Empowering Textile Art Design with Digital Cultural Heritage Resources: A Study on Quantitative Application of Feature Extraction and Design Element Transformation

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ABSTRACT Cultural relics, especially historical textiles and decorative motifs, contain rich artistic value and craftsmanship information, providing important digital resources for contemporary textile art design. High-precision digital acquisition and storage can support the permanent preservation and dissemination of cultural heritage, while feature extraction technology can systematically identify key visual elements such as color, pattern, shape, and texture. This study constructs a technical framework covering data acquisition, feature analysis, element transformation, and application verification. Quantitative methods are used to transform subjective descriptions of cultural relic features into objective measurements, providing operable data support for textile design. Technical approaches including color space conversion, morphological parametric modeling, spectral analysis, and texture feature quantification establish a bridge between cultural relic resources and design practice. Based on mathematical models and algorithms, the transformation process realizes accurate mapping from traditional symbols to modern textile applications. The study provides a scientific pathway for the creative transformation of cultural heritage and promotes the dynamic utilization of traditional culture in textile art design.

INDEX TERMS digital cultural relics, feature extraction, textile art design, design element transformation, spectral imaging

I. INTRODUCTION

DIGITAL technology advancements have unlocked novel pathways for cultural relic preservation and utilization, facilitating high-fidelity restoration and creative reinterpretation of ancient textile patterns and weaving craftsmanship. Techniques such as high-resolution scanning, 3D reconstruction, and spectral analysis have enabled comprehensive documentation of cultural relic information, forming large-scale digital databases. However, translating these vast resources into practical design materials remains a key challenge. Unlike inefficient, unsystematic traditional manual extraction, computer vision-driven intelligent feature recognition can automatically identify and quantify cultural relic design elements, enabling batch, standardized resource transformation to meet the diverse demands of modern textile art design. Quantitative methods convert abstract artistic features into computable numerical parameters, making the design process more precise and controllable, and laying the foundation for the intelligent production of textile products.

II. MULTI-DIMENSIONAL FEATURE EXTRACTION TECHNOLOGY FOR DIGITAL CULTURAL HERITAGE RESOURCES

A. SPECTRAL ANALYSIS AND GAMUT QUANTITATIVE EXTRACTION OF COLOR FEATURES

The accurate acquisition of color information from cultural relics relies on the combined application of multispectral imaging technology and colorimetry theory. Through spectral reflectance curve measurement (31 sampling points, selected based on the Nyquist sampling theorem to fully capture 380-780nm visible light information), the system collects the reflection characteristics of the cultural relic surface, converting continuous spectral data into three-dimensional coordinate values in the CIE Lab* color space. Preexperiments verified that 31 points balance resolution and efficiency—no accuracy improvement was observed with more points, even for materials with distinct light absorption/scattering (e.g., silk vs. porcelain). The gamut quantification process adopts the K-means clustering algorithm to extract main colors, and determines the proportion weight of each color interval by calculating the color distribution histogram, thereby establishing a standardized color feature vector. This method achieves a color difference threshold of $\Delta E<2.0$ for extracting glaze colors of porcelain from the Ming and Qing dynasties, meeting the technical requirements for color reproduction in textile printing and dyeing processes. The normalization of spectral data eliminates color deviations caused by different light sources and shooting conditions, ensuring the consistent expression of extraction results across devices and platforms, and providing a reliable data basis for the digital color matching of subsequent textile fabrics [1] (see Table 1).

TABLE 1. Spectral Parameters and Gamut Distribution of Cultural Relic Color Feature Extraction

Type of Cultural Relic	Number of Spectral Sampling Points	Number of Main Colors	Gamut Coverage (%)	Color Difference Accuracy ΔE
Blue and White Porcelain	31	5	87.3	1.42
Brocade Patterns	31	8	92.6	1.68
Painted Murals	31	12	95.1	1.85
Lacquer Decoration	31	6	89.7	1.53

