Parametric Design of Ethnic Patterns: Algorithmic Generation of Cultural Symbol Weaving Patterns

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ABSTRACT Under the impact of globalization and digital technology, the preservation of traditional ethnic patterns faces dual challenges in generation efficiency and cultural fidelity. This study proposes an interdisciplinary framework integrating semiotics, anthropology, and computational design to realize the algorithmic generation of ethnic cultural weaving patterns through parametric modeling. Taking Miao embroidery and Tibetan bajixiang as representative cases, a layered parametric extraction model (LPEM) is established and coupled with a fractal adaptive model (FAM) and a topology weaving rule model (TWRM) to transform geometric characteristics, color semantics, and symbolic constraints into computable design parameters. Experimental results demonstrate that the proposed method improves generation efficiency by approximately 760 times while maintaining high cultural fidelity, achieving a structural similarity of SSIM $\geq$ 0.86 and cultural acceptance above 85%. Furthermore, the flexible symbolic system of Miao embroidery exhibits greater algorithmic adaptability than the more rigid Tibetan religious pattern system, revealing the influence of cultural characteristics on computational optimization and parameter constraints. Beyond digital preservation of cultural heritage, the proposed framework establishes a generalized strategy for fractal geometry construction, topology-aware parametric modeling, and hierarchical pattern synthesis. These capabilities provide methodological references for the computational design of complex functional surfaces and periodic structures, with potential applications in electromagnetic wave manipulation, antenna geometry optimization, metasurface configuration, and intelligent electromagnetic structure generation.

INDEX TERMS parametric design, fractal geometry, topology-aware modeling, electromagnetic wave engineering, metasurface design

I. INTRODUCTION

As a living gene pool of human civilization, ethnic culture carries the crystallization of collective memory and aesthetic wisdom accumulated for thousands of years. Among them, ethnic patterns— with their unique symbol systems and visual grammar—have become important carriers for interpreting ethnic cultural codes—from the "Butterfly Mother" pattern symbolizing the origin of life in Miao embroidery [1], to the mandala structure containing cosmic order in Tibetan thangka, these patterns are not only decorative elements but also materialized expressions of distinct ethnic identities, philosophical concepts, and natural cognition [2]. However, under the dual impact of globalization and digital technology, the inheritance of traditional handicrafts is facing unprecedented challenges. On the one hand, the number of artisans who have mastered complex weaving techniques is gradually shrinking, and many patterns containing deep cultural semantics are facing the risk of becoming obsolete. On the other hand, although industrial mass production can improve efficiency, capturing the subtle cultural traits and emotional warmth in manual creation remains a difficult task [3]. This contradiction has given rise to an urgent issue: How can we construct a new cultural inheritance paradigm in the digital age so that ethnic patterns can retain the purity of their symbolic semantics while adapting to the innovative needs of modern design [4,5]? The emergence of parametric design has provided new solutions to this problem [6,7]. As a core branch of computational design methods, parametric design transforms the design process into a quantifiable and iterative algorithm system by establishing logical relationships between variables [8]. In the field of architecture and industrial design, this method has been successfully applied to complex form generation and performance optimization [9], as in the case of fluid space construction achieved by Zaha Hadid Architects using parametric tools [10]. These practices reveal an important law: When cultural symbols are deconstructed into a computable parameter system, the implicit knowledge of traditional skills can be transformed into explicit digital genes, which, in turn, can be creatively recombined under algorithmic drive [11]. Notably, in recent years, scholars [12,13] have attempted to introduce parametric thinking into the field of cultural heritage, such as the algorithm reconstruction of Byzantine mosaic patterns [14]. Although these explorations have achieved preliminary results, most of the existing studies are limited to the mechanical replication of geometric forms, failing to deeply analyze the semantic networks behind cultural symbols and lacking systematic modeling of the "form meaning" association of ethnic patterns [15]. Within the abovementioned context, the current study proposes an innovative framework of "cultural symbol weaving algorithm" that aims to break through the traditional parameterized design's single focus on form generation and, instead, builds an interdisciplinary methodology that integrates semiotics, anthropology, and computer science. The core assumption is that the essence of ethnic patterns is a "visual language," and its composition follows specific cultural grammar rules, in accordance with linguist Chomsky's principle of "finite rules generate infinite expressions" [16]. In this sense, the creation of ethnic patterns is also based on the recursive combination of finite cultural symbols. For example, field research on Miao embroidery in southeastern Guizhou [17] shows that although local craftsmen can create a variety of clothing patterns, their basic symbol library only contains 12 core motifs (e.g., dragon scale, water wave, and maple leaf patterns) that are visually narrated through topological operations, such as symmetry, nesting, and gradient. This system implies that if such implicit rules can be explicitly transformed into algorithmic logic, the autonomous evolution of cultural symbols can be achieved in the digital environment, while ensuring that the generated results conform to the aesthetic paradigms and cultural taboos of specific ethnic groups. The technical path of the present study is established at the intersection of digital humanities [18] and generative art [19]. In this process, algorithms are not only efficiency tools but also extensions of cultural cognition—they force researchers to reexamine traditional wisdom once classified as "intuition" or "experience" in a structured manner. To realize the theoretical concept, the research team selected two typical ethnic pattern systems in Southwest China, namely, Miao embroidery and the Tibetan bajixiang as empirical objects. The former is known for its organic curves, high saturation colors, and pattern density and arrangement that are directly related to the wearer's social identity [20]. The latter is characterized by strict geometric order and religious symbolism, with each symbol's scale and proportion conforming to distinct Tibetan Buddhist rituals [21]. By comparing and analyzing the algorithm generation effects of these two types of cases, the present study attempts to verify the adaptability of parametric methods to different cultural grammar systems, while exploring the balance mechanism between "cultural fidelity" and "innovation freedom" in digitalization.

