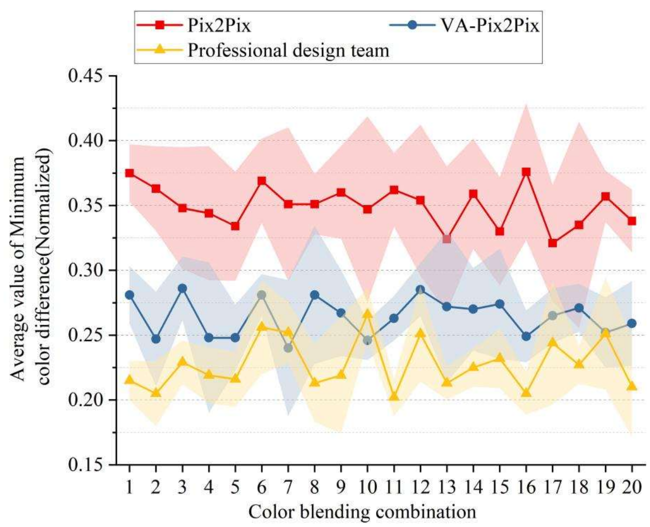

Figure 6: The objective evaluation results under the three schemes

As shown in Figure 6, the normalised minimum colour difference average value of the colour combination obtained by the image translation model without eye-tracking technology (i.e., visual aesthetics) is 0.351, while the normalised minimum colour difference average values of the intelligent colour matching algorithm proposed in this study and the professional designer team are 0.264 and 0.227, respectively. This validates the superiority of the model incorporating visual aesthetics, which even outperforms professional manual colour matching.

III. B. 3) Subjective evaluation of colour schemes

Thirty university students majoring in design were invited to volunteer to provide subjective evaluations of colour scheme combinations. The evaluation was on a 5-point scale, with 5 points indicating very satisfied, 4 points indicating relatively satisfied, 3 points indicating average, 2 points indicating relatively dissatisfied, and 1 point indicating dissatisfied.

The subjective evaluation results of the 30 university students are shown in Figure 7.

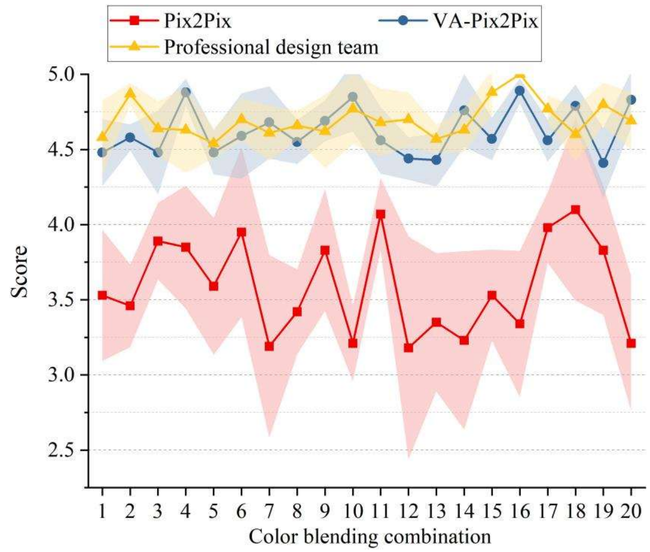

Figure 7: The subjective evaluation results of 30 professional college students

In terms of subjective evaluation, the image translation model without integrated eye-tracking technology achieved an average score of 3.59 when pairing the extracted colours. In contrast, the professional design team achieved scores generally above 4.00, with an average of 4.62, when pairing the colours extracted by the model. Finally, when the extracted colours were paired using an intelligent colour pairing algorithm that integrates visual aesthetics, the score was even higher than that of the professional designer team's pairing scheme, with an average score of 4.69. This indicates that the quality of the pairing scheme generated by the intelligent colour pairing algorithm that integrates visual perception can be further improved, approaching the level of professional designers.

IV. Research on spatial perception optimisation evaluation

After verifying the effectiveness of colour optimisation technology, the research perspective shifted to the spatial perception dimension. Chapter 4 used seven areas in Location A as empirical objects and combined the entropy-weighted TOPSIS model with IPA behavioural analysis to explore how spatial components can influence visitor perception through design interventions, thereby achieving a cross-scale optimisation loop from colour to space.

IV. A. Analysis of the results of the entropy-weighted TOPSIS spatial perception study

Taking Area A as the research subject, this study conducts spatial perception research and optimisation of environmental art design for the seven regional spaces a, b, c, d, e, f, and g within it.

With space as the overall cognitive object, the perceptual experience in this scenario is a subjective judgement formed through the human body's complex cognitive system processing multiple elements and their relationships. This study establishes a comprehensive evaluation system for spatial perception in environmental art design by assigning evaluation criteria to each indicator based on current status surveys and relevant application standards. This evaluation system is then combined with the entropy-weighted TOPSIS model to score and rank the spatial perception of the seven regional spaces in Area A. The spatial perception calculation results for the seven regions based on the TOPSIS evaluation method are shown in Table 3.

