

CustomDancer: Customized Dance Recommendation by Text-Dance Retrieval

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Abstract. Dance serves as both a cultural cornerstone and a medium for personal expression, yet the exponential growth of online dance content has intensified the need for personalized retrieval systems. While text-based dance retrieval offers a promising avenue for users to articulate preferences through natural language, existing methods face critical challenges: aligning abstract textual semantics with motion kinematics, reconciling cross-modal heterogeneity, and overcoming the scarcity of annotated data. To address these gaps, we present CustomDancer, a novel framework that bridges music, motion, and text through multimodal fusion. Our work introduces TD-Data, the largest open-source dataset for text-dance retrieval, comprising about 4,000 professionally annotated clips across 22 genres, refined via a three-stage pipeline integrating dance preprocessing, expert annotation, and AI-driven text refinement. The CustomDancer framework employs domain-adapted encoders for text, music, and motion, alongside a hybrid fusion module combining additive and multiplicative interactions to align auditory and kinematic features. Experiments demonstrate the superiority of our framework and effectiveness of our datasets. This work establishes foundational benchmarks for personalized dance interaction while addressing key challenges in cross-modal retrieval.

Keywords: AI for Art, Multimedia Learning, Multimedia Retrieval, Text-Dance Retrieval

1. Introduction

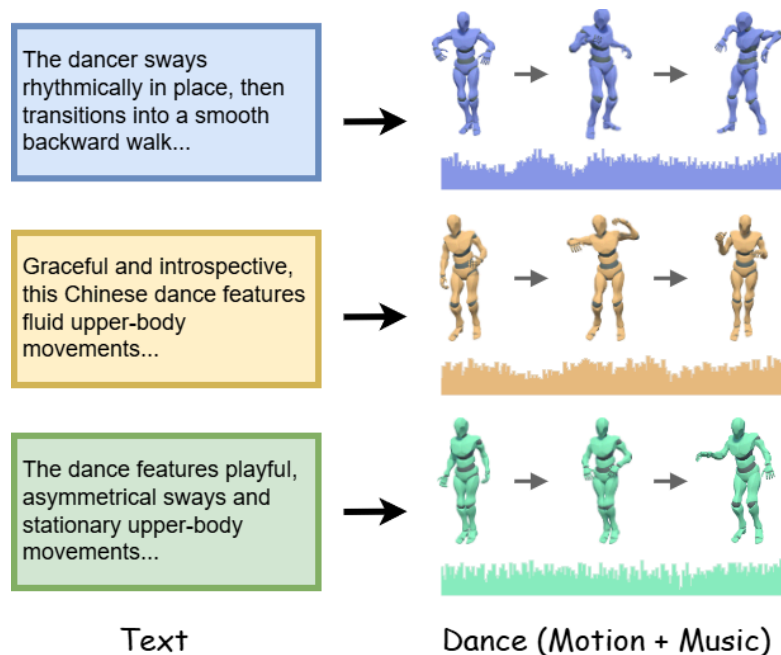


Figure 1. Overview of Text-Dance Retrieval task

Dance, an ancient and profound art form, is of paramount significance in human society. It acts as a living repository of cultural heritage, with each dance style, be it the passionate Flamenco or the elegant Ballet, carrying the history and values of its origin. Simultaneously, it serves as a universal medium for personal expression, enabling individuals to communicate emotions that words may fail to convey. In the digital age, the online sphere has witnessed an explosive growth of dance content. From viral dance challenges on social media to high - quality professional performances, the sheer volume can be overwhelming. This surge has thus made the development of personalized dance recommendation systems a pressing necessity. Text-based dance retrieval offers a viable pathway, empowering users to articulate their requirements through natural language, whether describing stylistic preferences (“sharp, robotic locking movements”) or emotional tones (“fluid and melancholic”). This capability unlocks applications across dance education (e.g., searching pedagogical demonstrations), fitness technology (e.g., recommending Zumba routines), and entertainment systems (e.g., generating themed playlists). However, this task faces dual challenges: globally, aligning abstract textual semantics (e.g., “joyful energy”) with holistic motion patterns, and locally, mapping precise phrases (e.g., “360-degree spin on tiptoes”) to kinematic details. These challenges are compounded by dance’s inherent subjectivity and the scarcity of annotated data.