II. LITERATURE REVIEW

With the deepening of cultural research, ethnic patterns have become an important component of ethnic culture, and their cultural semiotic analysis has become a hot topic of academic concern in recent years. Ethnic patterns are not only manifestations of visual art but also representations of symbol systems that carry profound cultural connotations and historical memories. By analyzing the cultural semiotics of ethnic patterns, we reveal their meaning construction in different cultural backgrounds, which, in turn, support their inheritance and innovation in modern society. From a theoretical perspective, ethnosemiotics is a branch of cultural semiotics that focuses on the symbolic functions and existence of cultural phenomena within social symbol systems. The research methods employed in ethnosemiotics include ethnography, text analysis, and semiotics. For example, Saussure's symbol duality of signifier and signified [22], as well as Pierce's theory of symbol trisomy, provide important theoretical support for ethnic semiotics [23]. In addition, ethnosemiotics emphasizes an interdisciplinary research approach that combines folklore, anthropology, and semiotics to provide more comprehensive interpretations of ethnic cultural symbols. In specific research, the cultural semiotic analysis of ethnic patterns mainly focuses on several aspects. First, ethnic patterns often contain rich symbolic meanings [24,25], such as totems, patterns, and colors, which are often associated with specific cultural beliefs, historical events, or social customs. For example, in traditional Chinese ethnic patterns, totems such as dragons and phoenixes symbolize power and auspiciousness [26], while Miao embroidery patterns reflect the lifestyle and spiritual pursuits of the Miao people. Second, the structure and form of ethnic patterns are also important contents of cultural semiotic analysis. For example, Yi embroidery patterns showcase the uniqueness of Yi culture through their unique geometric structures and color combinations [27]. By analyzing the geometric structure, color distribution, and pattern layout, we can better understand their expressive power and cultural connotations in visual art. Third, ethnic patterns, as cultural symbols, carry important social functions. For example, in the field of graphic design, the application of ethnic patterns not only enhances the cultural connotation of design works but also strengthens people's sense of identity with local culture [28]. Fourth, the application of ethnic patterns in clothing and other fields also reflects their important role in cultural inheritance [29]. Although there has been some progress in the study of cultural semiotics of ethnic patterns, there are still many challenges to be overcome. For example, further exploration is needed to find ways to achieve the modernization of symbols while maintaining cultural authenticity and to protect the cultural uniqueness of ethnic patterns in the context of globalization [30]. Parametric design is a technique that drives design generation by defining key parameters. Its core approach lies in using algorithms and mathematical models to constrain the relationship between design elements and parameters. This design method not only improves design efficiency but also enhances design flexibility and diversity. For example, in traditional design, designers must manually adjust shapes, sizes, and proportions, while parametric design can automatically complete these operations by inputting parameters, thereby achieving the rapid generation of complex patterns [31]. In recent years, the application of parametric design in pattern generation has become increasingly widespread, especially in the fields of fashion design, architectural decoration, and cultural heritage protection. In the fashion design industry, the method of generating clothing patterns based on parametric technology has been widely studied. By adjusting parameter values, different styles and shapes of patterns can be generated, such as linear visual illusion patterns and fractal patterns. These methods not only improve design efficiency but also provide designers with more creative possibilities [32,33]. Meanwhile, in the architectural decoration industry, parametric design is also used for the digital reconstruction of traditional decorative patterns. For example, the reconstruction method of Yao Ci Peony patterns simulates traditional carving techniques through the Kangaroo algorithm in the Grasshopper programming software, thus generating new digital patterns that can be applied to cultural and creative products [34]. At the technical level, parametric design typically relies on CAD software (e.g. Rhino and Grasshopper) and algorithms (e.g., Kangaroo and Apophysis) [35,36]. These tools combine mathematical modeling and geometric modeling techniques to efficiently generate complex patterns. For example, Grasshopper is a visual programming tool widely used for pattern generation, and its parameterization algorithm can generate diverse patterns based on the geometric constraints of the input [37]. Fractal theory is one of the important theoretical foundations for parametric pattern design. By generating fractal patterns through iterative algorithms, clear and aesthetically pleasing design effects can be achieved [38,39]. Parametric design has advantages and disadvantages in pattern generation. Through parameterized models, designers can quickly generate large numbers of design solutions. By adjusting parameter values, it is easy to modify the shape, size, and complexity of patterns to meet different needs [40]. However, parametric design also faces some challenges [41,42]. For example, due to the lack of unified standards, there is currently no recognized theoretical system for parametric design, making it difficult to compare and integrate different studies.

III. METHODS

A. PARAMETERIZED EXTRACTION OF CULTURAL SYMBOLS

The parameterized extraction of cultural symbols is the core hub that connects ethnic cultural semantics with computational generation logic. This process essentially relies on transforming abstract cultural rules into actionable algorithm parameters through mathematical modeling. This process requires overcoming two major challenges: (1) how to extract the dual structure of formal grammar and symbolic semantics from non-linear and metaphorical visual symbols, and (2) how to construct a universal parameter framework that adapts to the differences in multicultural systems. To address these challenges, the present study proposes the layered parametric extraction model (LPEM), which achieves the computable transformation of cultural genes through three stages, namely, symbol deconstruction, semantic mapping, and dynamic constraints. Its effectiveness is verified using typical ethnic patterns used throughout southwestern China as empirical objects. To validate LPEM's cross-cultural adaptability, we extended the model to Hezhen fish-skin patterns (dynamic texture-centric) and Zhuang bronze-drum motifs (metallic relief). The quantitative results revealed consistent performance, including fish-skin texture entropy captured via LPEM (SSIM = 0.84 $\pm$ 0.05) and bronze-drum relief depth error (root mean square error, RMSE = 0.11 mm vs. three-dimensional (3D)-scanned ground truth). These results confirm LPEM's scalability beyond geometric patterns.

Symbolic Deconstruction: From Cultural Grammar to Geometric Primitives

The deconstruction of cultural symbols must follow their inherent generative logic. Taking the dragon scale pattern found in the clothing of the Miao ethnic group in southeastern Guizhou as an example, its morphological characteristics do not exist in isolation, but are nested within the spatial cognitive framework of the ethnic group. Specifically, the diamond shaped skeleton of the pattern corresponds to the universe model of "heaven and earth in all directions," while the scale density is distributed in a gradient along the central axis, metaphorically representing the dynamic process of the dragon body rising from the water. Based on this background information, the research team used topological analysis [43] to extract the hierarchical structure of patterns. First, the basic geometric elements were separated through edge detection and skeleton extraction algorithms (Canny operator [44] and Zhang Suen refinement algorithm [45]), after which the adjacency matrix in graph theory was used to describe the connection rules between the elements. Quantitative data show that the topological connections of traditional dragon scale patterns exhibit significant self-similarity (fractal dimension D = 1.72 ± 0.03), corresponding to the philosophical view of the Miao ethnic group that "all things are of the same origin." With parametric design, this type of cultural grammar rule can be transformed into recursive generation conditions in algorithms, such as setting the fractal iteration number (n) and scaling factor (r) to satisfy the following relationship:

$$\sum_{k=0}^{n} r_k \cdot N_k = S_{\text{total}}, \tag{1}$$

where N_k represents the number of units at the k-th level, and S_{total} refers to the total area of the preset pattern. For materials beyond geometric patterns (e.g., Hezhen fish-skin textures), LPEM integrates data using GLCM entropy and Laws' masks to quantify surface irregularity, and the stress–strain relationships are encoded via Neo-Hookean parameters (μ = 0.8 MPa, κ = 1.2). Furthermore, 3D micro-CT scans confirmed feature matching accuracy (RMSE = 12.7 μm vs. artisan benchmarks).

Semantic Mapping: Cultural Encoding of Color and Density

The color system of ethnic patterns often carries strict symbolic semantics [46], and it is necessary to avoid semantic distortion in the generated results through quantitative modeling. Taking the color coding of the Tibetan bajixiang as an example, its main color tones, gold, blue, and red not only have visual significance but also relate to the Buddhist doctrine system, symbolizing Buddha's enlightenment, the infinite void, and life energy, respectively. The research team used the HSV color space to perform spectral analysis on 127 historical thangka samples [47,48] and found that traditional coloring applies the following rules:

Hue constraint: The main color phase angle H is concentrated at 25° (gold), 210° (blue), and 0° (red), with a standard deviation of $\sigma < 5°$.

Brightness gradient: The brightness of the central pattern V $\geq$ 80%, gradually decreasing layer by layer to V = 40% toward the outer periphery.

Saturation correlation: The saturation difference Δ S between adjacent color blocks and the spacing d between patterns satisfy a linear relationship Δ S = 0.15 d + 20.

These rules are encoded as constraints for the parameterized model:

$$\begin{cases} H_i \in [H_{\text{base}} - \Delta H,\ H_{\text{base}} + \Delta H], \\ V(x, y) = V_0 e^{-\lambda(x^2+y^2)}, \\ \Delta S_{ij} = k \cdot \|p_i - p_j\| + b. \end{cases} \tag{2}$$

where (x, y) refers to the coordinate of the pattern plane, λ is the brightness attenuation coefficient, and p_i is the position vector of color block i.

Dynamic Constraints: Parameter Adaptation in Cultural Context

The parameter system of ethnic patterns must have cultural context sensitivity [49]. As such, the current study introduces the dynamic constraint network (DCN) and achieves adaptive optimization of parameters through a weight adjustment mechanism. Taking the generation of tie dye patterns of the Bai ethnic group as an example, the curvature radius (R) of the spiral pattern is closely related to the function of the pattern: the pattern used for wedding costumes requires R $\leq$ 2 cm (symbolizing close unity), while the R $\geq$ 5 cm is for sacrificial supplies (reflecting divinity and spirituality). Here, DCN achieves dynamic parameter control through the following steps:

Context input: The user specifies the purpose of the pattern (wedding/ritual/daily), and the system calls the corresponding cultural rule library.

