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Digital Reconstruction of Traditional Dance Movement Genealogies and Comparative Analysis across Stylistic Schools

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SUMMARY: *Traditional dance preservation requires more than video recording because stylistic knowledge is embedded in continuous body motion, rhythm, force, spatial orientation and recurrent movement motifs. This study proposes a genealogy-aware digital reconstruction method for traditional dance movements and conducts comparative analysis across stylistic schools. A corpus containing six traditional dance schools, 144 performance sequences and 3456 segmented movement units is constructed. Each movement unit is encoded by skeletal posture, kinetic variation, rhythm envelope and Laban Movement Analysis descriptors. A multi-relation movement graph is then built by integrating temporal adjacency, morphological similarity, rhythmic affinity, co-occurrence relation and expert correction. The graph is organized into three levels: core motor lexicon, motif family and stylistic branch. Experiments show that the proposed model achieves 0.923 F1, 0.762 ARI and 0.638 style-separation index, outperforming ST-GCN, CTR-GCN, PoseC3D and ablated variants. The reconstructed genealogy reveals that Yangge, Guozhuang and Andai share step-pulse and weight-shift motifs, while Dunhuang dance and Dai Peacock dance are closer in palm arc, torso incline and gaze-turn structures. Error analysis shows that sleeve-sweep movements produce the largest boundary deviation because skeleton data cannot fully capture delayed costume trajectories. The proposed method provides an interpretable computational framework for traditional dance archiving, stylistic comparison and digital transmission.*

KEYWORDS: *traditional dance; movement genealogy; motion capture; Laban Movement Analysis; stylistic comparison*

1 Introduction

The preservation, revitalization, and teaching of traditional dance is shifting from video retention to computable archiving. Digital museum exhibits, non-genetic heritage programs, dance rehearsal training, and virtual character performances all require finer-grained movement material, whereas traditional video recordings often only preserve the appearance of a particular performance. The really difficult issue for researchers and teachers is not so much the ability to record a dance, but rather the ability to break down continuous movements into comparable movement units and to further illustrate how these units are retained, morphed, and differentiated across genres. Weight shifts, palm arcs, sleeve sweeps, knee flexibility, shoulder rhythms, and eye turns in traditional dances often encompass morphology, rhythm, force generation, and symbolism simultaneously, and it is difficult to consistently preserve these relationships in a single video or textual description.

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Digital ICH research has formed a clearer technical route. Existing research has been conducted in the directions of digital life cycle of intangible cultural heritage, motion capture, dance modeling, 3D visualization and interactive exhibition, which has pushed dance from static recording to data-based organization [1]. A review of dance digitization further suggests that video, motion capture, audio, and gesture estimation can work together to support cultural heritage preservation, transforming dance movements from viewing objects to retrievable, analyzable, and reproducible data objects [2]. Motion capture templates have been used in folk dance preservation scenarios to guarantee movement authenticity and heritage consistency, illustrating the need for traditional dance digital archives to preserve both movement trajectories and stylistic constraints [3]. These studies provide the basic premise of this paper: traditional dance can be preserved computationally, but the preservation object should not stop at the level of the full video.

High-quality data bases are also beginning to emerge from the digitization practices of traditional Chinese dance. Taking Dunhuang dance as an example, the Chang-E dataset utilizes motion capture to record eight types of full-body movements of Dunhuang dance, and provides data formats such as skeleton, human body mesh, and multiview video, which provides a sample base for digital preservation and re-creation of classical dance movements [4]. Related work has also used Dunhuang dance motion capture data for immersive exhibitions and digital character generation, demonstrating that traditional dance data can serve cultural displays, artistic creation, and movement research [5]. Folk dance movement template frameworks, semantic annotations, and dance ontology studies also illustrate that preserving trajectories alone is not sufficient; movement names, body parts, beat positions, performance contexts, and stylistic attributes need to be co-entered into the archival structure [6, 7].

Existing research on the organization of dance movements consists of three main categories. The first category is oriented towards dance collection management, which uses movement similarity and semantic associations to organize large-scale dance segments, emphasizing the retrieval and classification of dance materials [8]. The second category is oriented towards movement quality interpretation, which describes features such as Body, Effort, Shape and Space with the help of Laban Movement Analysis, enabling dance styles to be expressed in terms of body involvement, force generation nature, body shape and spatial orientation [9, 10]. The third category is oriented towards symbolic transcription and movement recognition, transforming skeletal data into Labanotation, or recognizing movement categories using graph convolution, Transformer and 3D convolution models [11-13]. These directions solve the problems of data organization, movement semantics and category recognition, respectively, but traditional dance genre comparison still lacks a genealogical structure that can connect movement units, movement matrices and genre branches.

The shortcomings of current methods are mainly reflected in three aspects. First, most digital archives are still based on videos, movement segments or category labels, which makes it difficult to represent the inheritance, co-occurrence and variant relationships among movements. Second, skeleton action recognition models are good at accomplishing category judgments, but are less likely to explain the origin of specific actions that are similar to one genre to another. Third, LMA and Labanotation provide strong explanatory properties, but in the absence of graph structure organization, it is difficult to form computable genealogical relationships among descriptors. Genre differences in traditional dance are usually not determined by individual gestures, but by the combination of movement motifs, rhythmic organization and body shaping. If we only output the classification result of “belonging to a certain genre”, it is still impossible for researchers to determine what movement materials are shared between genres, and it is also difficult to indicate whether certain differences come from hand paths, lower limb rhythms, or body orientations.

Based on the above problems, this paper considers traditional dance movement as a genealogical object composed of movement units, movement motifs and genre branches, and proposes a method for digitizing and comparing traditional dance movement genealogies across genres. Taking Dunhuang Dance, Northern Yangge, Tibetan Potzhuang, Mongolian Andai, Dai Peacock Dance and Uyghur Sainaim as the research objects, this paper cuts the continuous dance sequences into movement units and integrates three-dimensional skeleton, dynamics change, rhythmic envelope and LMA descriptors to construct a genealogy-aware movement graph. The graph takes movement units as nodes and chronological adjacency, morphological similarity, rhythmic association, genre co-occurrence and expert correction relationship as edges to further form a three-layer structure of core movement lexicon, movement matrices and genre branches.

The contributions of this paper include three points. First, a traditional dance movement unit coding scheme is constructed to incorporate gesture, dynamics, rhythm and LMA semantics into a unified feature space, so as to make the movement materials of different genres comparable. Second, we propose a genealogy-aware action graph construction method, so that the similarity relationship between actions, co-occurrence relationship and expert knowledge participate in the calculation of side weights. Third, a cross-genre comparison protocol is designed to explain the shared matrices and sources of divergence among traditional dance genres through 3D action spectral embedding, style distance matrix, ablation experiments, error analysis and efficiency evaluation.