Existing approaches in adjacent domains prove insufficient. Text-to-motion generation models prioritize generic actions like walking or jumping, overlooking dance-specific nuances such as stylistic footwork or expressive torso movements. Music-to-dance systems treat music as an immutable input, limiting users’ ability to freely refine choreography via feedback. Text-music retrieval methods focus on audio descriptors (tempo, instrumentation) rather than choreography-relevant features (limb articulation, spatial trajectories). Moreover, the absence of large-scale text-music-motion datasets—due to the expertise required for dance annotation—hampers progress.

Despite certain advancements in the related fields, there is still a lack of exploration on how to efficiently obtain dances that meet users' needs.

To bridge this gap, we first introduce TD-Data, the largest open-source dataset for text-dance retrieval, crafted through a three-stage pipeline. Derived from FineDance, TD-Data contains about 4,000 dance clips (14.6 hours) across 22 genres, performed by 27 professionals. Our pipeline begins with dance preprocessing: segmenting sequences into 12-second clips and filtering kinematically inconsistent motions via anomaly detection. Next, expert annotators label clips using a structured taxonomy of 8 motion attributes (e.g., dance style, signature movement, emotion) and 6 musical properties (e.g., genre, rhythm). Finally, GPT-4o refines these tags into natural language descriptions while preserving choreographic semantics, yielding texts like “Jazz dance pulses with rhythmic swaying, driven by the vibrant energy of rhythm and blues...”.

Building upon this dataset, we propose CustomDancer, a retrieval framework that synergizes music, motion, and text through four components: 1) A Text Encoder leveraging CLIP’s linguistic capabilities, augmented by MLP adapters for feature alignment; 2) A Music Encoder combining transformer layers and 1D-CNNs to model rhythmic patterns; 3) A Motion Encoder also processing SMPL parameters via temporal self-attention and 1D-CNNs; 4) A Music-Motion Blender employing concatenation of element-wise additive and multiplicative interactions to fuse auditory and kinematic features. The model aligns text and dance representations through contrastive learning, minimizing the distance between textual queries and their corresponding music-motion pairs.

Comprehensive experiments validate our approach. Quantitatively, CustomDancer achieves state-of-the-art (SOTA) level performance, Recall@1 at 10.23% on TD-Data. Ablation studies confirm the effect of Feature Fusion Strategy and Temporal Modeling Architectures. In user study, CustomDancer achieves 86.2% and 83.3% of ground-truth alignment quality for text-motion correspondence and text-music relevance, respectively, demonstrating near-professional choreographic fidelity. Qualitative analysis reveals accurate mappings between phrases like “aggressive krumping” and rapid stomping motions.

Our contributions are summarized as follows:

1. We benchmark the Text-Dance Retrieval task and introduce the largest open-source dataset, TD-Data, along with an efficient data collection pipeline.
2. We propose an efficient framework for Text-Dance Retrieval, effectively capturing the intricate relationships among music, motion, and text.
3. We conduct robust and extensive experiments, demonstrating the superiority of TDancer and the effectiveness of the TD-Data dataset.

2. Related work

2.1. Text-to-Motion Generation

Text-to-Motion Generation aims to synthesize human motion sequences from natural language descriptions, addressing the translation of high-level semantic concepts into kinematic representations. The input typically consists of textual prompts (e.g., "a person walking backward"), while the output comprises 3D skeletal sequences or parametric motion data (e.g., SMPL parameters). Current methodologies can be broadly categorized into three paradigms. Template-Based Approaches: Early works relied on predefined motion primitives and rule-based mapping between text keywords and kinematic templates. For instance, [1] employed syntactic parsing to align verbs/nouns with motion clips from databases. While efficient, these methods lack generalization to unseen descriptions. Deep Generative Models: With the advent of deep learning,