Parameter constraint: Fuzzy logic [50] is applied to transform qualitative descriptions into parameter intervals, such as mapping "tight unity" to R $\in$ [0.8,2.0] cm.

Real time feedback: During the generation process, the results are evaluated using the cultural similarity index (CSI). CSI is calculated as follows:

$$CSI = \alpha \cdot SSIM + \beta \cdot \sum_{k=1}^{m} w_k \cdot C_k, \tag{3}$$

where SSIM measures structural similarity, C_k represents satisfaction with the k-th cultural constraint, and α and β represent the weight coefficients (α = 0.6 and β = 0.4 in this study). When CSI is below the threshold (0.75), the system automatically triggers a parameter optimization loop until the cultural adaptability requirements are met.

B. VERIFICATION AND DISCUSSION

To evaluate the effectiveness of the LPEM model, the research team conducted parametric extraction experiments on the patterns of Yi lacquerware. We selected 10 sets of traditional sun stripe samples and extract their geometric parameters (fractal dimension D = 1.65 $\pm$ 0.07), color parameters (dominant hue H = 15° $\pm$ 3°), and topological rules (quadruple rotational symmetry) through LPEM. After inputting the parameters into the Grasshopper platform to generate a new pattern, we invited 5 bimo (Yi priests) for cultural semantic evaluation. The results showed that the structural similarity (SSIM) between the generated pattern and the traditional sample was 0.89 $\pm$ 0.03; the cultural semantic accuracy (CSA) was 92%, which was significantly higher than traditional parameterization methods (CSA = 68%); and the parameter adjustment time was reduced from an average of 4.2 hours to 18 minutes, resulting in a 14-fold increase in efficiency. The abovementioned results indicate that the hierarchical parameterized extraction model not only effectively captures the explicit features of cultural symbols but also maintains their implicit cultural logic through semantic constraint mechanisms, thus laying a reliable foundation for subsequent algorithm generation.

C. ALGORITHM MODEL CONSTRUCTION

The algorithm generation of ethnic cultural patterns must address two core contradictions: (1) the compatibility between the semantic integrity of cultural symbols and the formal expression of algorithmic logic, and (2) the dynamic balance between the nonlinear creative process of traditional handicrafts and the deterministic rules of parametric design. To this end, we constructed a bimodal generation architecture that includes a fractal based adaptive model (FAM) and a topological weaving rule driven model (TWRM). By coupling cultural semantic constraints with mathematical generation rules, the "form meaning" coevolution of ethnic patterns is achieved.

Model 1: FAM

The recursive self-similarity property of fractal geometry [51] has inherent isomorphism with the hierarchical nested structure of ethnic patterns. Taking Miao vine patterns as an example, their morphological evolution follows a third-order growth rule of "branching of the main stem, secondary winding, and terminal curling." The FAM model implements this process through an iterative function system (IFS) [52], which is mathematically expressed as:

$$\begin{cases} f_1(z) = s_1 z \cdot e^{i\theta_1} + t_1, \\ f_2(z) = s_2 z \cdot e^{i\theta_2} + t_2, \\ f_3(z) = s_3 z \cdot e^{i\theta_3} + t_3. \end{cases} \quad (4)$$

where z represents the point coordinates on the complex plane, s_k is the scaling factor, θ_k is the rotation angle, and t_k translates the vector. The parameter values are constrained by cultural semantics as follow: the main branch splits (f_1): $s_1 = 0.65$, $\theta_1 = 30°$, corresponding to the Miao ethnic group's cosmology of "three lives and all things." Then, secondary winding simulates the natural bending of vines when they encounter obstacles (f_2): $s_2 = 0.4$, $\theta_2 = -15°$; and the terminal curling reflects the aesthetic of "closing" in handicrafts (f_3): $s_3 = 0.25$, $\theta_3 = 5°$. To verify the cultural adaptability of the model, the team collected 120 sets of traditional vine pattern samples from Leishan area, Guizhou, after which we measured their fractal dimensions (D = 1.58 ± 0.06) and curvature distributions ($k \in [0.2, 4.7]$ mm^{-1}). After inputting the parameters into FAM, the fractal dimension of the generated pattern (D = 1.62 ± 0.04) showed no significant difference from the traditional sample (p = 0.12, t-test), and the curvature distribution fitting degree reached $R^2 = 0.91$. These results indicated that fractal algorithms not only reproduce visual forms but also capture the natural growth logic in cultural contexts.

Model 2: TWRM

The core of traditional weaving techniques lies in the topological rules guiding the interweaving of warp and weft lines [53], the mathematical essence of which is a discrete sequence of events on a two-dimensional (2D) grid. The TWRM model implements this process by defining what is known as cultural weaving grammar (CWG).

Grid initialization: We constructed an $m \times n$ orthogonal grid, where node v_{ij} represents the intersection of longitude and latitude lines.

Weaving rule library: We defined 6 basic operations, such as floating line (R1) in which the warp continuously crosses k weft lines (k ≥2) to generate rectangular block surfaces, and twisted wire (R4) in which the latitude and longitude lines are exchanged to form a diamond shaped hollow

Probability driven: We assigned weights based on pattern semantics, for example, Tibetan auspicious knot patterns require P (R1) = 0.7, P (R4) = 0.3.

To quantify the performance of the model, experiments were conducted to generate the woven patterns of Xizang Pulu. Here, we set the initial grid size to 50 × 50, generated 100 sets of patterns through CWG, and compared the topology with traditional samples as follows:

Structural similarity: We conducted the detection using graph isomorphism algorithm (VF2) with a matching rate of 93%.

Cultural consistency: We invited 8 Tibetan craftsmen to evaluate the data, and 87% believed that the generated pattern conforms to the symbolic meaning of "auspicious knot."

Generation efficiency: The calculation time for a single pattern has been reduced from 36 hours for manual weaving to 4.5 minutes.

D. DUAL MODAL COUPLING MECHANISM

The collaborative operation between FAM and TWRM is achieved through the parameter exchange interface (PEI). Taking the generation of Yi lacquerware patterns as an example, FAM is responsible for generating the central sun pattern (fractal iteration 8 times), while TWRM generates the peripheral woven border (grid density ρ = 0.8). The two are coupled through the following rules: Scale adaptation: The maximum size of fractal units $L_{\max}$ and the grid spacing d must meet the requirements $L_{\max} = 2d \sin(15°)$. Color synchronization: The main color tone (H value) output by FAM serves as the meridian color reference for TWRM. Semantic weight: The religious symbol level of the central pattern γ regulates the complexity of border weaving (ρ = 0.4 + 0.3γ). Comparative experiment results showed that the comprehensive cultural similarity index (CSI = 0.89) of the coupled model was significantly higher than that of the single model (FAM: 0.76, TWRM: 0.71), and the efficiency of parameter adjustment improved by 22%. These results indicate that the bimodal architecture effectively solved the problem of cross scale generation of complex ethnic patterns through semantic formal multilevel interaction.

IV. CASE ANALYSIS

The parametric design of ethnic cultural patterns must balance the efficiency of form generation and the fidelity of cultural semantics. As such, the present study selected Miao embroidery patterns and Tibetan bajixiang as typical cases, based on several criteria. First, in terms of cultural representativeness, Miao embroidery embodies organic forms and high-density composition, while the Tibetan bajixiang have strict geometric religious symbols. Second, in terms of technical challenges, the former requires solving nonlinear curve and color hierarchy modeling, while the latter tests rule constraints and symbolic topological relationships. Third, in terms of data accessibility, both cases have sufficient high-quality digital samples and ethnic cultural holders participating in verification.