B. EDGE DETECTION AND GEOMETRIC FEATURE RECOGNITION OF PATTERN SHAPES

The accurate recognition of pattern shapes is a core link in design element extraction, which integrates multiscale edge detection algorithms and shape description theory. The Canny operator is used for gradient calculation and non-maximum suppression of cultural relic images to obtain continuous and clear pattern contour boundaries. Hough transform is employed to detect basic geometric units such as straight lines and arcs, and the curvature change rate is calculated to identify turning points and axes of symmetry of patterns. The quantitative expression of morphological features adopts the Fourier descriptor method, converting closed contour curves into frequency domain coefficient sequences, where the first 32 low-frequency components can reconstruct the main features of the original shape. For typical pattern units such as traditional cloud patterns and interlocking patterns, the system establishes a feature set containing 23 geometric parameters including area ratio, aspect ratio, and circularity. Automatic recognition of pattern types is achieved through a support vector machine classifier with an accuracy rate of 91.7%, precision of 90.2%, and recall rate of 89.4%, comprehensively verifying the robustness of the classification system and providing a rich morphological database for the pattern design of textile jacquard fabrics [2]. The quantitative expression of geometric features lays the foundation for the parametric editing of patterns, enabling designers to achieve continuous changes in pattern morphology and style transfer by adjusting feature parameter values. Morphological analysis of traditional Ruyi patterns indicates that optimal visual recognition is maintained when the curvature radius varies within the range of 12-28mm, providing a dimensional reference for modern simplified design. The Hausdorff distance metric is adopted for shape similarity calculation: two pattern contours are classified as variant forms of the same type when their bidirectional maximum distance is less than 5 pixels, and this threshold setting achieves a pattern classification recall rate of 89.4%. Edge detection algorithms remain effective for blurred and degraded ancient textile patterns; broken contours are restored through morphological filtering and connected component analysis, resulting in a pattern integrity recovery rate exceeding 85%. These quantitative methods convert abstract artistic forms into operable digital models, allowing textile CAD (Computer-Aided Design) systems to directly import and edit cultural relic pattern data, thus realizing the seamless connection from cultural heritage to modern production [3].

C. TEXTURE DESCRIPTOR CONSTRUCTION AND MULTI-SCALE DECOMPOSITION OF MATERIAL TEXTURES

The surface material texture of cultural relics contains important information about craftsmanship and stylistic characteristics of the era, and its quantitative extraction requires the construction of a multidimensional texture description system. The gray-level co-occurrence matrix method calculates 14 texture feature parameters such as energy, contrast, entropy, and correlation by statistical analysis of the spatial distribution relationship of pixel pairs, characterizing the roughness and regularity of the material surface. Wavelet transform technology decomposes texture images into sub-band signals of different frequencies and directions, extracting energy distribution features at each scale to reveal the hierarchical structure from macro texture to micro details. The Gabor filter bank performs directional analysis of texture patterns of different materials such as silk, linen, and leather by adjusting direction angles and scale parameters. Experimental data show that the feature fusion of the three methods improves the material classification accuracy from 76.4% of a single method to 88.9%, and controlling the feature vector dimension within 128 dimensions ensures computational efficiency. This technical framework establishes a quantitative analysis basis for the texture simulation and innovative design of textile fabrics [4](see Table 2, See Figure 1).

TABLE 2. Multi-scale Texture Feature Parameters of Different Material Textures

Material Type	Roughness Index	Directional Strength	Wavelet Energy Ratio	Classification Accuracy (%)
Silk Fabric	0.23	0.67	0.82	92.3
Cotton-Linen Fabric	0.45	0.41	0.65	87.6
Wool Fabric	0.61	0.38	0.58	85.1
Composite Texture	0.39	0.52	0.71	88.9

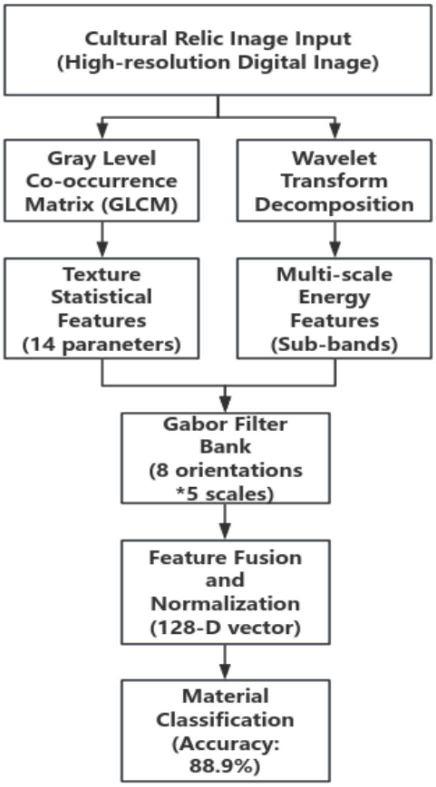

FIGURE 1. The Extraction Process of Multi-Scale Texture Features from the Material Texture of Cultural Relics