2 Methods

2.1 Data acquisition and movement-unit encoding

This paper constructs a sample library of six types of traditional dance movements, covering Dunhuang Dance, Northern Yangge, Tibetan Potzhuang, Mongolian Andai, Dai Peacock Dance, and Uyghur Sainam. The samples consisted of three types of sources: demonstration collection by professional dancers, relabeling of public teaching images, and motion-capture reference clips. The professional capture was done by 36 performers with genre training background, 6 performers from each genre; the public images were selected from frontal or oblique frontal shots, with less body occlusion and identifiable movement boundaries; and the motion capture reference footage was used to calibrate skeletal scales, rhythmic boundaries, and key postures. All samples were uniformly converted to 30 fps and represented at 21 major joint points for head, torso, shoulder, elbow, wrist, hip, knee, ankle, and foot end positions. Traditional dance samples were first transformed into a standardized skeleton sequence, then sliced into movement units and coded into multiple sets of features, as shown in Figure 1.

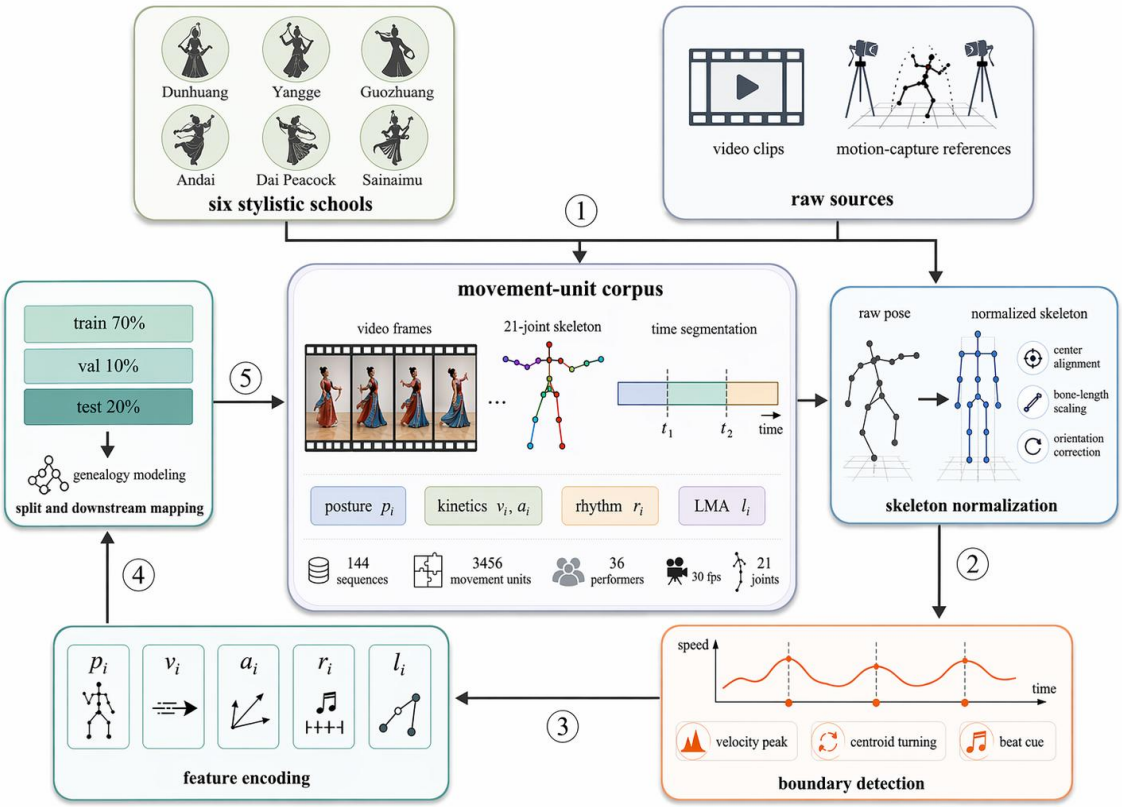

Figure 1: Traditional dance corpus and movement-unit encoding mechanism.

In order to reduce the influence of performer height, stage orientation and shooting scale on action comparison, this paper performs a three-step preprocessing of the skeleton sequence. The first step takes the center of the pelvis as the coordinate origin and translates all the joint coordinates to the local coordinate system of the human body. The second step normalizes the bone length scale consisting of shoulder width and hip width to bring the joint distances of different performers into a comparable range. The third step corrects the whole-body orientation based on the hip orientation and shoulder line, so that similar movements will not be misjudged as different movements due to differences in stage orientation. The 2D poses in the video samples are first corrected by temporal filtering and bone length constraints, and then mapped to a uniform skeleton format; the motion capture samples retain the 3D coordinates and are resampled according to the same joint definitions.

Action unit cuts are jointly determined by peak velocity, center of gravity turns, beat boundaries, and expert annotations. Many movements in traditional dance do not end in a static stance, e.g., sleeve delay after a sleeve sweep, wrist extension after a palm arc, and center of gravity recovery after a rotational step may span adjacent movements. Therefore, instead of using only the velocity nadir as a boundary, body center of mass velocity, wrist velocity, foot-end contact state, and beat peak are used together for candidate boundary generation in this paper. Candidate boundaries were reviewed by two dance professional annotators, and clips with more than 5 frames of disagreement were subjected to a second discussion. The final sample library contains 144 dance sequences and 3456 movement units, and the training, validation, and test sets are divided by 70%, 10%, and 20%, and it is guaranteed that the neighboring segments of the same performer are not distributed across the sets. The composition of the traditional dance movement system is shown in Table 1.

Table 1: Composition of the traditional dance movement corpus

Stylistic School	Sequences	Movement Units	Performers	Frame Rate	Mean Unit Length
Dunhuang Dance	24	612	6	30 fps	2.8 s
Yangge	24	585	6	30 fps	2.5 s
Guozhuang	24	561	6	30 fps	2.9 s
Andai	24	548	6	30 fps	2.6 s
Dai Peacock Dance	24	573	6	30 fps	3.1 s
Sainaimu	24	577	6	30 fps	2.7 s
Total	144	3456	36	30 fps	2.8 s

The combined characteristics of the action units, as shown in equation (1).

$$x_i = [p_i, v_i, a_i, r_i, l_i], \quad X = \{x_i\}_{i=1}^{N} \tag{1}$$

where x_i denotes the composite features of the ith action unit, p_i, v_i, a_i, r_i and l_i denote the attitude, velocity, acceleration, rhythm and LMA descriptors respectively, and X denotes the set of samples containing the Nth action unit. All continuous features are standardized using z-score, rhythmic features are normalized by the proportion of time within the action unit, and LMA descriptors are jointly generated by expert annotation and model prediction. In order to reduce the subjective labeling errors, the LMA labels adopt a two-round review mechanism, where the Body and Space labels are verified by joint participation and orientation thresholds, and the Effort and Shape labels are confirmed by a professional annotator before entering the training set.