sequence-to-sequence architectures (e.g., LSTMs, Transformers) became prevalent. Models like MotionCLIP [2] integrated contrastive language-motion pretraining to align text embeddings with motion features. Recent advancements leverage diffusion models (e.g., MDM [3]) to iteratively refine motion outputs conditioned on text. Cross-Modal Retrieval: Hybrid frameworks retrieve and refine motion sequences from large databases using text queries. For example, [4] combined semantic similarity search with GAN-based motion refinement. Limitations: While these methods excel at generating generic actions (walking, jumping), they struggle with dance-specific nuances. Dance motions require fine-grained control over stylistic elements (e.g., hip sway in salsa) and temporal synchronization with external rhythms—aspects rarely addressed in current text-to-motion literature⁹.

2.2. Music-to-Motion Generation

Music-to-Motion Generation focuses on synthesizing motion sequences synchronized with musical beats, where the input is audio (e.g., spectrograms) and the output is rhythmic motion data. Key methodologies include three types. Beat-Aligned Synthesis: Early systems like [5] extracted tempo and beat features from music to drive procedural animation cycles (e.g., foot tapping). These methods prioritize temporal alignment but lack stylistic diversity. End-to-End Learning: Modern approaches employ encoder-decoder architectures to directly map music features to motion sequences. For example, [6] used cross-modal transformers to model long-range dependencies between musical phrases and dance movements. Style-Transfer Models: Frameworks like AIST++ [7] disentangle motion into content (rhythm) and style (genre-specific movements), enabling genre-aware synthesis. Limitations: Existing systems treat music as an immutable input, limiting users' ability to customize choreography through textual feedback. This rigidity conflicts with personalized dance recommendation scenarios where users may desire hybrid styles (e.g., "hip-hop to classical transition").

2.3. Text-Dance Retrieval

Text-Dance Retrieval bridges text queries with dance sequences by jointly considering musical and kinematic relevance. Prior work in related domains includes two types. Text-Music Retrieval: Systems like [8] map text descriptions (e.g., "upbeat jazz") to music features using contrastive learning. However, these methods ignore choreographic attributes critical for dance alignment. Text-Motion Retrieval: Approaches such as [9] retrieve generic motions (e.g., sports actions) via text embeddings but fail to model dance-specific semantics.

Challenges in Text-Dance Retrieval: Dance descriptions demand expertise to articulate stylistic details (e.g., "isolation in popping"), resulting in scarce annotated data. Existing datasets either lack textual annotations (e.g., FineDance [10]) or focus solely on music-motion pairs. The absence of text-music-motion triples impedes progress, as naive fusion of text-music and text-motion retrieval systems leads to suboptimal alignment (e.g., mismatched genre and movement intensity). To address this gap, we benchmark Text-Dance Retrieval as a novel task and introduce TD-Data, the first dataset with expert-curated text descriptions for dance sequences, coupled with a retrieval framework that synergizes music and motion modalities.