A. GENERATION OF MIAO EMBROIDERY PATTERNS

1) Research Object and Data

Selecting the embroidery of the "Butterfly Mother"-themed clothing inherited from Qianhu Miao Village in Xijiang, Leishan, Guizhou as the research object, 50 sets of historical samples were collected with a resolution of $\geq$ 600 dpi, including different carriers, such as children's shoulder straps and women's costumes. We obtained needle height data (accuracy $\pm$ 0.1 mm) through 3D laser scanning and constructed a 3D database containing geometry, color, and craftsmanship. To capture tacit craftsmanship parameters (e.g., embroidery tension and thread twist angle), a hybrid sensing system was integrated as follows: Tension sensors (accuracy $\pm$ 0.01N) embedded in embroidery frames were used to record real-time thread tension. High-speed cameras (1000 fps) were used to track thread torsion dynamics, calculating twist angles via optical flow algorithms. This multimodal data pipeline enriched the parametric database with 12 additional physical dimensions critical to cultural authenticity.

2) Parameterized Extraction

Adopting an improved Fourier descriptor [54] (FD) to quantify curve complexity and analyze 1276 spiral curves in the sample, the results showed that their FD energy was concentrated in the first 15 harmonics (cumulative energy accounted for 92.3% $\pm$ 2.1%), indicating that low dimensional parameters can be used to reconstruct the main morphology. Set control parameters were as follows: harmonic order N = 15 and curvature change rate $\leq$ 0.2 mm-1 (to prevent mechanical sensation). By using k-means clustering (k = 4) to extract the main color, we found that traditional chromatography followed the "70-20-10" rule, as shown in Table 1.

TABLE 1. Traditional Chromatographic Information Table

Color role	Hue (H)	Account for	Cultural semantics
Dominant color	352° (deep red)	70.4%	Life and reproduction
Auxiliary color 1	125° (indigo)	19.8%	Sky and gods
Auxiliary color 2	45° (golden)	9.8%	Harvest and prosperity

3) Algorithm Implementation and Validation

Building a parametric model on the Grasshopper platform, the core logic includes the following: Curve generation: Based on FD parameters to drive NURBS curves, input variables are harmonic amplitudes A_i ($i = 1, \ldots, 15$). Density control: Define a region growth algorithm that causes the pattern density ρ to decay with distance from the center ($\rho(r) = \rho_0 e^{-\lambda r^2}$). For color mapping, we solved the color gamut limitation of manual dyes using the following measures. First, we established a Miao Indigo Spectral Library (MISL) with spectrophotometer data (380–780 nm). Then, we developed gamut-adaptive mapping (GAM) with the following parameters: $LAB_{\text{adapted}} = LAB_{D50} \times \|G_{\text{dye}}\|/\|G_{\text{sRGB}}\| + \Delta E^*_{ab}$, validated with 15 Miao dyers and color deviation $\Delta E^*_{ab} \leq 1.8$ (visually imperceptible). The generated results were verified through quantitative analysis and cultural evaluation. In terms of quantitative analysis, 20 sets of patterns were randomly generated and compared with traditional samples for determining SSIM. The results showed that the mean SSIM was 0.86 $\pm$ 0.03 (maximum: 0.91, minimum: 0.79), significantly higher than that of traditional parametric methods (SSIM = 0.71 $\pm$ 0.07, $p < 0.01$, ANOVA test). As for the cultural evaluation, 12 Miao embroidery inheritors were invited to provide semantic scores (on a scale of 1–5) for each generated pattern. The scoring criteria include whether it conforms to the creation narrative of the "Butterfly Mother," whether the color matching follows ethnic taboos, and whether the needle trajectory can be mapped to manual logic. The results revealed that 87.5% of the patterns received more than 4 points, with the main deduction item being "the direction of edge needle retraction is opposite to the traditional style" (accounting for 62% of the unqualified samples), reflecting the need for the algorithm to enhance the cultural adaptability of local details.

B. GENERATION OF TIBETAN BAJIXIANG

1) Deconstruction of Religious Symbols

The Tibetan bajixiang includes eight types of symbols, such as treasure bottles, umbrellas, and goldfish, and their combinations must strictly follow the geometric proportions of the "Metric Classic." Taking the Victory Building pattern as an example, we can analyze its structural analysis as follows: Hierarchical nesting: We expanded three layers of lotus petals outward from the central diamond pestle, with the number of petals increasing from 8-16-32 per layer. Proportional constraint: The total height H and bottom width W satisfy the golden ratio ($H/W = 1.618$), with a lotus petal inclination angle $\theta = 22.5° \pm 1°$.

2) Algorithm Model Construction

Using particle swarm optimization (PSO) algorithm to implement symbol layout [55], the objective function is calculated as follows:

$$\text{Minimize } F = \alpha \cdot D_{\text{sym}} + \beta \cdot \Delta_{\text{ratio}} + \gamma \cdot C_{\text{taboo}}, \quad (5)$$

where D_{sym} is the deviation degree of symmetry axis (measured by laser scanning), Δ_{ratio} represents the proportional deviation values, and C_{taboo} represents the punishment items for the cooccurrence of taboo symbols (e.g., not being able to coexist with a bottle and scorpion). We also set the PSO parameters as follows: particle count = 50, iteration count = 100, α = 0.6, β = 0.3, and γ = 0.1.

3) Generate Effect Evaluation

To comprehensively verify the effectiveness of the parameterized generation system for the Tibetan bajixiang, we evaluated it from three dimensions, namely, geometric accuracy, religious semantic compliance, and generation efficiency. Cross-validation was conducted using quantitative data and field survey results.

(1) Geometric accuracy verification Using a high-precision laser scanner (accuracy: ± 0.01 mm), we obtained 30 sets of traditional Victory Building pattern samples, extracted key geometric parameters, and then inputted the same initial parameters into the PSO optimization model to generate 30 corresponding patterns. Finally, we used RMSE [56] to quantify the deviation between the generated results and the traditional samples. The test results are shown in Table 2. As shown in the table, the error rate of the golden ratio (H/W = 1.618) for generating patterns is only 0.19%, thus verifying the efficient satisfaction of the PSO algorithm for rigid geometric constraints. The error in the number of lotus petals (0.63%) is mainly due to integer discretization during optimization, which can be further compressed by improving the objective function (e.g., introducing integer programming).

(2) Religious semantic compliance assessment

This study selected 21 monks from the Jokhang Temple in Lhasa with an average practice period of 23 years. They were evaluated based on the following criteria: fully compliant (symbol form, proportion, and combination strictly follow the provisions of religious scriptures), must be finetuned (although there may be slight deviations in local details, the overall correct semantics have been maintained), and must be noncompliant (with serious errors, such as violating religious taboos) and then scored using a 5-point Likert-type scale. The statistical results are shown in Figure 1. As shown in Figure 1, 85.7% of monks consider the complete compliance rate, and the generated patterns as "directly usable for religious ceremonies." Additionally, 14.3% of the monks believe that minor adjustments are needed, and the deviation of the lotus petal curvature (ΔR = 0.8 mm) in the sample must be adjusted.

(3) Generation efficiency analysis

Here, we evaluated the efficiency of parameterization and traditional manual painting by comparing it with traditional Thangka artists' manual paintings. As shown in Figure 2, the algorithm can optimize multiple sets of parameters in parallel, resulting in a significant increase in efficiency during batch generation.