2.2 Genealogy-aware movement graph construction

Based on the coding of action units, this paper further constructs a spectrum-aware action graph. Each action unit corresponds to a node, and the node attributes are represented by comprehensive features. Edge weights are jointly determined by four types of relationships: temporal adjacency in the same dance sequence, similarity of movement patterns and dynamical trajectories, high-frequency co-occurrence within genres, and attribution of action matrices obtained by expert correction. This design enables the action map to simultaneously preserve local timing, cross-sample similarity and genre knowledge, and avoids the degradation of action genealogy into common clustering results. On the basis of action unit features, this paper constructs a spectrum-aware action graph so that timing, morphology, rhythm and expert knowledge are jointly involved in the calculation of edge weights, as shown in Fig. 2.

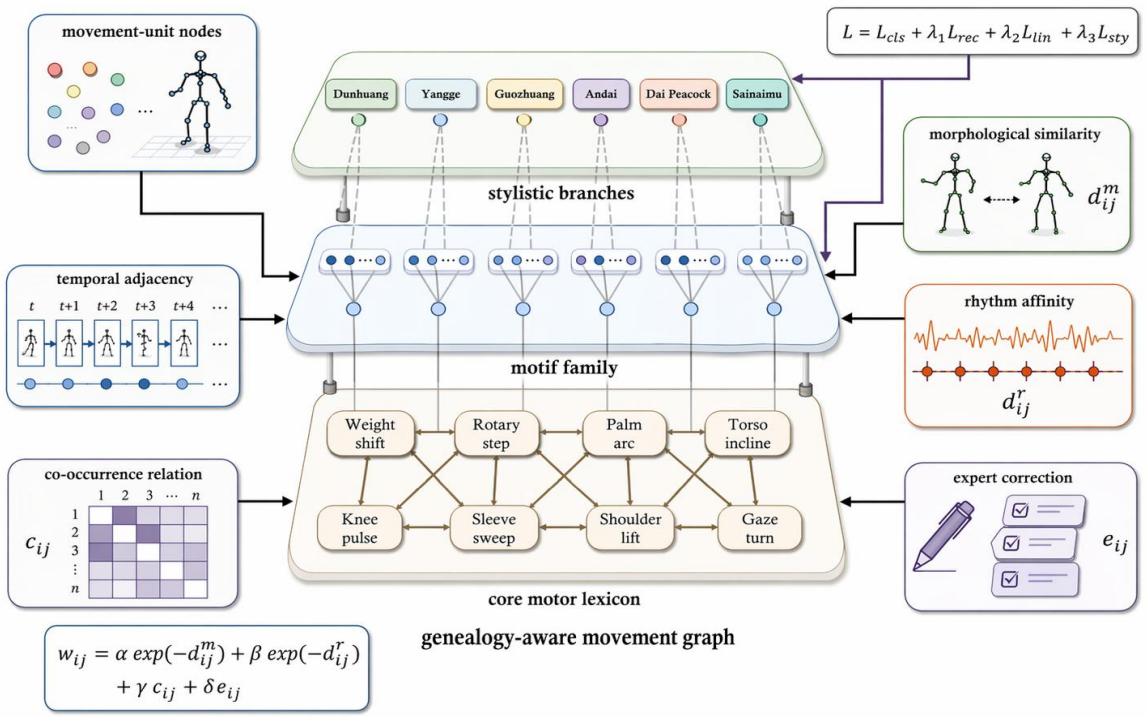

Figure 2: Genealogy-aware movement graph construction mechanism.

The core task of the movement map is to organize discrete movement units into a three-layer genealogical structure. The first layer is the core movement lexicon, which retains movement archetypes that repeat across genres and are structurally stable, including Weight shift, Rotary step, Palm arc, Torso incline, Knee pulse, Sleeve sweep, Shoulder lift, and Gaze turn. the second layer is the movement motif layer, which aggregates variants of the same archetype into motifs. The second layer is the movement motif layer, which aggregates variations of the same archetype in terms of direction, amplitude, speed, and power delivery into motifs. The third layer is the genre branching layer, which records the stable expression of the movement motifs in specific genres. For example, Palm arc is often associated with torso sideways tilting and sight turning in Dunhuang dance, more dependent on continuous wrist curves and fingertip extension in Dai Peacock dance, and often coexisting with shoulder rhythms and rhythmic syncopation in Sai Naim. In order to unify the movement patterns, rhythmic organization, genre co-occurrence and expert knowledge into the same graph structure, the calculation of side weights is defined as shown in equation (2).

$$w_{ij} = \alpha exp(-d_{ij}^m) + \beta exp(-d_{ij}^r) + \gamma c_{ij} + \delta e_{ij}, \quad \alpha + \beta + \gamma + \delta = 1 \tag{2}$$

where w_{ij} denotes the side weight between the ith and jth movement units, d_{ij}^m denotes the morphodynamic distance, d_{ij}^r denotes the rhythmic distance, c_{ij} denotes the co-occurrence intensity in the same genre or dance section, and e_{ij} denotes the expert correction relation. The coefficients α, β, γ and δ control the contribution of morphology, rhythm, co-occurrence and expert knowledge in the side weights, respectively. In this paper, we perform a grid search on the validation set and finally set α=0.35, β=0.25, γ=0.25, δ=0.15. This setting

allows skeleton similarity to remain dominant while retaining sufficient weights for rhythmic and genre knowledge.

Morphodynamic Distance d_{ij}^{m} Calculated from joint angle path, bone segment orientation and velocity profile. Rhythmic Distance d_{ij}^{r} is calculated from movement duration, peak energy position and beat offset. Co-occurrence Intensity c_{ij} counts the frequency of co-occurrence of two movement units in the same dance section, in the same genre and in adjacent phrases. Expert Correction Relationship e_{ij} is labeled by professional dance researchers, and is mainly used to deal with movements with similar skeletons but different stylistic semantics, as well as movements with large differences in skeletons but belonging to the same parent theme. After the graph is constructed, this paper adopts spectral clustering to generate the initial action matrices, and then utilizes graph neural networks to learn node embedding and perform spectral hierarchy constraints.