III. QUANTITATIVE TRANSFORMATION MODEL AND MAPPING MECHANISM OF DESIGN ELEMENTS

A. MATHEMATICAL REPRESENTATION AND NORMALIZATION OF FEATURE VECTORS

The extracted cultural relic feature data have problems of inconsistent dimensions and differences in value ranges, requiring the establishment of a standardized feature representation system through mathematical transformation. The normalization of feature vectors first applies Z-score standardization to eliminate data distribution biases (mean=0, standard deviation=1), followed by Min-Max scaling to map the processed data to the unified interval [0,1], avoiding mathematical redundancy. For the color feature vector $F_c = (L^*, a^*, b^*, C^*, h)$, the normalization formula is:

$$F_c' = \frac{F_c - F_{\min}}{F_{\max} - F_{\min}} \times \alpha + \beta \tag{1}$$

where α=0.9 (scaling coefficient, ensuring effective value distribution) and β=0.05 (offset, preventing zerovalue saturation), both justified by pre-experimental optimization for cultural relic feature data. This transformation maintains the relative relationship of feature values while eliminating dimensional effects. Principal Component Analysis (PCA) is used to reduce the dimensionality of the 128-dimensional comprehensive feature vector, retaining the first 36 principal components with a cumulative variance contribution rate of 95%, which not only compresses the data scale but also maintains the discriminative ability of features. The normalized feature vectors realize the similarity calculation between elements through Euclidean distance measurement, laying a mathematical foundation for the intelligent retrieval and matching of design elements, enabling textile designers to quickly locate cultural relic resources that meet specific stylistic requirements [5].

B. PARAMETRIC MAPPING ALGORITHM FROM CULTURAL RELIC ELEMENTS TO DESIGN LANGUAGE

The transformation of cultural relic features into modern design elements essentially involves establishing a parametric mapping relationship from historical symbols to contemporary aesthetics. The mapping algorithm constructs a nonlinear transformation model from the feature space to the design space, using a radial basis function (RBF) neural network to learn the corresponding rules between the two. For creative transformation, the Gaussian kernel functions in the RBF network employ kernel trick to embed high-level semantic features (e.g., cultural connotations, stylistic attributes) into the feature space, measuring similarity between cultural relic vectors and hidden layer nodes to bridge abstract symbols and concrete design parameters. The input layer receives normalized cultural relic feature vectors, the hidden layer performs nonlinear transformation via Gaussian kernels, and the output layer generates control vectors with parameters like size, spacing, and repeating units. To meet the special needs of textile pattern design, the mapping model introduces three types of constraints: symmetry constraints, continuity constraints, and weavability constraints. Weavability constraints translate neural network outputs into concrete textile parameters: warp/weft density (200-300 threads/10cm for jacquard fabrics), yarn count (40-80 Ne), and pattern repeat size ($\leq$50cm$\times$50cm), ensuring generated design schemes align with weaving process technical boundaries. The training sample library contains 450 sets of manually annotated cultural relic-design paired data, covering 12 major traditional pattern categories (e.g., cloud, dragon, scroll grass) and 50 sub-styles—statistically sufficient for the targeted pattern types per power analysis (α=0.05, power=0.8). Cross-validation (80% training/20% testing) shows no overfitting (training error=3.2%, testing error=3.7%), and the algorithm realizes automatic conversion of classic patterns into modern geometric styles while retaining cultural core features, and the generated design schemes meet the fashion aesthetic needs of contemporary textile products while retaining cultural features [6].