3. Dataset

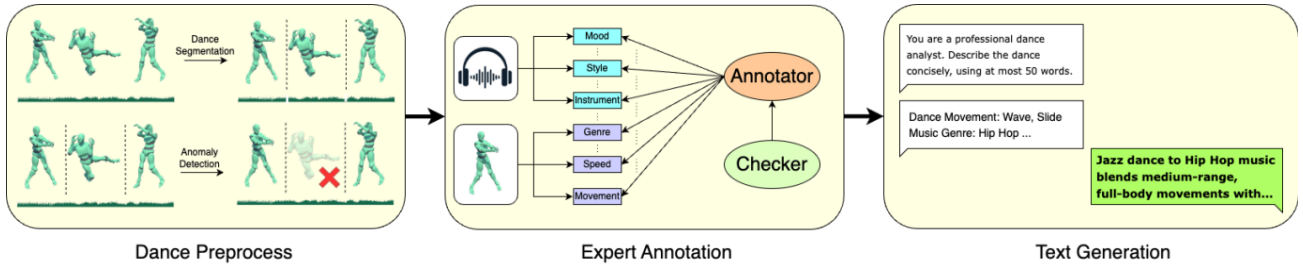


Figure 2. Overview of data collection pipeline

3.1. Data collection

Text-Dance Retrieval leverages 3D motion data (e.g., SMPL parameters) rather than 2D videos because 3D representations explicitly encode precise spatiotemporal kinematics (joint rotations, velocities), enabling accurate alignment with textual descriptions of body movements. In contrast, 2D video features suffer from viewpoint dependency and lack explicit biomechanical semantics critical for fine-grained dance retrieval. While the FineDance dataset provides high-quality 3D dance sequences paired with music, it lacks detailed textual descriptions of dance and music attributes. To address this gap, we propose TD-Data, a novel dataset for text-dance retrieval, constructed via a three-stage pipeline: Dance Preprocessing, Expert Annotation, and AI-Driven Text Generation.

Dance Preprocess. **Dance Segmentation:** To balance computational efficiency and preserve dance integrity, we segment raw motion sequences into 12-second clips. This duration captures complete dance phrases: a typical eight-beat dance cycle spans ~ 4 seconds, and 12 seconds accommodates three such cycles, sufficient to represent coherent motion groups with stylistic variations.

Anomaly Detection: Motion capture systems occasionally produce unnatural poses (e.g., during twists or lateral jumps) due to occlusions or sensor limitations. We manually inspect segmented clips to filter biomechanically implausible motions (e.g., discontinuous joint trajectories, inverted limb angles), ensuring only kinematically valid sequences proceed to annotation.

Expert Annotation. We decompose dance descriptions into a hierarchical taxonomy of music and motion attributes, informed by professional choreographic terminology:

- **Music Attributes:** Genre (Jazz, Hip-Hop), Rhythm (Staccato, Steady), Tempo (BPM range), Emotional Valence (Arousal-Dominance scale).
- **Motion Attributes:** Signature movements (Arms, Legs, Torso), Fluidity (Abruptness, Gracefulness), Spatial Dynamics (Back and Forth Movements, Mass Movement), Stylistic Intensity (1–5 scale).

Two certified dance professionals independently annotate each clip: one as the annotator labeling attributes, the other as the validator verifying consistency. Discrepancies trigger re-annotation until consensus is achieved, ensuring inter-annotator agreement

AI-Driven Text Generation. To transform structured tags into natural language, we employ GPT-4o initialized with the role: “You are a professional dance analyst. Describe the dance concisely in ≤ 50 words, varying sentence structures while preserving choreographic semantics.” For example, tags {Genre: Jazz; Focus: Arm Swings; Speed: Fast} are converted to: “A vibrant jazz sequence characterized by rapid, rhythmic arm swings, accentuating syncopated drum beats with playful

upper-body articulation.” This process enriches linguistic diversity while maintaining technical accuracy.

3.2. Data statistics

Derived from FineDance, TD-Data comprises 4,000 high-fidelity 3D dance clips (14.6 hours, 30 FPS) across 22 genres (Ballet, Krump, etc.), performed by 27 professional dancers to minimize individual stylistic bias. Each clip captures full-body kinematics (52 joints, including hand articulations), enabling granular motion-text alignment. The dataset includes about 4,000 unique descriptions to accommodate linguistic variability. We partition the data into training (2,800 clips) and test (1,200 clips) sets via stratified random sampling, preserving genre distributions.