In order to simultaneously constrain the three types of objectives of action recognition, genealogical reconstruction and genre separation, the total model loss is defined as shown in equation (3).

$$\mathcal{L} = \mathcal{L}_{cls} + \lambda_1 \mathcal{L}_{rec} + \lambda_2 \mathcal{L}_{lin} + \lambda_3 \mathcal{L}_{sty} \tag{3}$$

where $\mathcal{L}$ denotes the total model loss, $\mathcal{L}_{cls}$ denotes the action category categorization loss, $\mathcal{L}_{rec}$ denotes the action unit reconstruction loss, $\mathcal{L}_{lin}$ denotes the spectral hierarchy constraint loss, and $\mathcal{L}_{sty}$ denotes the genre separation constraint loss. The coefficients λ_1, λ_2 , and λ_3 are set to 0.40, 0.25, and 0.20, respectively.The categorization loss ensures that the class of action units is recognizable, the reconstruction loss constrains the embedding space to retain the original motion structure, the spectral hierarchy constraints keep the variants of the same motifs in the same neighborhood, and the genre separation constraints make the stabilized representations of different genres separable. The combination allows the model to both aggregate homologous movements and preserve genre branching differences.

2.3 Comparative protocol across stylistic schools

The cross-genre comparison is organized around three tasks. The first task is movement genealogy reconstruction, which evaluates whether the model is able to aggregate homologous movement units to the same movement motif and distinguish their genre variants. The second task is genre distance computation, which evaluates the degree of similarity between different traditional dances in terms of gesture pathways, dynamics changes, rhythmic organization and LMA descriptors. The third task is movement identification and ablation evaluation, which examines the actual contribution of genealogical constraints, rhythmic envelopes and LMA descriptors to the model performance. In order to ensure that the spectral reconstruction and genre comparison have a consistent evaluation caliber, this paper sets up a unified data division, comparison model and index system, as shown in Figure 3.

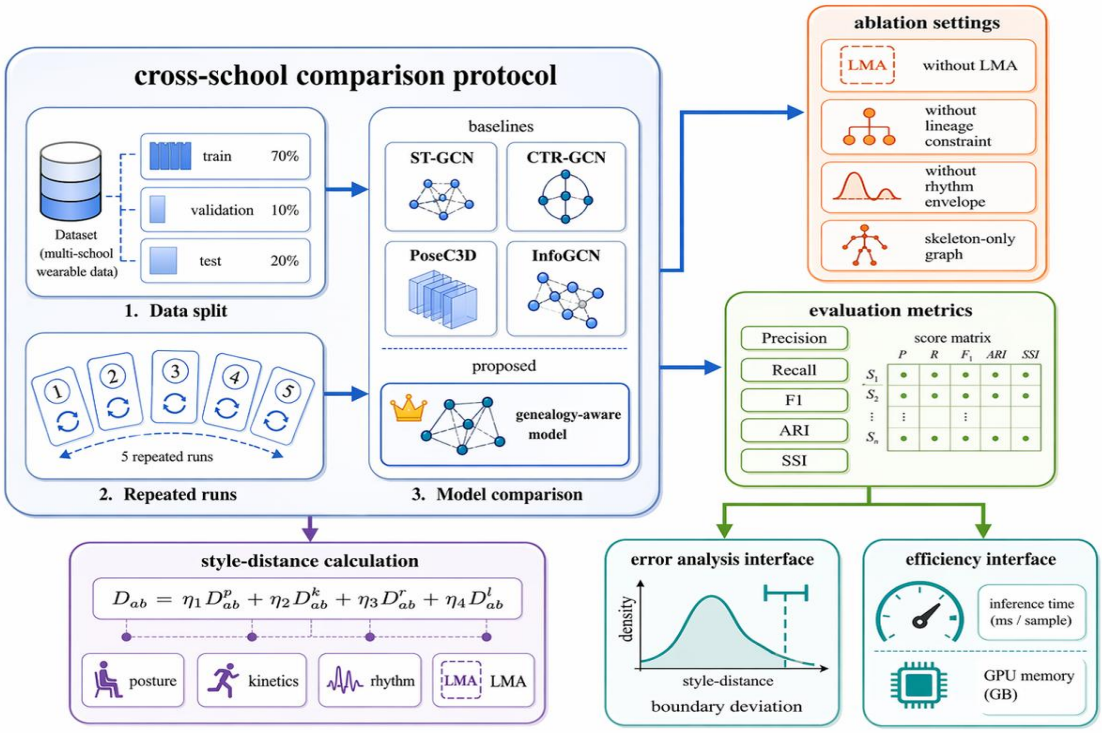

Figure 3: Cross-school comparison and evaluation protocol.

In this paper, we adopt ST-GCN, CTR-GCN, PoseC3D and InfoGCN as the main baselines.ST-GCN can model skeleton sequences as spatio-temporal graphs, and is the basic graph convolution model in skeleton action recognition.CTR-GCN enhances the ability of joint relationship modeling through channel-level topology refinement.PoseC3D transforms skeleton representations into 3D thermal atlases to enhance the robustness to PoseC3D transforms the skeleton representation into a 3D heat map body to improve robustness to pose noise and cross-dataset conditions. infoGCN learns the skeleton representation through informative constraints to provide enhanced latent spatial organization for action recognition. In recent years, Transformer and hybrid graph models have also shown better global dependency modeling capabilities, but it is still difficult to recover the action master hierarchy by directly applying a generic action recognition model in small-sample and strong interpretive scenarios of traditional dance.

In order to quantify the comprehensive style differences between different genres under a unified caliber, the genre distance is defined as shown in equation (4).

$$D_{ab} = \eta_1 D^p_{ab} + \eta_2 D^k_{ab} + \eta_3 D^r_{ab} + \eta_4 D^l_{ab}, \quad \eta_1 + \eta_2 + \eta_3 + \eta_4 = 1 \tag{4}$$

where D_{ab} denotes the combined style distance between genre a and genre b, D^p_{ab}, D^k_{ab}, D^r_{ab} and D^l_{ab} denote the gesture path distance, dynamics distance, rhythm distance, and LMA descriptor distance, respectively [14-18]. The coefficients η_1, η_2, η_3 and η_4 were all set to 0.25, which was used to ensure that the four types of differences contributed equally in the initial distance calculation. The contribution of each component to the near-neighborhood and far-neighborhood relationships was further counted in the result analysis, which was used to explain the reasons for the proximity or separation of the genres. Functional groups and assessment metrics, as shown in Table 2.