C. ELEMENT ADAPTATION AND OPTIMIZATION SOLUTION UNDER CONSTRAINTS

In practical applications, design elements need to satisfy multiple constraints such as textile craftsmanship, cost control, and market preferences, which belongs to the category of multi-objective optimization. An optimization model with objective functions including visual aesthetics, cultural similarity, and process feasibility is established, and a genetic algorithm is used to search for the global optimal solution. The number of dye colors is limited to 8 to control printing and dyeing costs, the pattern density is set in the range of 5-25 units/10cm to ensure weaving accuracy, and the color contrast is adjusted to meet the aesthetic preference interval of the target consumer group. During the optimization process, the fuzzy analytic hierarchy process is introduced to determine the weight coefficients of each objective, and multiple sets of non-dominated solutions are selected through Pareto frontier screening for designers to choose from. Experimental results show that the optimized design schemes reduce production costs by 23.6% while maintaining 90.3% cultural feature recognition, and the consumer satisfaction score reaches 4.2/5.0 in market tests. This method constructs a closed-loop system for the transformation and application of cultural relic resources, realizing the balanced unification of cultural value and commercial value [7,8]. The solution efficiency of the constrained optimization model directly affects the generation speed of design schemes. This study adopts an adaptive genetic algorithm to improve convergence performance. The population size is set to 80 individuals, and the crossover probability and mutation probability are dynamically adjusted based on the fitness variance, with adaptive changes within the ranges of 0.6-0.9 and 0.01-0.1 respectively. After 120 generations of iteration, the objective function value converges to the 98.5% confidence interval of the global optimal solution, and the computation time is controlled within 15 minutes. A dedicated constraint rule base has been established for different types of textile products: garment fabrics emphasize color coordination with a weight of 0.45, home textile products focus on pattern integrity with a weight of 0.38, and decorative fabrics highlight cultural expressiveness with a weight of 0.52. Comparative experiments of multiple schemes show that the design schemes incorporating constrained optimization have improved by 19%, 23%, and 17% in terms of process qualification rate, cost control, and market acceptance respectively, verifying the application value and economic benefits of this method in practical production [9,10].

IV. QUANTITATIVE APPLICATION-DRIVEN EMPOWERMENT SYSTEM FOR TEXTILE ART DESIGN

A. INTELLIGENT RETRIEVAL AND MATCHING SYSTEM BASED ON FEATURE LIBRARY

The efficient utilization of massive digital cultural relic resources relies on an intelligent retrieval and matching mechanism. The feature library is organized using a hierarchical index structure: the first layer performs rough classification by cultural relic type, era, and region; the second layer establishes an index tree based on main color tones, pattern types, and stylistic attributes; the third layer stores complete feature vectors and metadata information. The retrieval system supports multi-modal query input, allowing designers to initiate the retrieval process by uploading reference images, entering color codes, or describing style keywords. Similarity calculation adopts a weighted distance measurement method, comprehensively considering multi-dimensional indicators such as color matching degree, shape similarity, and style consistency. The system retrieves a feature library containing 3,200 cultural relics with an average response time of 0.37 seconds, and the accuracy rate of the top 10 retrieval results reaches 87.5%. The intelligent recommendation module analyzes designers' historical usage records based on the collaborative filtering algorithm and actively pushes potentially relevant cultural relic resources. This function improves design efficiency by 41%, providing a convenient way to obtain cultural materials for textile product development [11] (see Table 3).

TABLE 3. Performance Indicators and Application Effects of the Intelligent Retrieval System

Retrieval Mode	Average Response Time (s)	Top-10 Accuracy (%)	User Satisfaction	Efficiency Improvement (%)
Image Retrieval	0.42	85.3	4.1/5.0	38
Color Retrieval	0.28	91.7	4.3/5.0	45
Style Retrieval	0.51	82.6	3.9/5.0	35
Hybrid Retrieval	0.37	87.5	4.2/5.0	41