4. Method

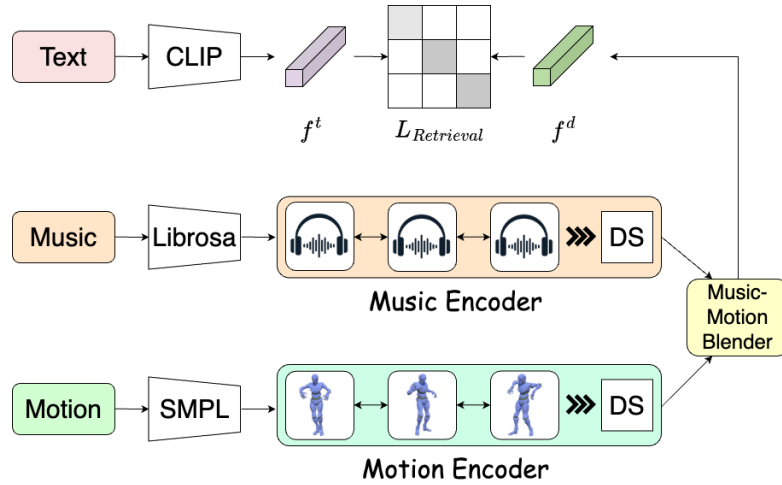


Figure 3. Overview of Text-Dance Retrieval framework CustomDancer

4.1. Problem definition

The text-dance retrieval task aims to establish cross-modal alignment between textual descriptions and dance sequences. Formally, given a textual query (t), the system retrieves the most semantically relevant dance sequence $D = F_{t2d}(t)$ where $(D = \{d_0, d_1, \dots, d_n\})$ represents a sequence of matched dance segments comprising synchronized music and human motion. Conversely, for a given dance fragment (d), the retrieval system identifies the most relevant textual descriptions $T = F_{d2t}(d)$ where $(T = \{t_0, t_1, \dots, t_n\})$ represents the sequence of matched text descriptions. The ideal objective is to bridge the semantic gap between high-level textual concepts (e.g., dance styles, emotional expressions, or movement patterns) and low-level spatio-temporal dance characteristics, enabling accurate cross-modal matching while preserving temporal consistency between music and motion modalities.

4.2. Framework overview

To holistically model the triadic relationship among text, music, and motion, we propose CustomDancer—a specialized framework for text-dance retrieval. As illustrated in Figure 3, our architecture comprises four core components:

1. Text Encoder: Processes textual input to extract semantic features.
 2. Music Encoder: Analyzes musical input to capture rhythm and melodic patterns.
 3. Motion Encoder: Encodes human movement dynamics from 3D motion data.
 4. Music-Motion Blender: Fuses multi-modal dance features for cross-modal alignment.
- Given an input text, we extract its latent representation through:

$$f^{text} = TextEncoder(text) \quad (1)$$

For music input, we derive temporal-acoustic features via:

$$f^{music} = MusicEncoder(music) \quad (2)$$

Human motion is encoded as:

$$f^{motion} = MotionEncoder(motion) \quad (3)$$

The blended dance representation is computed through:

$$f^{dance} = MusicMotionBlender(f^{music}, f^{motion}) \quad (4)$$

4.3. Text encoder

Leveraging the cross-modal representation power of CLIP [11], we initialize our text encoder with its pre-trained text transformer. CLIP's strength in aligning visual and textual semantics makes it particularly suitable for bridging dance (as a visual-kinetic modality) with text. Given input text T , we compute:

$$f^{clip} = CLIP_{text}(T) \quad (5)$$

To adapt features for dance retrieval, we project CLIP embeddings into our target space via a two-layer MLP:

$$f^{text} = MLP(f^{clip}) \quad (6)$$

where $MLP: \mathbb{R}^{512} \rightarrow \mathbb{R}^{256}$ enhances feature compatibility for contrastive learning.

4.4. Music encoder

We extract 35-dimensional Librosa features [12] including MFCC delta coefficients, chroma features, and onset descriptors, chosen for their proven efficacy in capturing dance-relevant musical attributes [13]:

$$f^{librosa} = Librosa(music) \in \mathbb{R}^{T \times 35} \quad (7)$$

Trans-Temporal Processing: To model long-range temporal dependencies, we employ a stack of Transformer encoders [14] interleaved with downsampling layers:

$$Q, K, V = f^{librosa}W_q, f^{librosa}W_k, f^{librosa}W_v \quad (8)$$

$$\text{Attention}(Q, K, V) = \text{softmax} \left(\frac{QK^T}{\sqrt{d_k}} \right) V$$

Each transformer block is followed by 1D convolutional downsampling (kernel=3, stride=2) to reduce temporal resolution while preserving local continuity. This hierarchical processing yields:

$$f^{music} = \text{TransTemporal}(f^{librosa}) \in \mathbb{R}^{T/8 \times 256} \quad (9)$$