Table 3: The spatial perception computing results based on TOPSIS method

Region	Positive Ideal Distance	Negative Ideal Distance	Summary Score Index	Order
a	0.5228	0.3858	0.5071	5
b	0.3142	0.6114	0.6225	3
c	0.1309	0.8467	0.8685	1
d	0.6452	0.2679	0.3029	6
e	0.4736	0.5047	0.5907	4
f	0.2580	0.7037	0.7219	2
g	0.8060	0.1472	0.1492	7

The comprehensive score index distribution range for the seven regional spaces in Area A is 0.1492–0.8685, with significant polarisation. Area c leads with a score of 0.8685, while Area g ranks last with a score of 0.1492. Zone C has the largest negative ideal distance of 0.8467, indicating it is closest to the ideal spatial state; Zone G has the largest positive ideal distance of 0.8060, reflecting the greatest deviation from the ideal state. Zones C and F, with scores exceeding 0.7, are cultural experience-oriented spaces, forming a cluster of high-quality perceptual spaces. Zone B (0.6225) and Zone E (0.5907) are at an intermediate level. Zone D (0.3029) and Zone G (0.1492) have scores below 0.4, indicating they are commercially oriented spaces where perceptual experiences require urgent optimisation.

IV. B. Analysis of IPA Model Research Results

Behavioural agents in a specific spatial context develop certain cognitive preferences within that space, which are reflected in their behavioural activities. The 'space-behaviour interaction' theoretical model posits that space and behaviour must be integrated, enabling research into both aspects within a dynamic equilibrium. Additionally, spontaneous activities within the spatial context of environmental art design serve as a crucial means of stimulating the creativity of a place. Based on the analysis of spatial perception outcomes, this paper combines the ways in which tourists engage in behavioural activities within a space through 'spontaneous drive,' 'commercial drive,' 'cultural drive,' and 'social drive' to construct an evaluation system for tourists' spatial perception methods in environmental art design. It then analyses tourist behavioural activities using the IPA model and proposes optimisation strategies for the data results from the perspective of perception methods.

IV. B. 1) Spatial full sample analysis

Based on the analysis of spatial perception, this paper further combines the IPA model to explore how tourists perceive space. The results of the full sample IPA model are shown in Table 4 and Figure 8.

Table 4: The results of the full-sample IPA model

Behavioral activities	Specific behaviors	Importance	Satisfaction
Self-taken driven	Spontaneous actions	4.25	3.92
	Reading information	3.78	3.45
	Searching on the internet	4.10	3.81
Business-driven	Having a purchase plan of their own Shopping and consumption	4.32	4.15
	Dining consumption	4.55	4.28
	Exhibit viewing	4.43	4.37
Cultural driven	Watching performances	4.33	3.57
	Guided commentary participation	4.21	3.58
	Willingness to take a photo and share	4.05	3.42
Social driven	Seeing others take photos on social platforms	4.15	4.03
	Seeing official promotions on social platforms	3.92	3.79
	Specific behaviors	3.71	3.63

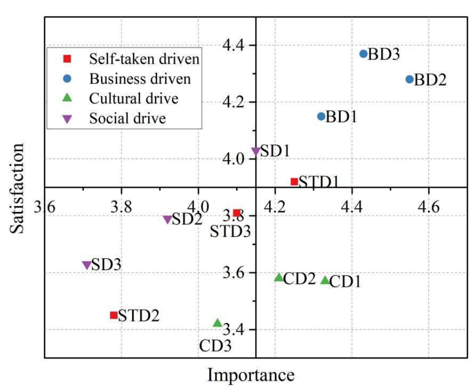

Figure 8: The results of the full-sample IPA model

The full sample data shows that visitors generally place a high importance on various types of behavioural activities, with an average score of 4.15. However, there are significant differences in satisfaction levels. Among self-driven behaviours, ‘spontaneous behaviour’ is considered the most important, with a score of 4.25, but satisfaction levels are slightly lower at 3.92, indicating that visitors expect a more free-flowing interactive experience in the space. Commercially driven activities have the highest overall satisfaction, with an average of 4.27, particularly ‘dining consumption’ (4.33) and ‘shopping consumption’ (4.28), indicating that commercial consumption effectively enhances spatial perception. In terms of the importance of culturally driven behaviour, ‘exhibition visits’ scored 4.33, but satisfaction was the lowest, with an average of only 3.57, reflecting that cultural activities did not fully meet visitors' expectations, such as ‘participation in guided tours,’ which had a satisfaction score of only 3.42. In socially driven behaviour, both the importance (4.15) and satisfaction (4.03) of ‘willingness to check-in and share’ were high, indicating that social interaction is a key driver of spatial experience. Overall, commercial-driven satisfaction is higher than cultural-driven satisfaction, highlighting the urgency of optimising the delivery of cultural content.

IV. B. 2) Multi-level IPA analysis based on the entropy-weighted TOPSIS model

Based on the classification of the results of the entropy-weighted TOPSIS model described above, this paper further investigates the distribution of the two types of cultural experience-oriented spaces and commercial-oriented spaces with significant differences in the IPA model, as shown in Figures 9 and 10.