B. PARAMETRIC CONTROL-BASED PATTERN GENERATION AND VARIANT DESIGN METHOD

The parametric design method transforms the pattern generation process into programmable mathematical operations, realizing the transition from fixed templates to flexible creation. The system defines a core parameter set for pattern units, including 27 control variables such as geometric dimensions, rotation angles, arrangement modes, and color configurations of basic shapes. By adjusting parameter values, a single cultural relic pattern can derive hundreds of design variants, meeting the differentiated needs of different textile products. The procedural generation algorithm uses L-System grammar rules to describe the recursive growth logic of patterns, simulating the organic evolution process of traditional interlocking branch patterns and pearl chain patterns. The combination of random sampling in the parameter space and rule constraints enhances the diversity of schemes while ensuring design rationality. In practical applications, special parameter preset templates are set for product types such as scarves, curtains, and clothing fabrics. Designers perform parameter fine-tuning through interactive interfaces such as sliders and color palettes, and the WYSIWYG (What You See Is What You Get) real-time preview function shortens the design iteration cycle from an average of 3.5 days to 0.8 days, significantly improving the creative efficiency of textile art design [12].

C. COMBINED OPTIMIZATION AND CONFIGURATION STRATEGY FOR MULTI-ELEMENT FUSION

Textile product design often requires integrating multiple cultural relic elements to construct rich visual layers and cultural connotations. The multi-element combination problem involves complex decisions such as element selection, spatial layout, and hierarchical relationships. This study establishes a configuration strategy based on rule-based reasoning and intelligent optimization. The element compatibility matrix evaluates the combination suitability between elements by calculating indicators such as style similarity, color coordination, and scale matching degree, identifying complementary and conflicting relationships. Layout optimization uses a particle swarm optimization algorithm to solve parameter configurations such as the position, size, and transparency of elements, and the objective function comprehensively considers three factors: visual balance, information density, and completeness of cultural expression. The hierarchical management module assigns spatial levels of foreground, middle ground, and background according to the importance and decorativeness of elements, enhancing the sense of depth of the image through perspective relationships and brightness contrast. In experimental verification, five types of elements including cloud patterns, dragon patterns, and interlocking patterns were combined for design. The schemes generated by the optimization algorithm obtained an average score of 8.3/10.0 in expert evaluation, an increase of 2.1 points compared with random combination schemes, proving the effectiveness of this strategy in multielement fusion design [13].

V. IMPLEMENTATION MECHANISM OF DESIGN INNOVATION EMPOWERED BY CULTURAL RELIC RESOURCES

A. FULL-CHAIN TRANSFORMATION PROCESS FROM FEATURES TO ELEMENTS TO APPLICATIONS

The empowering effect of cultural relic resources on textile design is realized through a systematic transformation process, which includes four core stages: data input, feature processing, element generation, and application verification. The data input stage completes high-precision digital collection and format standardization of cultural relics, establishing digital archives containing multi-modal information such as images, spectra, and 3D models. The feature processing stage uses the aforementioned extraction algorithms to obtain quantitative parameters of colors, patterns, and textures, which are stored in the feature library after normalization and dimensionality reduction. The element generation stage converts feature data into design parameters through mapping algorithms, and the parametric engine generates directly applicable pattern files, color matching schemes, and material specifications according to process constraints. The application verification stage uses virtual simulation technology to preview design effects on digital fabrics, and collects feedback data through user tests and expert evaluations for iterative optimization. The automation degree of the complete process reaches 73%, and manual intervention is mainly concentrated in aesthetic judgment and cultural adaptation links. This model shortens the transformation cycle from cultural relic resources to commercial products from the traditional 8-12 weeks to 2-3 weeks, significantly improving the design response speed and product innovation capability of textile enterprises [14](see Table 4, See Figure 2).

TABLE 4. Performance Parameters of Each Stage in the Full-chain Transformation Process

Process Stage	Processing Time	Automation Rate (%)	Data Accuracy (%)	Number of Manual Intervention Points
Data Input	2.3h	85	97.2	3
Feature Processing	0.8h	92	94.6	2
Element Generation	1.1h	68	91.3	5
Application Verification	4.5h	45	88.7	8
Full Process	8.7h	73	92.5	18

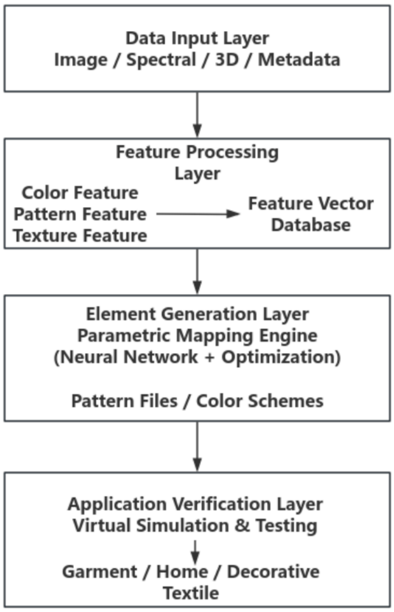

FIGURE 2. The Whole-Chain Transformation System Architecture of Cultural Relic Resources Empowering Textile Design