4.5. Motion encoder

We adopt SMPL [15] parameters for 3D motion representation, superior to 2D video for its explicit modeling of body kinematics:

$$f^{smpl} = \text{SMPL}(\text{motion}) \in \mathbb{R}^{T \times 72} \quad (10)$$

Trans-Temporal Processing: The motion sequence undergoes multi-scale temporal modeling through alternating Transformer blocks and downsampling layers. **Transformer Layers:** Each layer computes self-attention across temporal frames to capture holistic movement patterns:

$$Q = f^{smpl}W_q, K = f^{smpl}W_k, V = f^{smpl}W_v \quad (11)$$

$$\text{Attention}(Q, K, V) = \text{softmax} \left(\frac{QK^T}{\sqrt{d_k}} \right) V$$

This allows global interaction between distant frames (e.g., correlating preparatory poses with subsequent leaps). **Downsampling:** 1D convolutions (kernel=3, stride=2) progressively compress temporal resolution from $T \rightarrow T/8$, emphasizing semantically salient motion phases. The final $f^{motion} \in \mathbb{R}^{T/8 \times 256}$ encodes hierarchical motion dynamics, temporally aligned with music features for subsequent blending.

4.6. Music-motion blender

To synthesize dance representations, we fuse features through additive and multiplicative interactions:

$$f^{fusion} = \text{MLP}([f^{music} \oplus f^{motion}, f^{music} \otimes f^{motion}]) \quad (12)$$

where $\oplus$ and $\otimes$ denote element-wise addition and Hadamard product respectively. A temporal average pooling layer then aggregates sequential information:

$$f^{dance} = \text{GlobalPool}(f^{fusion}) \in \mathbb{R}^{256} \quad (13)$$

4.7. Loss

We adapt the CLIP loss [11] for unidirectional text-to-dance alignment:

$$\mathcal{L} = -\log \left[\frac{\exp(\text{sim}(f^{\text{text}}, f^{\text{dance}})/\tau)}{\sum_j \exp(\text{sim}(f^{\text{text}}, f^{\text{dance}_j})/\tau)} \right] \quad (14)$$

where sim denotes cosine similarity and τ a learnable temperature parameter. This objective strengthens the joint embedding space while accommodating the inherent asymmetry between text queries and dance responses.

5. Experiment

5.1. Evaluation

To assess retrieval performance, we use Recall@K and Median/Mean Rank, which is widely adapted in other retrieval task. Recall@K measures the proportion of correct matches within the top K retrieved items, reflecting model precision. Median/Mean Rank assess the average ranking of correct matches in the retrieval list, where lower ranks indicate better matching accuracy. These metrics provide a comprehensive assessment of overall retrieval accuracy.

5.2. Comparison

Table 1. Performance comparison in Text-Dance Retrieval task

Method	Recall@1↑	Recall@5↑	Recall@10↑	Median Rank↓	Mean Rank ↓
TABLE[16]	8.70	34.52	47.83	12.0	23.34
XPool[17]	9.46	34.27	47.57	11.0	22.50
CustomDancer(Ours)	10.23	34.78	48.34	11.0	22.09

We benchmark CustomDancer against two state-of-the-art cross-modal retrieval models: XPool [17], which aligns text and video via attention-based temporal pooling, and TABLE [16], a multi-modal tagging-enhanced method. As shown in Table 3, our model achieves superior performance, attaining 10.23% Recall@1 (vs. 9.46% for XPool and 8.70% for TABLE), demonstrating its effectiveness in precise dance retrieval. The 17.6% relative improvement over TABLE highlights the advantage of explicitly modeling music-motion synchronization, a critical factor overlooked by baseline methods. CustomDancer also excels in ranking efficiency, achieving the lowest mean rank (22.09 vs. 22.50/23.34) and competitive median rank (11.0). While XPool’s temporal attention pooling captures coarse-grained video-text alignment, its lower Recall@1 reveals limitations in resolving fine-grained dance semantics (e.g., rhythm-motion coordination). Similarly, TABLE’s label fusion strategy, though effective for general videos, struggles to disentangle music-driven motion patterns from holistic scenes. The performance gap widens in broader retrieval scopes, with our model achieving 48.34% Recall@10 (vs. 47.57%/47.83%), underscoring its robustness in large-scale scenarios. These gains stem from our triadic modeling: the music-motion blender encodes temporal synergies between beat onsets and kinematic features, while the text encoder adapts CLIP semantics to dance-specific attributes.