Table 2: Feature groups and evaluation metrics

Category	Variables	Function in Model	Metrics
Posture	Joint coordinates, bone directions, joint angles	Describes body configuration	DTW distance, cosine similarity
Kinetics	Velocity, acceleration, angular velocity	Captures force and motion tendency	Kinetic variance, peak ratio
Rhythm	Energy peak, phrase length, beat offset	Describes temporal organization	Rhythm deviation, periodicity
LMA Descriptors	Body, Effort, Shape, Space	Supports interpretable movement semantics	Descriptor agreement
Genealogy	Prototype, motif, branch	Reconstructs movement inheritance relation	F1, ARI, modularity
Style Comparison	Intra-school and inter-school distance	Measures stylistic separation	SSI, silhouette score

The evaluation indexes include Precision, Recall, F1, Adjusted Rand Index and Style-Separation Index. Precision and Recall are used to evaluate the accuracy and coverage of action motif recognition, and F1 is used to measure the reconstruction quality in a comprehensive way. ARI measures the consistency between the model clustering and the expert labeled motifs. SSI measures the relative difference between intra-class and inter-class distances, with higher values indicating clearer genre branching. All experiments were repeated five times and the mean results are reported. The ablation settings include four cases: removing LMA descriptors, removing spectral constraints, removing rhythmic envelopes, and retaining only the skeleton graph structure. Efficiency analysis counts the individual action unit inference time, parameter size, and explicit memory occupation, and is used to assess the feasibility of deploying the method in digital archival and instructional systems.

3 Results and Discussion

3.1 Digital reconstruction of movement genealogies

This section first tests whether the movement genealogy can be reconstructed in a stable manner. The validity of traditional dance movement genealogies does not only depend on the movement classification accuracy, but also on whether the model can aggregate shared movement materials into interpretable movement motifs and preserve the branching characteristics of each genre. To this end, this paper inputs 3456 action units into the genealogy-aware model and outputs 3D embeddings, action motif nodes, and genre branching connections. The genealogy-aware model maps the action units to a 3D embedding space jointly composed of morphological structure, rhythmic organization and LMA semantics, as shown in Figure 4.

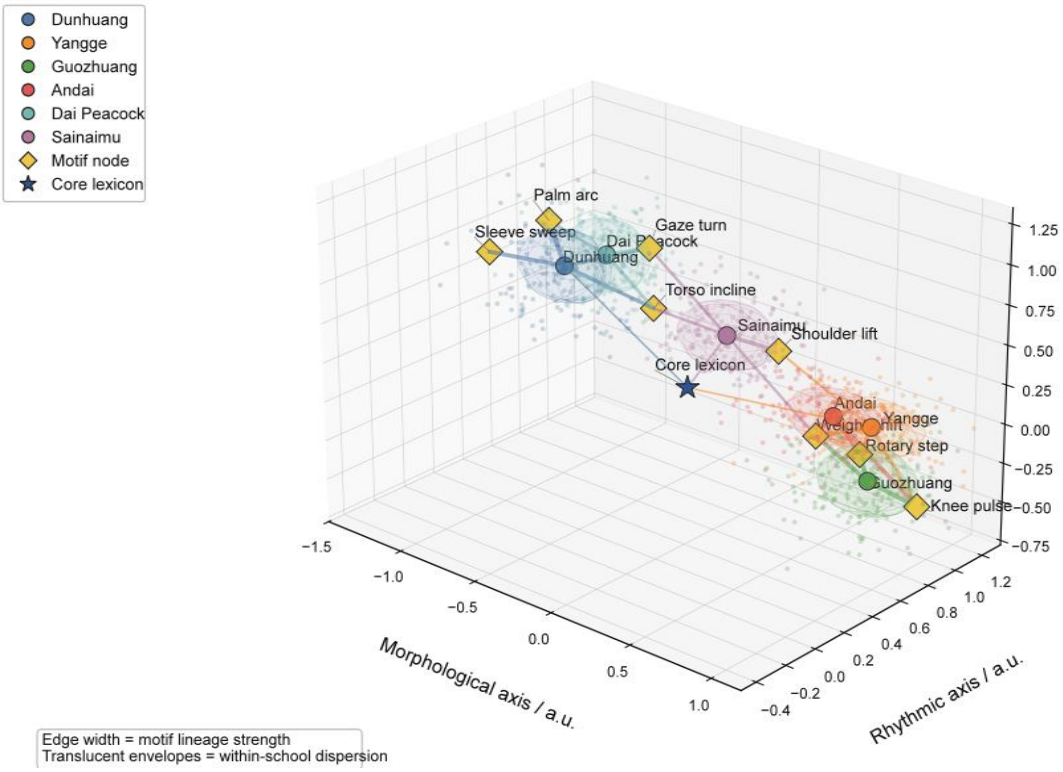

Figure 4: Three-dimensional reconstructed movement-genealogy manifold.

In Figure 4, the six types of traditional dances form mutually divisible three-dimensional clusters, with colored dots indicating movement units, translucent envelopes indicating discrete ranges of movements within the same genre, diamond-shaped nodes indicating core movement motifs, and the width of the connecting lines indicating the genealogical edge power between genres and motifs. Dunhuang and Dai Peacock form close neighbors around Palm arc, Torso incline and Gaze turn, suggesting that their similarity mainly comes from the upper limb arc, torso incline and sight turn. Yangge, Guozhuang and Andai's clusters' centers are closer to the Rotary step, Knee pulse and Weight shift, suggesting that their shared structure focuses on the stride cycle, Knee elasticity and Weight shift. Sainaimu is located in the transition region between upper limb semantics and lower limb rhythms, showing that it retains hand arcs and shoulder rhythms, but also has strong beat syncopation characteristics.

To further quantify the effect of spectral reconstruction, this paper compares the Precision, Recall, F1, ARI and SSI of the five types of models, as shown in Table 3.

Table 3: Main comparison results of genealogy reconstruction

Model	Precision	Recall	F1	ARI	SSI
ST-GCN baseline	0.814	0.820	0.817	0.631	0.482
CTR-GCN baseline	0.842	0.835	0.838	0.658	0.506
PoseC3D baseline	0.851	0.843	0.847	0.672	0.519
Without LMA descriptors	0.849	0.837	0.843	0.681	0.544
Without lineage constraint	0.866	0.856	0.861	0.704	0.561
Genealogy-aware model	0.928	0.918	0.923	0.762	0.638

In Table 3, the F1 of the Genealogy-aware model reaches 0.923, which is 10.6 percentage points higher than the ST-GCN baseline and 7.6 percentage points higher than the PoseC3D baseline, and the ARI improves from 0.631 to 0.762 in the ST-GCN baseline, which indicates

that the Genealogy-aware map has a stable contribution to the clustering consistency of the action matrices. SSI improves from 0.482 to 0.638, indicating that the model is able to maintain genre branching differences while aggregating homologous actions. After removing the LMA descriptor, F1 decreases to 0.843, indicating that it is difficult to distinguish “morphologically close but genre-semantically different” actions by skeleton trajectories alone. After removing the genealogical constraints, F1 drops to 0.861, indicating that hierarchical relationships have a direct effect on the aggregation of action motifs.