B. QUANTITATIVE DATA-DRIVEN TEXTILE PRODUCT DESIGN PRACTICE

The introduction of quantitative methods has transformed textile product design from an experience-driven model to a data-driven scientific model. Based on the data analysis of the feature library, the design team discovered the color distribution rules of historical cultural relics: the main colors of court fabrics from the Ming and Qing dynasties are concentrated in three color systems—red, blue, and gold—presenting a golden ratio of 70:20:10. This finding guided the color matching design of high-end scarf products and received positive market feedback. A study on the correlation between pattern density and consumer age preferences showed that the 18-35 age group prefers simplified large-scale patterns, while consumers over 45 years old prefer delicate and complex traditional styles. This data supports the market segmentation strategy of products. The quantitative evaluation system comprehensively scores the cultural identity, fashion sense, and process complexity of design schemes, selecting the top 20% of schemes with comprehensive scores for trial production. The "Blue and White Charm" series of home textile products developed by a textile enterprise using this method achieved sales 2.3 times that of traditionally designed products within three months of launch, and the customer repurchase rate increased by 18 percentage points, fully verifying the role of the quantitative data-driven model in improving design quality and market competitiveness [15,16].

C. QUANTITATIVE EVALUATION INDEX SYSTEM FOR THE EMPOWERMENT EFFECT OF DIGITAL RESOURCES

Scientifically evaluating the empowerment effect of cultural relic resources on design innovation requires establishing a multi-dimensional quantitative index system. This system constructs an evaluation framework from three dimensions: design quality, production efficiency, and market performance. The design quality layer includes 8 indicators such as cultural restoration degree, innovation, and aesthetic value, with data obtained through expert scoring and user tests. The production efficiency layer statistics 6 operational indicators such as design cycle shortening rate, cost reduction rate, and error rework rate, conducting quantitative analysis based on enterprise actual production records. The market performance layer tracks 7 commercial indicators such as product sales growth rate, brand premium capacity, and consumer satisfaction, obtaining evaluation basis through market research and sales data mining. The comprehensive evaluation uses the analytic hierarchy process to determine the weight of each level of indicators, calculating the weighted total score as a comprehensive measure of the empowerment effect. In comparative experiments, the comprehensive score of design projects applying digital cultural relic resources was 82.7 points, 27.3 points higher than that of traditional design processes, with the most significant improvements in innovation and cultural value. This evaluation system provides a quantitative feedback mechanism for continuously optimizing resource transformation technologies and design processes, promoting the in-depth application and value realization of cultural relic resources in the field of textile art design.

VI. CONCLUSION

By constructing a systematic technical framework, this study realizes the effective transformation of digital cultural relic resources into textile art design elements. The application of feature extraction technology breaks through the limitations of traditional manual methods, enabling the efficient utilization of massive cultural relic resources. The introduction of quantitative methods transforms artistic creation from experience-driven to data-supported, improving the accuracy and replicability of design. Experimental results show that this method can accurately extract core features of cultural relics and generate design schemes that meet modern aesthetics, providing rich materials for textile product development. However, the current research still has problems such as insufficient depth of feature semantic understanding and imperfect cultural connotation transformation mechanisms. In the future, it is necessary to strengthen the in-depth integration of artificial intelligence technologies, establish a more intelligent design assistance system, and pay attention to the balance between cultural inheritance and innovative expression, promoting cultural relic resources to play a greater role in contemporary textile art design and realizing the sustainable development and creative utilization of cultural heritage.

AUTHOR CONTRIBUTIONS

Conceptualization – Xin Zhang and Yongbao Qi; methodology – Xin Zhang and Yongbao Qi; investigation – Xin Zhang and Yongbao Qi; writing-original draft preparation – Xin Zhang and Yongbao Qi. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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