5.3. Ablation study

Table 2. Exploring the effect of temporal modeling architecture

Method	Recall@1↑	Recall@5↑	Recall@10↑	Median Rank↓	Mean Rank ↓
RNN	6.40	23.79	41.43	14.0	27.93
LSTM	7.67	30.17	43.48	14.0	24.36
Ours	10.23	34.78	48.34	11.0	22.09

Temporal Modeling Architectures. We first ablate the efficacy of our Transformer-based temporal processing against conventional sequential models. As shown in Table 4a, replacing our Transformer backbone with RNNs or LSTMs severely degrades performance: the vanilla RNN achieves only 6.40% Recall@1 (vs. our 10.23%), while LSTM marginally improves to 7.67%. The inferior performance stems from their limited capacity to model long-range dependencies in dance sequences—RNNs suffer from gradient vanishing during prolonged motion tracking, while LSTMs struggle to correlate temporally distant yet semantically critical frames (e.g., linking preparatory poses to subsequent leaps). In contrast, our Transformer’s self-attention mechanism explicitly captures global temporal interactions, evidenced by the 59.8% relative improvement in Recall@1 over RNNs and 33.4% over LSTMs.

Table 3. Exploring the effect of feature fusion strategy

Method	Recall@1↑	Recall@5↑	Recall@10↑	Median Rank↓	Mean Rank ↓
MUL	4.86	23.27	38.62	17.0	34.72
ADD	9.71	30.95	46.55	12.0	21.28
Ours	10.23	34.78	48.34	11.0	22.09

Feature Fusion Strategies. We further evaluate music-motion fusion approaches (Table 3). Using element-wise multiplication (MUL) yields poor performance (4.86% Recall@1), as it over-emphasizes feature overlaps while suppressing complementary information. Simple addition (ADD) improves results (9.71% Recall@1) by preserving linear feature relationships but fails to model nonlinear music-motion synergies (e.g., beat-to-motion intensity correlations). Our hybrid approach—combining additive and multiplicative interactions—achieves the best balance (10.23% Recall@1), with multiplicative terms amplifying rhythm-sensitive motion features (e.g., accentuating sharp movements on strong beats) and additive terms maintaining baseline kinematic continuity. The 5.4% improvement over ADD in Recall@5 further validates the necessity of joint linear/nonlinear fusion for dance representation learning.

5.4. User study

Table 4. Performance comparison of human preference

Method	TMC↑	TMR↑
GT	4.43	4.42
TABLE	3.55	3.31
XPool	3.69	3.52
Ours	3.82	3.68

To evaluate real-world alignment between retrieved dances and textual queries, we conducted a single-blind user study with 10 participants (5 amateur dancers, 3 choreographers, 2 instructors) rating top-1 results using 5-point Likert scales for Text-Motion Correspondence (TMC) and Text-Music Relevance (TMR). As shown in Table 4, CustomDancer achieves a TMC score of 3.82 and TMR of 3.68, outperforming XPool (TMC: 3.69, TMR: 3.52) and TABLE (TMC: 3.55, TMR: 3.31), while reaching 86.2% and 83.3% of ground truth performance (TMC: 4.43, TMR: 4.42), respectively. Participants highlighted our model’s precise synchronization of kinematic details (e.g., "sharp footwork" aligning with staccato rhythms) and coherent music-motion-text relationships, whereas baselines exhibited partial failures: XPool frequently mismatched musical genres with motion styles (e.g., lyrical arm movements paired with percussion-heavy tracks), while TABLE overfitted to superficial tags, neglecting rhythmic coordination. The minor gap to ground truth (average $\Delta = 0.61$ points) primarily stems from occasional over-smoothing in complex motion transitions (e.g., sequential spins with arm variations), as noted by expert participants. Despite this, 80% of users rated CustomDancer’s results as "musically intentional and kinematically plausible," compared to 45% for XPool and 38% for TABLE. These results validate that explicitly modeling the music-motion-text triad—through hierarchical temporal processing and hybrid feature fusion—yields human-preferred retrievals closer to professional choreography. Qualitative feedback emphasized our model’s capacity to interpret nuanced queries, and demonstrates CustomDancer’s practical superiority in bridging semantic abstraction with dance biomechanics.