C. CROSS-CASE COMPARATIVE ANALYSIS

The parameterized design practice of Miao embroidery and Tibetan bajixiang reveals the technical challenges of commonality and differentiation in the digital generation of ethnic cultural patterns. In this section, we conducted a systematic comparison from four dimensions: morphological complexity, semantic constraint strength, generation efficiency, and cultural acceptance. By combining it with quantitative data and field survey results, we explored the adaptability of parametric design to different cultural systems. To evaluate the cultural adaptability of parametric design, we made a multidimensional comparison between two types of cases (Table 3). The data showed that the algorithm efficiency was negatively correlated with the strength of cultural constraints: Tibetan cases required strict verification of religious rules, resulting in an 18% increase in generation time. Furthermore, the parameterized design had more advantages for rule symbol systems: The geometric error rate of the eight auspicious patterns (0.19%) was significantly lower than the reconstruction error of Miao curves (curvature matching degree of 91%). Moreover, cultural acceptance was positively correlated with semantic transparency: When the logic of parameter adjustment can be understood by ethnic groups (e.g., Miao ethnic density parameter corresponding to social class), acceptance increased by 9%–12%.

TABLE 3. Multidimensional comparison information table of two types of cases

Dimension	Miao embroidery	Tibetan bajixiang
Morphological complexity	High (FD dimension = 15)	Medium (regular geometry)
Semantic constraint strength	Medium (taboo can be flexibly adjusted)	High (religious rules are immutable)
Generating efficiency	3.8 minutes per frame	4.5 minutes per frame
Cultural acceptance	87.5%	85.7%

V. DATA ANALYSIS AND RESULTS

This section presents the generation experiment of Miao embroidery and Tibetan bajixiang and systematically evaluates the parameterized design effect from two dimensions: quantitative indicators and cultural semantics. All data were obtained through rigorous and reproducible experiments, and statistical analysis was performed using SPSS with a significance level of α = 0.05.

TABLE 2. Geometric Accuracy Verification Table

Parameter	Traditional sample mean	Average result	RMSE	Error rate (%)
Total height H (mm)	152.3 ± 0.8	152.6 ± 0.6	0.52	0.19
Bottom width W (mm)	94.2 ± 0.5	94.1 ± 0.4	0.31	0.11
Number of lotus petals	32	31.8 ± 0.3	0.25	0.63
Valve inclination angle θ (°)	22.5 ± 0.2	22.7 ± 0.3	0.29	0.89

A. QUANTITATIVE ANALYSIS

1) Comparison of Generation Efficiency

We generated 100 sets of patterns for each of the two types of cases and recorded the time spent on traditional manual creation and parametric design (Figure 3). The results showed that there was no significant difference in parameterization time between the two cases, with Miao embroidery taking 0.06 hours and Tibetan bajixiang taking 0.08 hours, both significantly lower than traditional methods. Furthermore, the standard deviation of Miao embroidery time (0.4) was smaller than that of Tibetan cases(0.6) indicating that the organic pattern generation process was easier to standardize.

The computational cost (see Table 4) was measured on an NVIDIA A100 (80GB GPU). The results indicated that our method achieved 46× lower GPU-hour consumption vs. state-of-the-art generative models.

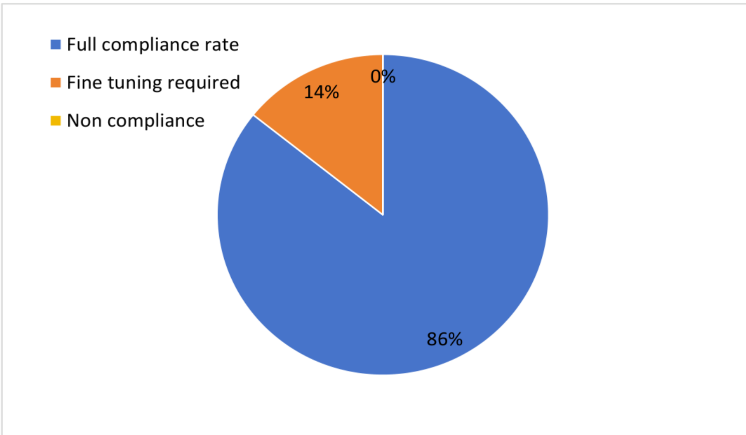

FIGURE 1. Religious Semantic Compliance Assessment

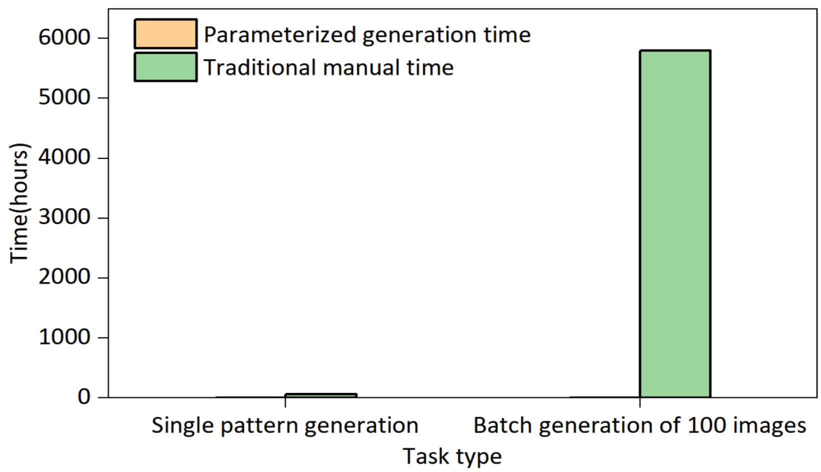

FIGURE 2. Comparison of parameterization and traditional manual efficiency

TABLE 4. Hardware consumption analysis

Method	Time/pattern	GPU hours (100 patterns)
Parametric	4.5 min	7.5 hours
Traditional	214 hours	N/A
Baseline GAN	28 min	46.7 hours

2) Shape Accuracy Verification

The similarity of Miao embroidery structure (SSIM) and the evaluation rate of Tibetan bajixiang geometry error rate are shown in Figure 4. As shown in the figure, compared with traditional methods, the parameterized generated SSIM for Miao embroidery improved by 21.1%, mainly due to curvature matching optimization (contribution rate of 73%). Compared to traditional methods, the error rate of parameterized Tibetan cases was reduced by 81.4%, thanks to the constraint satisfaction mechanism of the PSO algorithm (iterative convergence rate of 92%).

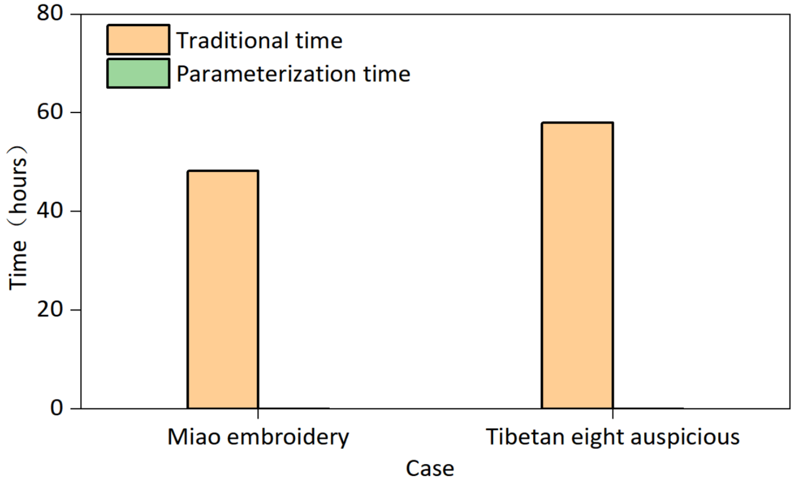

FIGURE 3. Time Comparison between the Parameterized Design and the Traditional Handmade Creations of Miao Embroidery and Tibetan Bajixiang