The results of genealogical reconstruction also show the sharing pattern of traditional dance movement materials: Weight shift is a core motif connected to all six genres, but it is used in different ways in different genres. In Yangge and Guozhuang, the Weight shift is often associated with the Torso incline, which creates a more pronounced body contouring; in Sainaimu, the Weight shift is associated with the Shoulder lift and the Gaze turn, which presents a stronger rhythmic syncopation. This result suggests that movement genealogy is able to break down “genre similarity” into specific movement motifs, rather than just giving overall category judgments.

3.2 Comparative analysis across stylistic schools

After completing the genealogical reconstruction, this paper further analyzes the stylistic distances between the six types of traditional dances. The purpose of genre comparison is not to simply determine whether two genres are similar or not, but to determine whether the similarity comes from gestural pathways, power changes, rhythmic organization or LMA semantics. The combined stylistic distance was calculated by the four categories of components together, with smaller distances indicating that the two genres were closer in terms of movement unit structure and matrices combination. To further compare the structural differences between genres, this paper calculates the integrated style distance and characteristic contributions of six types of traditional dances, as shown in Figure 5.

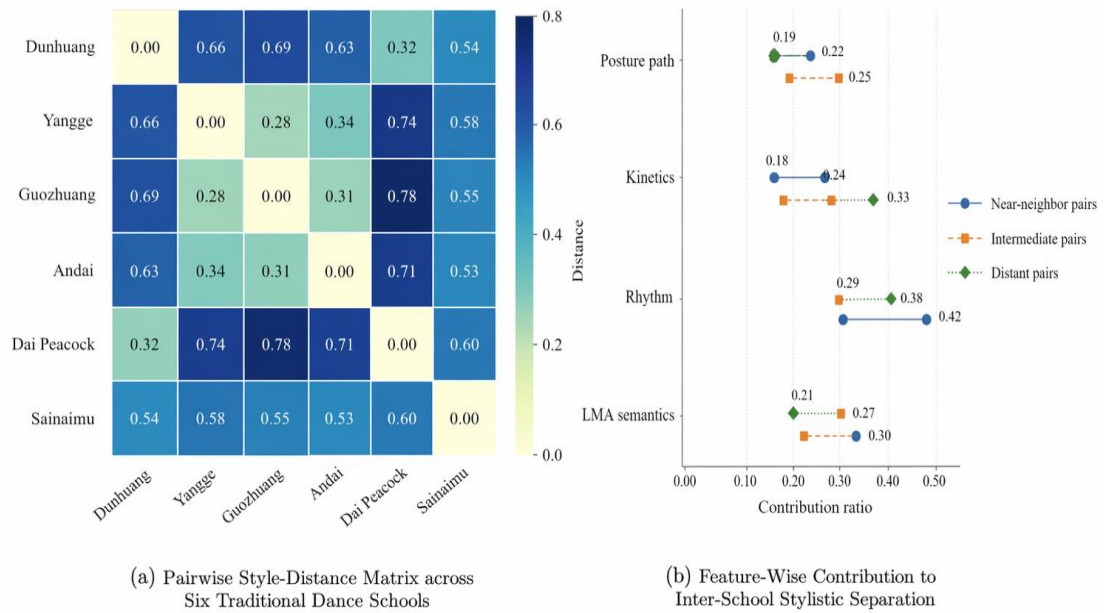

Figure 5: Style-distance matrix and feature contribution across six schools.

In Figure 5, Yangge's distance from Guozhuang is 0.28, Guozhuang's distance from Andai is 0.31, and Yangge's distance from Andai is 0.34, which are the three closest relationships in the matrix. This result is related to the common emphasis on pace circulation, knee flexibility,

and center of gravity shifting. dunhuang's distance from Dai Peacock of 0.32 is lower than that from Yangge, Guozhuang, and Andai, suggesting that upper limb curvature, lateral tilt, and visual turn constitute the main common structures of the three. dai Peacock's distance from Guozhuang of 0.28 and Guozhuang of 0.31 suggests that upper limb curvature, lateral tilt, and visual turn constitute the main common structures of the two. The distance between Dai Peacock and Guozhuang reaches 0.78, which is the maximum value of the whole matrix, indicating that the two schools have the most obvious differences in the composition of the movement motifs and power rhythms, and the distance between Sainaimu and the other schools is in the range of 0.51-0.60, which indicates that the structure of the movement is intermediary, sharing the local motifs with both the upper limb arc and the rhythmic organization of lower limb rhythms. genre, and the lower limb rhythmic genre.

The right contribution point map further reveals the source of stylistic distance. The rhythmic component contributes the most to the proximity of Yangge, Guozhuang, and Andai, with an average contribution rate of 41.7%; the LMA component contributes 35.2% to the proximity of Dunhuang and Dai Peacock, mainly from the Shape and Space descriptors; and the gesture path contributes to the proximity of Dunhuang and Dai Peacock. The similarity between Dunhuang and Dai Peacock is 38.4%, indicating that the two have a stable shared structure in terms of upper limb trajectory and body orientation. In contrast, the long distance between Dai Peacock and Guozhuang is mainly caused by the combination of rhythmic and dynamical components, and the two differ significantly in the hand arc, foot contact rhythm, and center of gravity change speed.

This result suggests that traditional dance genre differences cannot be fully explained by skeletal coordinate distances. In the case of Dunhuang and Dai Peacock, for example, they are not identical in the rhythm of the complete dance section, but they form a stable and similar relationship in the Palm arc, Torso incline and Gaze turn. Yangge and Guozhuang, for example, do not share identical upper limb patterns, but lower limb rhythms, knee flexibility, and center of gravity recovery reduce their combined distance significantly.The mediating position of Sainaimu also suggests that a genre can share movement material from multiple genealogical branches at once, and that genealogical maps can present this hybrid structure in more detail than a single categorical model.

3.3 Ablation, error source and interpretability analysis

To test the usefulness of each module of the model, this section compares the performance changes between the full model and the four ablated versions at different training ratios, and further analyzes the movement boundary errors and inference costs. Traditional dance samples are often characterized by small size, high similarity, and strong stylistic constraints, so the stability of the model at low training ratios is equally important. To examine the actual contributions of spectral constraints, LMA descriptors and rhythmic envelopes, this paper compares the reconstruction performance under different training ratios, as shown in Fig. 6.