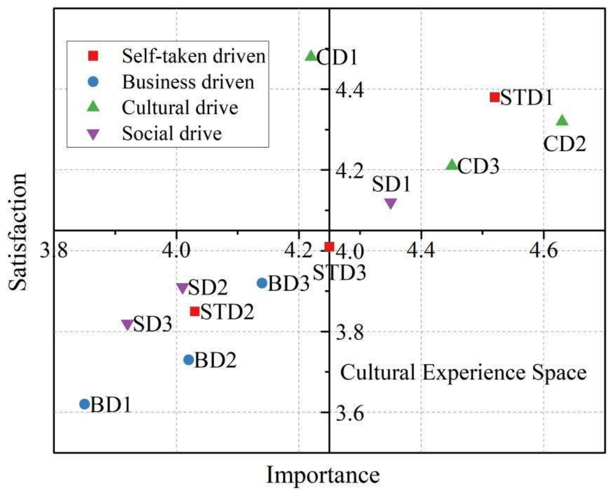

Figure 9: The distribution of cultural experience-oriented spaces in the IPA model

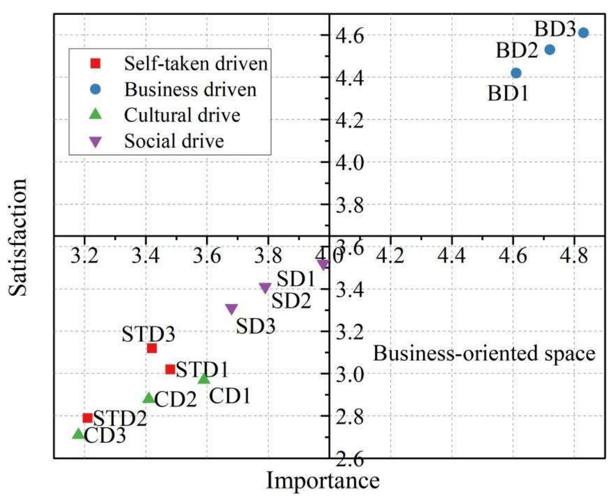

Figure 10: The distribution of commercial-oriented space types on the IPA model

The results show that there are also significant differences between cultural experience-oriented spaces and commercially oriented spaces. In cultural experience-oriented spaces, such as the art exhibition area in Zone C and the cultural performance area in Zone F, the importance of culture-driven behaviour (mean 4.63) and satisfaction (mean 4.34) were the highest, with the importance of 'exhibit viewing' reaching 4.22 and satisfaction 4.48, indicating that visitors highly value cultural content. Spontaneous-driven behaviour had higher satisfaction levels, with an average of 4.08, indicating that such spaces promote visitor participation through proactive design. Conversely, commercial-driven behaviour had lower importance (average 3.67) and satisfaction levels (average 3.76) in cultural experience-oriented spaces, suggesting that commercial elements are not a core focus.

In commercially oriented spaces, such as the shopping centre in Zone D and the dining district in Zone G, commercially driven behaviour dominates, with the highest importance (average 4.72) and satisfaction (average 4.52), and 'dining consumption' satisfaction reaching 4.61. Culturally driven behaviour is the weakest, with an average satisfaction score of only 2.85, such as 'participation in guided tours,' which has a satisfaction score of only 2.71, reflecting that cultural activities are marginalised in commercial spaces. Spontaneously driven behaviour has the lowest satisfaction score, with an average of 3.04, indicating that visitors lack the motivation to explore. Socially driven behaviour is moderate in both types of spaces, but satisfaction is higher in cultural experience-oriented spaces.

V. Conclusion

This study achieves cross-scale optimisation of colour and spatial perception in environmental art design through intelligent algorithms. The main conclusions are as follows:

The proposed colour preference extraction model achieved an SSIM of 0.676 across 100 test images, representing an 8.1% to 8.8% improvement over MCM/K-Means/OM, with a PSNR of 22.16 dB (peaking at 24.39 dB), marking a 7.1% to 18.3% increase. This demonstrates its superiority in maintaining visual perception consistency.

The colour difference detection error ΔE of the colour schemes generated by the intelligent algorithm integrating visual aesthetics averaged 0.983, meeting the human eye's visual indifference requirement. The normalised colour difference mean was only 0.264, lower than the 0.227 achieved by professional designers. The subjective evaluation score reached 4.69, higher than the 4.62 achieved by professional designers.

In spatial perception quantification, the evaluation of seven areas in Site A based on entropy-weighted TOPSIS showed that the comprehensive score for cultural experience-oriented spaces was >0.7 (Area C: 0.8685); the score for commercially oriented spaces was <0.4 (Area G: 0.1492).

The IPA model revealed that in cultural experience-oriented spaces, the satisfaction with culturally driven behaviour reached 4.34; in commercially oriented spaces, the satisfaction with culturally driven behaviour was only 2.85, reflecting differences in behaviour-driven factors.

This study is the first to incorporate colour span, aesthetic parameters, and spatial perception scores into a unified optimisation framework, providing a data-driven scientific paradigm for environmental art design.

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