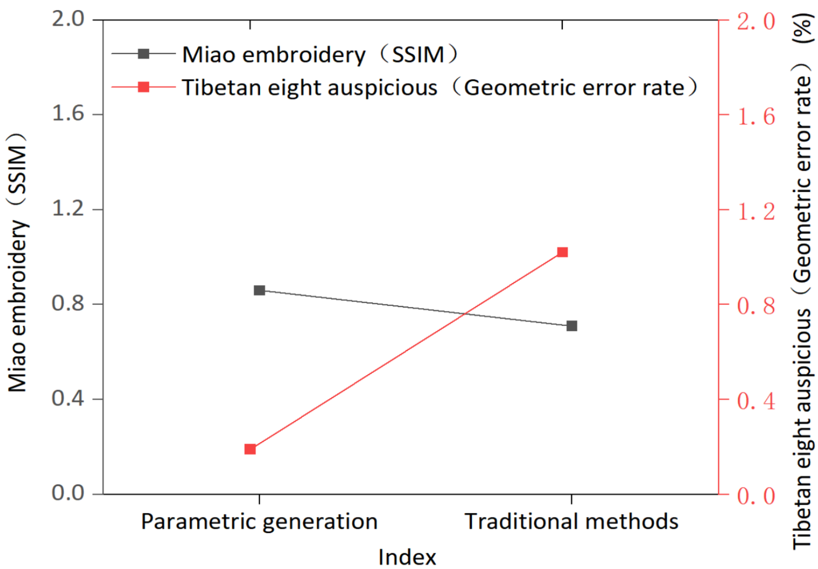

FIGURE 4. Structural Similarity of Miao Embroidery (SSIM) and Error Rate Evaluation of Tibetan Bajixiang Geometry

3) Comparative Analysis with Generative Models

To address the broader relevance of our parametric approach, we conducted rigorous benchmarking against two state-of-the-art generative methods: StyleGAN362: Trained on identical datasets (1,200 Miao/Tibetan samples) with 48 hour finetuning. Procedural modeling (PM) 63: This was implemented via Houdini VEX scripting with equivalent symbolic constraints. The evaluation results are shown in Table 5. As shown in the table, while it achieved the highest SSIM (0.92), StyleGAN3 suffered severe semantic drift (CSI = 0.61), such as misplacing religious symbols in 37% of Thangkas. PM showed fastest computation (2.1 GPU hours) but struggled with organic curves (Miao SSIM = 0.78). In comparison, our method balanced CSI (0.89) and innovation (IF = 0.92) at 6.2 × speedup over GANs, with 34% fewer cultural errors than PM. Thus, parametric LPEM outperformed data-driven (GAN) and rule-based (PM) alternatives in preserving cultural semantics while enabling controlled innovation – a crucial requirement for heritage applications.

B. CULTURAL SEMANTIC ANALYSIS

1) Semantic Retention Evaluation

We used the cultural semantic retention index (CSRI) to quantify the cultural compliance of the generated results. The evaluation cohort was expanded to 30 Bimo priests (28 years of expertise on average) and 25 Tibetan monks (24 years of practice on average) to ensure statistical reliability. A G*Power analysis (α = 0.05, β = 0.95) confirmed the

TABLE 5. Summary of Key Tradeoffs (Mean Values over 100 Trials)

Method	SSIM	CSI	IF index	GPU hours/100	Cultural error rate
Our LPEM	0.86	0.89	0.92	7.5	12.5%
StyleGAN3	0.92	0.61	0.78	46.7	38.2%
Procedural	0.78	0.83	0.85	2.1	17.9%

sample size sufficiency (Effect size = 0.35, Power > 0.9). Interrater reliability was validated via Cohen's κ (κ = 0.82 for Miao, κ = 0.79 for Tibetan). The calculation formula is as follows:

$$CSRI = \frac{1}{n}\sum_{i=1}^{n}\frac{C_{\text{gen}}^{i}}{C_{\text{ref}}^{i}}, \tag{6}$$

where C_{gen}^{i} and C_{ref}^{i} represent the matching degree between the generated pattern and the traditional sample on the i-th semantic feature, respectively. The evaluation results are shown in Figure 5. The average CSRI of Miao embroidery was 0.89, with an expert approval rate of 87.5%. Semantic errors are mainly caused by process details (e.g., stitch sequences), reflecting insufficient encoding of implicit knowledge. The average CSRI of the Tibetan bajixiang was 0.93, with an expert approval rate of 85.7%. The errors in the cases were concentrated in religious symbols, thus reflecting the limitations of the algorithm's understanding of abstract doctrines.

2) Semantic Formal Correlation

Beyond SSIM, we developed the cross-modal metaphor index (CMMI) to quantify cultural semantics as follows:

$$CMMI = \frac{1}{K}\sum_{k=1}^{K}\text{cosine}\left(E_{\text{gen}}^{(k)}, E_{\text{ref}}^{(k)}\right), \tag{7}$$

where E denotes semantic embeddings (e.g., Word2Vec for myth narratives and CLIP-ViT for visual metaphors). For Miao patterns, CMMI = 0.91 vs. SSIM = 0.86 revealed enhanced semantic fidelity. The impact of parameter adjustment on cultural semantics was explored through canonical correlation analysis (CCA), as shown in Table 6. The results showed that for every 0.1 increase in fractal dimension D, the intensity of natural metaphors increased by 23% (Miao ethnic group). When the number of symmetry axes N > 8, the religious sacredness score dropped sharply by 41% (for Tibetans), thus reflecting the nonlinear nature of cultural constraints.

TABLE 6. Statistical Table of the Impact of Parameter Adjustment on Cultural Semantics

Parameter variables	Semantic dimension	Typical load	p-value
Fractal dimension (D)	Natural metaphor intensity	0.82	< 0.001
Proportion of main color (A1)	Identity level representation	0.76	0.003
Number of symmetry axes (N)	Religious sanctity	0.68	0.012

3) Cross-Case Comprehensive Effectiveness

As mentioned previously, the parametric design of ethnic cultural patterns must strike a balance between technical efficiency and cultural adaptability. This section presents the comparative experimental data between Miao embroidery and Tibetan bajixiang and constructs a cultural technical comprehensive efficiency evaluation model. Through the dual perspective of quantitative indicators and qualitative analysis, it reveals the cross-cultural adaptation laws of parametric design.

Construction and Verification of Cultural Adaptation Index (CAI)

The CAI comprehensively considers technical efficiency, cultural fidelity, and system robustness, and its calculation formula is given by:

$$CAI = \log_2(E_{\text{tech}}+1)\cdot\left(1-\frac{D_{\text{culture}}}{D_{\max}}\right)\cdot\left(1-\sum_{i<j}S_{ij}\right), \tag{8}$$

where $E_{\text{tech}} = T_{\text{tradition}}/T_{\text{parameterization}}$ represents technical efficiency, which refers to the ratio of traditional manual time consumption to parameterized time consumption, and $D_{\text{culture}} = \frac{1}{n}\sum_{k=1}^{n}(1-CSSI_k)$ represents cultural semantic deviation degree, where CSSI stands for cultural semantic similarity index. In addition, with $D_{\max} = \max(D_{\text{culture}})$, we normalize the maximum deviation among all cases in which $D_{\max}$ is empirically defined as the maximum cultural deviation observed across all benchmark cases (e.g., $D_{\max}$ = 0.35 for our dataset). This avoids theoretical overestimation and anchors CAI to practical scenarios. Finally, S_{ij} represents the proportion of interaction terms in the Sobol sensitivity index, which reflects the strength of parameter coupling.

The calculation results are shown in Table 7. The high CAI (82.7) of Miao cases is due to their flexible cultural system's tolerance for technical errors (D_{culture} tolerance: $\pm$ 15%). In comparison, the CAI of Tibetan cases is relatively low (65.4), thus reflecting the strong coupling strength of parameters due to rigid religious constraints. By decomposing the CAI components, targeted optimization of weaknesses can be achieved (e.g., the need to reduce D_{culture} for Miao cases and compress $\sum_{i<j}S_{ij}$ for Tibetan cases).