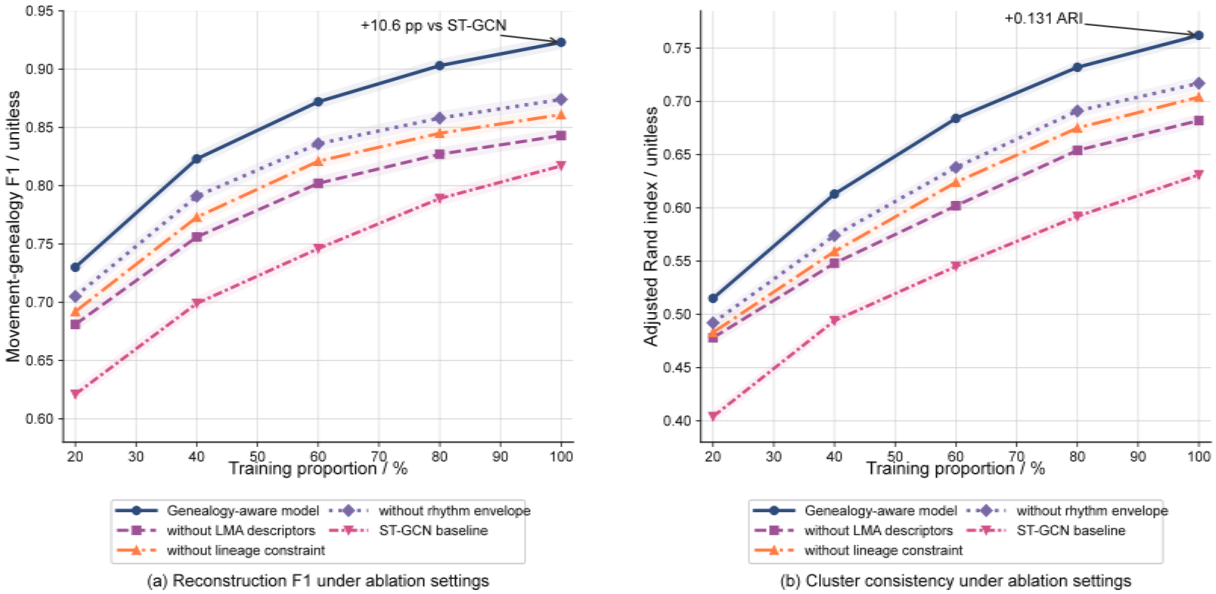

Figure 6: Reconstruction performance under ablation settings.

In Fig. 6, the F1 of the full model is 0.730, 0.872 and 0.923 at 20%, 60% and 100% training ratio, respectively, which is higher than that of the ST-GCN baseline. the F1 of the ST-GCN baseline is 0.817 at 100% training ratio, which is an improvement of 10.6 percentage points for the full model, and the ARI improves from 0.631 to 0.762, indicating that the genealogical structure has a stabilizing effect on the consistency of action matrices clustering. After removing the LMA descriptor, F1 decreases to 0.843 at 100% training ratio, indicating that it is difficult to differentiate stylistically and semantically similar or different actions only by relying on skeleton trajectories. After removing the spectral constraints, F1 is 0.861, indicating that the hierarchical relationship mainly affects the aggregation quality of homologous action units. After removing the rhythmic envelope, F1 is 0.874, indicating that the rhythmic information has a direct contribution to the boundary slicing and repetitive action recognition.

The curves at different training ratios also show that spectral constraints have higher value under small sample conditions. When the training ratio is 20%, the full model is 11.0 percentage points higher than the ST-GCN baseline; when the training ratio is increased to 100%, the difference is 10.6 percentage points, indicating that the advantage of the model in this paper does not only come from the increase in the number of samples, but also from the explicit constraints on the action matrices imposed by the structure of the action graph. The growth of the curve after removing the LMA descriptor slows down significantly after 40% training ratio, indicating that the genre semantic features are especially crucial for the model to distinguish fine-grained action variants at a later stage. The curve after removing the rhythmic envelope decreases more significantly at low training ratios, suggesting that rhythmic boundaries are supportive of action slicing when there are insufficient samples.

Movement unit boundary offset is the most important source of error in spectral reconstruction. A large number of movements in traditional dance are extensional in nature, and the end point of the movement may lag behind the skeleton velocity valley, especially for sleeve sweep, palm arc, and sight-delay types of movements. In this paper, the distribution of boundary deviations of four high-frequency movement motifs, namely Weight shift, Rotary step, Palm arc and Sleeve sweep, are summarized. The boundary deviation distributions of the four types of high-frequency action motifs are shown in Fig. 7.

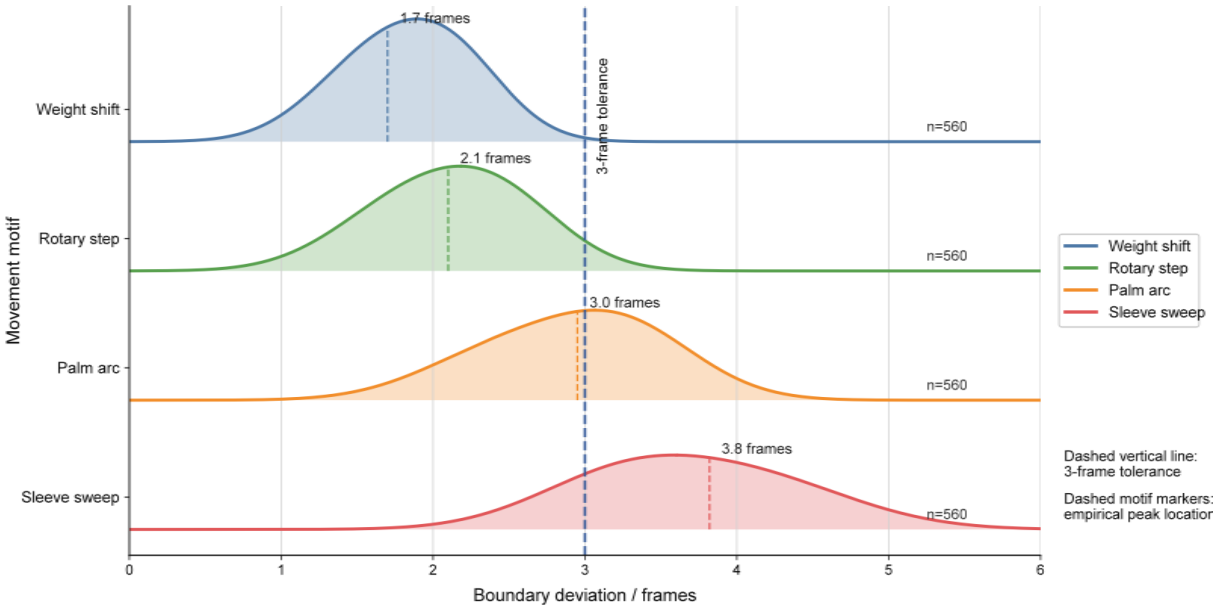

Figure 7: Boundary-deviation density of movement-unit reconstruction.