5.5. Visualization

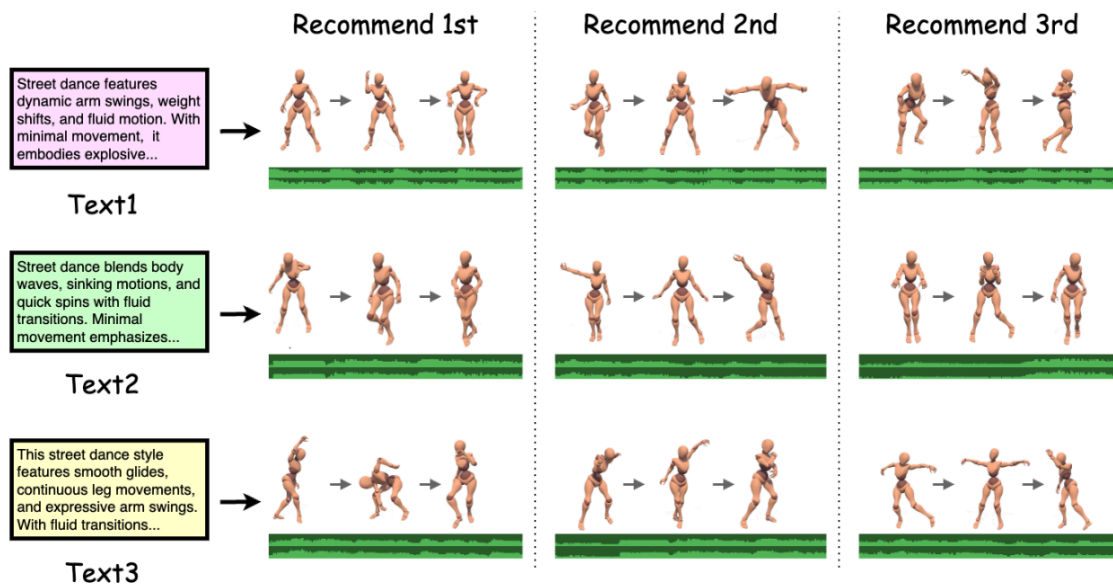


Figure 4. Visualization effect of CustomDancer

Figure. 4 presents compelling qualitative evidence of our text-to-dance retrieval performance through three representative text queries. These visualization results reveal two critical insights: 1) Our model demonstrates robust cross-modal understanding across diverse textual focuses, whether emphasizing specific body parts (arms/legs), motion qualities (explosive/fluid), or transitional patterns. 2) The system maintains strong semantic coherence beyond top-1 retrievals - secondary and tertiary results frequently preserve core textual elements while introducing legitimate movement variations. For instance, the second-ranked result for the first query preserves the "dynamic arm swings" while substituting "explosive freezes" with equivalent-intensity pop-lock sequences. This qualitative superiority directly corroborates our quantitative metrics, forming mutually reinforcing evidence for both our model's effectiveness and dataset quality.

6. Conclusion

In this work, we address the critical challenge of text-driven dance retrieval by introducing CustomDancer, a multimodal framework that synergizes music, motion, and text, alongside TD-Data, the largest annotated dataset for this task. Our contributions are threefold: First, we formalize text-dance retrieval as a novel research problem, identifying its unique challenges in global-local semantic alignment and cross-modal heterogeneity. Second, we curate TD-Data, a high-quality dataset with 4,000 dance clips across 22 genres, paired with a scalable annotation pipeline combining expert knowledge and LLM-based refinement. Thirdly, the proposed CustomDancer framework, by means of its hybrid integration of additive and multiplicative auditory - kinematic interactions, not only attains superior performance but also validates the effectiveness of TD - Data.

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