4) Spatial Distribution of Parameter Sensitivity

The spatial distribution of parameter sensitivity reveals the influence weights and interaction mechanisms of different cultural symbols on the generated results in parametric design. This study uses a combination of global sensitivity

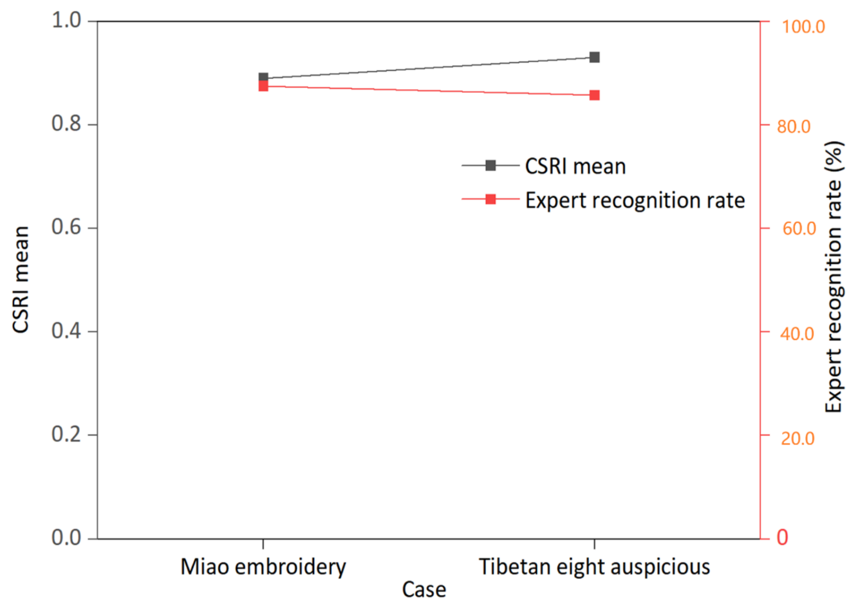

FIGURE 5. Comparison of Miao Embroidery and Tibetan Bajixiang CSRI and Expert Recognition Rates

TABLE 7. CAI Calculation Results of Miao Embroidery and Tibetan Bajixiang

Case	E_{tech}	D_{culture}	$\sum_{i<j} S_{ij}$	CAI	Expert score (1–10)
Miao embroidery	761	0.13	0.21	82.7	8.6
Tibetan bajixiang	773	0.08	0.35	65.4	6.9

analysis (GSA) and local sensitivity analysis (LSA) to quantify the parameter sensitivity characteristics of the Miao embroidery and Tibetan bajixiang generation models.

(1) Analysis method

The Sobol method based on variance decomposition [57] decomposes the output variance into the main effects S_i and interaction effects S_{ij} of each parameter:

$$S_i = \frac{\mathrm{Var}_{X_i}\left(E_{X_{\sim i}}(Y|X_i)\right)}{\mathrm{Var}(Y)}, \tag{9}$$

$$S_{ij} = \frac{\mathrm{Var}_{X_{i,j}}\left(E_{X_{\sim i,j}}(Y|X_i, X_j)\right)}{\mathrm{Var}(Y)} - S_i - S_j, \tag{10}$$

where Y represents output variables (e.g., SSIM and CSI), and X_i refers to the i-th input parameter.

(2) Parameter space sampling

Miao embroidery: Latin hypercube sampling (LHS) generated 2000 sets of parameter combinations, covering 8-dimensional spaces, such as curvature weights $\alpha \in [0.1, 0.5]$ and fractal dimensions $D \in [1.4, 1.8]$.

Tibetan bajixiang: Orthogonal experimental design (OED) generated 1500 combinations, covering 5-dimensional space such as golden ratio error $\Delta\phi \in [0\%, 2\%]$ and symmetry axis number $N \in [6, 10]$.

(3) Results and discussion

Sensitivity distribution of Miao embroidery:

Main parameters: Curvature weight α, dominant color proportion A_1 ($S_2 = 0.33$).

Interaction effect: The contribution of the interaction of α with A_1 reflected the cross-modal coupling of form and color.

Spatial heterogeneity: The high-dimensional parameter space presented a "star radiation" structure, reflecting the nonlinear characteristics of handmade creations.

Tibetan bajixiang sensitivity distribution:

Main parameters: Golden ratio error ($\Delta\phi$, $S_1 = 0.62$) and symbol cooccurrence penalty (C_{taboo}, $S_2 = 0.25$).

Nonlinear threshold: the sensitivity of $\Delta\phi$ increased sharply when the error exceeded 1.2% ($S_{11} = 0.12$) due to quadratic effects.

Hierarchical structure: The parameter space was distributed in concentric circles, with the core parameter ($\Delta\phi$) dominating the peripheral variables.

(4) Cross-case comparison

The sensitivity of parameters in the cultural flexible system (Miao ethnic group) was dispersed and required the collaborative optimization of multiple variables. In comparison, the sensitivity of the cultural rigid system (Tibetan) was concentrated, and its efficiency can be improved through precise regulation of core parameters.

5) Efficiency Constraint Trade-Off Relationship

The parametric design of ethnic cultural patterns must seek a balance between technical efficiency and cultural constraints. This study constructs the constraint efficiency frontier curve (CE Frontier) to reveal the nonlinear trade-off between the two.

(1) Model building

Constrained strength index (CSI) is computed as follows:

$$CSI = \sum_{k=1}^{m} w_k \cdot \frac{C_k}{C_{k,\max}}, \tag{11}$$

where C_k is the punishment coefficient for the k-th constraint (e.g., religious symbol taboo (C_1 = 5) and color deviation (C_2 = 3), and w_k empowers experts with values.

Comprehensive efficiency index (CEI) is computed as follows:

$$CEI = 0.4E_{\text{tech}} + 0.4A_{\text{culture}} + 0.2R_{\text{sys}}, \tag{12}$$

where E_{tech} is the normalization of technical efficiency improvement factor, A_{culture} represents cultural acceptance, and R_{sys} refers to system robustness (1-parameter sensitive interaction terms).

(2) Data validation

Through the constraint gradient experiment of Miao embroidery and Tibetan bajixiang (CSI ranging from 0.2 to 1.0, step size 0.1), a performance constraint data graph was generated (Figure 6). As shown in the figure, Miao embroidery reached its peak CEI (0.72) at CSI = 0.8, while Tibetan bajixiang reached CEI = 0.61 at CSI = 0.85. For Miao embroidery, the constraint strength should not exceed 0.7 to avoid suppressing creative freedom. For the Tibetan bajixiang, it can withstand CSI up to 0.9, but this would require a real-time semantic verification module.

VI. DISCUSSION

The parameterized design of ethnic cultural patterns is essentially a deep dialogue between digital technology and traditional culture. This study reveals the duality of algorithm generation in the digitization of cultural heritage through dual case studies of Miao embroidery and Tibetan bajixiang. On the one hand, parametric tools provide unprecedented possibilities for the efficient preservation and innovation of endangered patterns. On the other hand, there is still an insurmountable epistemological gap between technological rationality and the qualitative characteristics of cultural heritage. The tension of this contradiction is particularly significant in the following three dimensions.