In Fig. 7, the error peaks of Weight shift are concentrated around 1.7 frames, and the error peaks of Rotary step are around 2.1 frames, both of which are below the tolerance line of 3 frames, indicating that the center of gravity turn and pace rotation have a clear kinetic boundary. the error peaks of palm arc are around 2.8 frames, which are close to the tolerance line, mainly due to the fact that the palm arc movement is often accompanied by the wrist extension and vision delay. The error peak of Sleeve sweep is about 3.6 frames, and there is an obvious right tail, which indicates that the visual extension of water sleeve or long sleeve movements is later than the valley of skeleton velocity, and it is difficult to capture the complete trajectory of the end of the sleeve by the skeleton point alone. This result suggests that sleeve dances, long scarf dances and traditional dances with high costume involvement need to add costume edge trajectories or visual flow field features in addition to skeleton features.

Efficiency analyses are utilized to judge whether the model can be transformed into real-world digital archiving and instructional feedback situations. In recent years, skeleton action recognition models have been enhanced with topological modeling and temporal attention, and methods such as BlockGCN, SkateFormer, and two-stream graph Transformer have shown strong performance in generalized action recognition [19-23]. But, the traditional dancing situations also let models need to give movement parent explanations, genre branch relationships, and low inference costs. In consideration of the deployment demands of traditional dance digital archives and teaching systems, this paper further carries out comparison on the relation between model reconstruction quality and inference cost, which is shown in Fig. 8.

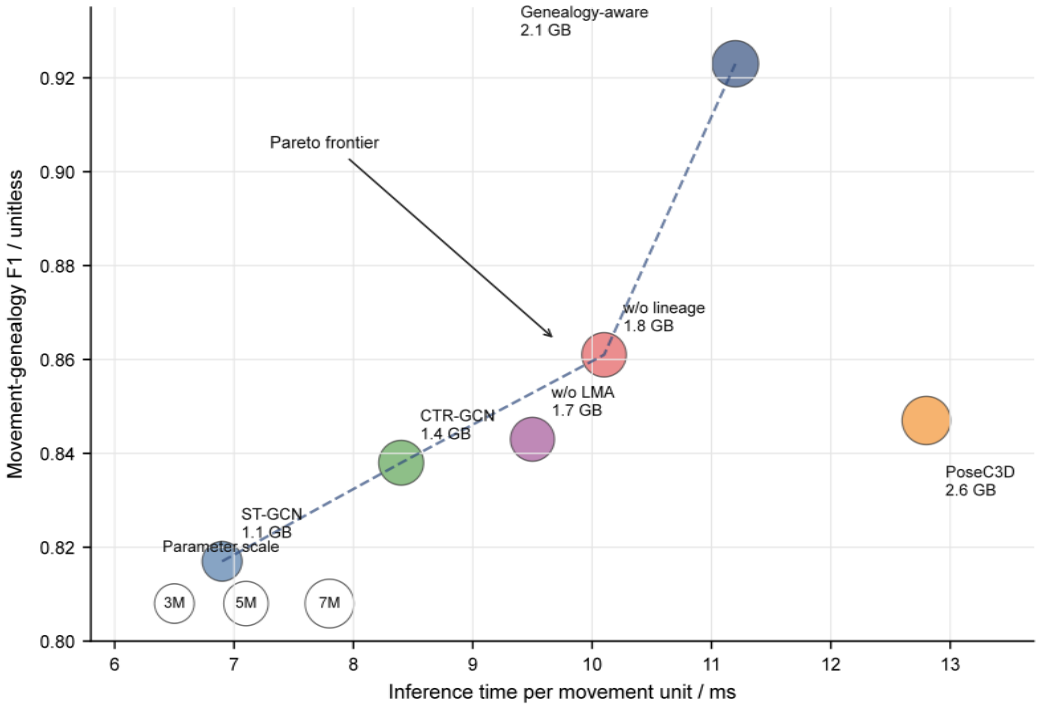

Figure 8: Efficiency–quality trade-off of reconstruction models.

In Fig. 8, the F1 of Genealogy-aware model is 0.923, the inference time of a single action unit is 11.2 ms, and the memory occupation is 2.1 GB, which is located at the upper-right end of the Pareto front. the inference time of PoseC3D is 12.8 ms, and the F1 is 0.847, which indicates that its 3D heatmap characterization has a high computational overhead in this task, but its spectrum interpretation ability is insufficient. The inference time of CTR-GCN is 8.4 ms, and the F1 is 0.838, which shows good efficiency, but it is difficult to recover the action master hierarchy. Compared with ST-GCN baseline, the complete model increases the inference time by 4.3 ms, and at the same time brings an increase of 10.6 percentage points in F1, which is suitable for offline digital archive construction, rehearsal analysis, and teaching feedback scenarios. Research on folk dance movement recognition and AI teaching has shown that motion capture, machine learning, and 3D convolutional networks can make their way into dance teaching assistance systems [24, 25]; this paper's method further provides interpretable genealogical relationships that can be used by teachers to locate stylistic biases, by students to understand the origin of the movements, and by archival systems to retrieve homologous movements.

Overall, the interpretation of the results of this paper's methodology can be returned to the specific movement objects in traditional dance research; the similarities between Dunhuang and Dai Peacock are mainly from Palm arc, Torso incline, and Gaze turn, while the similarities between Yangge, Guozhuang, and Andai are mainly from Rotary step, Knee pulse, and Gaze turn. The model output not only gives the genre distance, but also can indicate the origin of the action motifs for distance formation. The error analysis shows that the skeleton data has good representation of body joint movements, but is still insufficient for costume extension and group formation. The boundary provides a clear direction for subsequent research: traditional dance genealogy reconstruction needs to continue to be extended to the level of costume trajectories, musical beats and spatial formations.

4 Conclusion

This paper puts emphasis on the digital construction and cross-style comparison of traditional dance movement family tree, therefore builds a sample storehouse that includes six kinds of traditional dances, 144 dance segments and 3456 movement units, hence puts forward a genealogy-perceiving movement graph method which integrates skeleton, dynamics, rhythm and LMA descriptors. Our experiments have proved that the method is effective in aspects including 3D spectral embedding, stylistic distance, ablation analysis, error sources and efficiency cost.

(1) In this paper, traditional dances are disassembled from complete videos into movement units and formed into a three-layer structure of core movement lexicon, movement matrices, and genre branching, which enables movement materials such as weight shifting, palm arcs, sleeve sweeps, knee impulses, and sight turning to be organized and compared.

(2) The spectral perception model achieves 0.923 F1, 0.762 ARI and 0.638 SSI in the action spectral reconstruction task, which outperforms baselines such as ST-GCN, CTR-GCN and PoseC3D. The results show that the spectral constraints and LMA descriptors have stable contributions to action motif aggregation and genre separation.

(3) This paper is still limited by the sample size, expert annotation density, and costume motion representation capability. Subsequent studies can further introduce costume edge trajectories, multi-view visual flow, music beat structure and group dance formation information to enhance the genealogical expressiveness of sleeve dance-like movements, ceremonial movements and complex spatial scheduling.

About the Author

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