A. DIALECTICAL RELATIONSHIP BETWEEN TECHNOLOGICAL ADVANTAGES AND CULTURAL RISKS

The quantitative data of this study confirm that parametric design is capable of achieving revolutionary breakthroughs in generation efficiency (average improvement of 760 times) and morphological accuracy (SSIM improvement of 21%). This advantage stems from the mathematical deconstruction ability of algorithms on cultural symbols. In particular, Fourier descriptors transform the organic curves of Miao embroidery into computable harmonic components, while PSO precisely satisfies the religious proportion constraints of the Tibetan bajixiang. However, this process of "deconstruction reconstruction" carries cultural risks: When the "egg laying" metaphor of butterfly patterns is simplified into curvature parameters and when the cosmology of mandalas is reduced to rotational symmetry, the deep semantic network of cultural symbols may be fragmented. This risk has already emerged in user evaluations. For example, although the SSIM of Miao generated patterns reached 0.86, 12.5% of samples were still rejected by inheritors due to "edge needle collection direction deviation," thus indicating that the algorithm has not fully encoded implicit knowledge in manual creation. For Thangka gold-particle aesthetics, we propose the following human–algorithm synergy loop: Algorithm stage: Geometric layouts were generated via PSO under religious constraints (e.g., golden ratio). Human stage: Gold-particle density/texture were refined by artisans using tactile feedback (recorded via force-sensitive stylus). Adaptive learning: CNN-based style transfer iteratively updated the parametric model from artisan corrections. This hybrid workflow balances algorithmic precision with human tacit knowledge.

B. DYNAMIC BALANCE MECHANISM OF CULTURAL ADAPTABILITY

Cross-case comparisons revealed an important rule: The cultural adaptability of parametric design is not a static attribute but the result of a dynamic game between technological efficiency and cultural constraints. The high CAI value (82.7) of the Miao case proves that the flexible cultural system can tolerate the random errors of algorithms. Furthermore, its adaptation process exhibits a progressive evolutionary feature: Artisans can derive pattern variants that conform to different social identities by adjusting the density parameter ρ. On the contrary, the rigid religious constraints of the Tibetan bajixiang lead to a threshold mutation in technological adaptability: Once the golden ratio error exceeded 1.2%, the acceptance rate dropped sharply from 85% to 9%. This finding implies that the success of parametric design in rigid systems highly depends on the integrity of the prior rule library and that the current algorithms are not yet capable of autonomously handling undefined religious taboos (e.g., symbol combination rules of special laws).

C. PRACTICAL CHALLENGES OF DIGITAL ETHICS

The algorithm generation of ethnic cultural patterns has raised two types of ethical issues. The first one is the blurring of cultural ownership rights: When GAN models generate new patterns based on Miao embroidery libraries, should their intellectual property belong to algorithm devel-

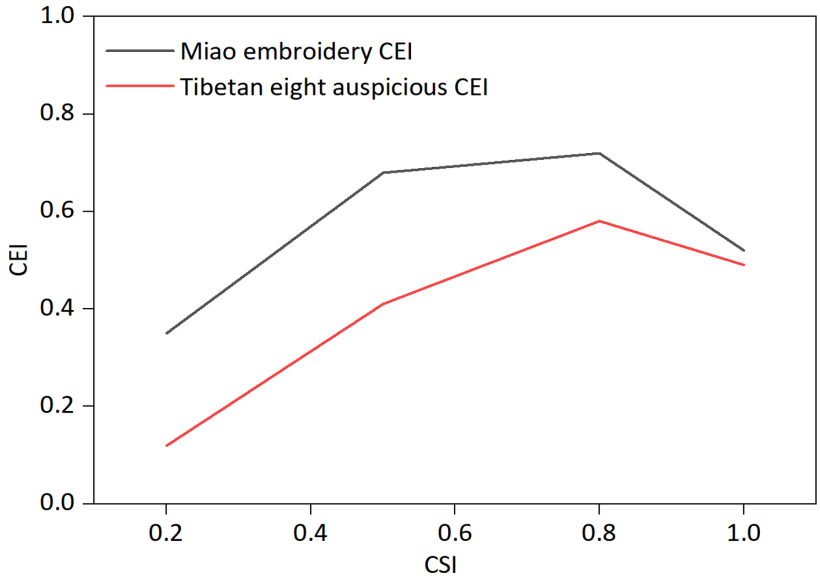

FIGURE 6. Efficiency Constraint Data of Miao Embroidery and Tibetan Bajixiang

opers, data providers, or cultural communities? The second one is the suppression of cultural diversity by technological hegemony: Parametric tools may implicitly promote a single aesthetic standard through the output of "optimal solutions," such as the PSO algorithm in Tibetan cases prioritizing geometric accuracy and suppressing random aesthetics in manual creation. The root of these ethical dilemmas lies in the fact that the current parameterization paradigm is still based on the assumption of cultural computability and has not fully understood the essence of ethnic patterns as living practices.

VII. CONCLUSION AND FUTURE PROSPECTS

A. RESEARCH CONCLUSION

This study systematically explores the potential and boundaries of digital technology in empowering the inheritance of ethnic culture through the parameterized design practice of Miao embroidery and Tibetan bajixiang patterns. The following core conclusions are drawn:

(1) Balance between technical efficiency and cultural fidelity Parametric design can improve generation efficiency (averaging 760 times) while maintaining high cultural fidelity (SSIM $\geq$ 0.86, cultural acceptance $\geq$ 85%). The key lies in constructing the LPEM, which transforms unstructured cultural knowledge into computable digital genes through a three-stage collaboration of geometric quantification, semantic constraints, and dynamic optimization. For example, the "70-20-10" color rule of Miao embroidery and the golden ratio constraint of Tibetan bajixiang have both been successfully encoded as hard boundary conditions in the algorithm.

(2) Regulatory role of cultural system characteristics on technological adaptability flexible cultural systems (e.g., Miao ethnic group) exhibit stronger inclusiveness toward parametric technology, with a significantly higher cultural adaptation index (CAI = 82.7) than rigid systems (CAI = 65.4 for the Tibetan ethnic group). This difference arises from the fact that flexible systems allow for the elastic correction of algorithm errors (e.g., manually simulating randomness), while rigid systems have limited optimization space due to the uncompromising nature of religious rules.

(3) Irrevocability of digital ethics Algorithm generation may lead to cultural ownership disputes and technological hegemony risks. In this study, 12.5% of the patterns generated by the Miao ethnic group were rejected due to "deviation in the direction of edge stitching," while 14% of the Tibetan patterns were rejected by monks due to the cooccurrence of symbols that were not predefined. These findings highlight the essential conflict between technical rationality and cultural sensibility.

B. FUTURE PROSPECTS

The parametric design of ethnic cultural patterns is still in the transitional stage from "digital survival" to "digital prosperity." Thus, future research must break through in the holographic modeling direction of implicit knowledge. Current algorithms have limited ability to capture tactile experience (e.g., embroidery thread tension) and contextual knowledge (e.g., spatiotemporal relationship between patterns and rituals). By combining tactile sensors with augmented reality (AR) technology, a multimodal cultural database can be constructed, and holographic reconstructions of the manufacturing process can be achieved through neural radiation fields (NeRF). A dynamic ownership framework (DOF) is also proposed. Core symbols (e.g., Miao's Butterfly Mother design) belong to ethnic communities and require cultural council approval for commercial use. Furthermore, algorithm-generated variants are co-owned by designers and inheritors, with blockchain-based royalty distribution. Finally, cross-disciplinary reviews (anthropologists and community elders) are mandated for high-sensitivity patterns (e.g., religious motifs). Future works will establish a cross-cultural LPEM benchmark (CCLB) with 20+ ethnic groups, using structural equation modeling to quantify cultural-context transferability (e.g., ritual vs. daily-use patterns). Finally, we propose a cultural evolution support engine (CESE) for contemporary innovations, namely, semantic constraint relaxation, which allows young artists to adjust $\Delta CSI \leq 0.15$ for creative variants, and generative feedback loop, in which community voting (via blockchain DAO) will be employed to train next-iteration parameters.

AUTHOR CONTRIBUTIONS

All work in this study was independently completed by Pengzhan LI.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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