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Research Article

Let's All Dance: Enhancing Amateur Dance Motions

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Abstract Professional dance is characterized by high impulsiveness, elegance, and aesthetic beauty. In order to reach the desired professionalism, it requires years of long and exhausting practice, good physical condition, musicality, but also, a good understanding of choreography. Capturing dance motions and transferring them to digital avatars is commonly used in the film and entertainment industries. However, so far, access to high-quality dance data is very limited, mainly due to the many practical difficulties in capturing the movements of dancers, making it prohibitive for large-scale data acquisition. In this paper, we present a model that enhances the professionalism of amateur dance movements, allowing movement quality to be improved in both spatial and temporal domains. Our model consists of a *dance-to-music alignment* stage responsible for learning the optimal temporal alignment path between dance and music, and a *dance-enhancement* stage that injects features of professionalism in both spatial and temporal domains. To learn a homogeneous distribution and credible mapping between the heterogeneous professional and amateur datasets, we generate amateur data from professional dances taken from the AIST++ dataset. We demonstrate the effectiveness of our method by comparing it with two baseline motion transfer methods via thorough qualitative visual controls, quantitative metrics, and a perceptual study. We also provide temporal and spatial module analysis to examine the mechanisms and necessity of key components of our framework.

Keywords Animation, Music-to-Motion Alignment, Dance Motion Enhancement, Dance Motion Analysis

1 Introduction

Dance is a performing art form that consists of purposeful, rhythmical, and well-patterned sequences of body movement; it has aesthetic and often symbolic value [1]. Capturing dance motions and transferring them to avatars not only facilitates expressive film or animation production process, but also contributes to the conservation of cultural heritage and dance education. However, so far, access to high-quality dance data has been limited. Most currently available motion capture repositories typically contain basic human movements, while only a limited number of dance-specific databases comprise prime dance movements performed by professionals [2, 3]. This is because professional dance is characterized by dynamic body language, high impulsiveness, elegance, smoothness, fluidity, and aesthetic beauty that usually require the performer to have long-term dance experience and skills, followed by extensive practice sessions, excellent physical condition, and acquaintance with years of dance studies. This poses a practical challenge when capturing realistic and high-quality dance motions, which is restrictive for large-scale acquisitions, or regular acquisition [4]. To perform a professional dance, the performer should be familiar with *the content and rhythm of the choreography*, and achieve the *specific physical amplitude of the choreography with the appropriate energy and balance* [5]. On top of that, in order to achieve a satisfactory dance quality during the motion capture process, dancers have to repeat the performance many times to avoid mistakes.

In this paper, we present a technique that enhances professionalism of dance moves, allowing the movement quality to be improved in both the spatial and temporal domains, meeting the following key constraints: (i) production

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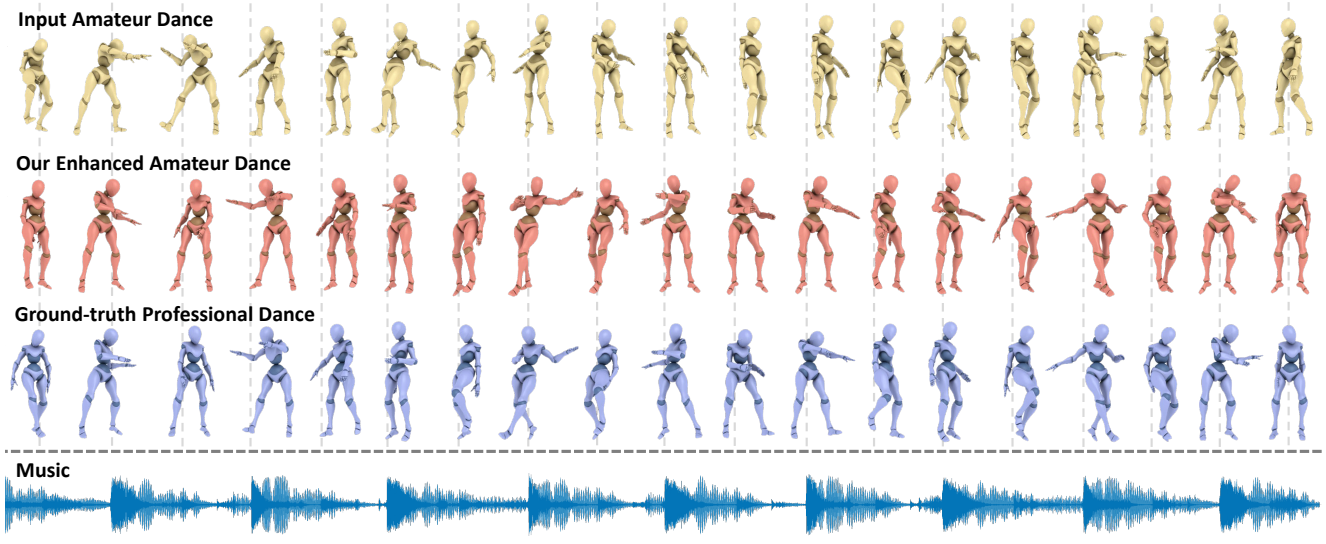


Fig. 1 Our approach enhances the professionalism of dances performed by non-professional dancers. Top: input amateur dance sequence. Second row: our enhanced dance motion. Third row: corresponding ground-truth professional dance. Note that our results have similar temporal and spatial features to the ground-truth dance sequence.

of flowing and smooth dance moves, (ii) expansion of the anatomical and physical amplitude of human movements, to meet the demanding restrictions of the choreography, and (iii) good synchronization of movements to the rhythm of the music. In this way, our method reduces the need to hire professional dancers, facilitates the process of obtaining high-quality dance movements even from amateurs, enriches existing databases with professional data to enable better training of deep networks, and finally aligns dance motion data to a given audio file.

One obvious approach to deal with the challenge of enhancing professionalism of dance movements is to leverage a deep style-transfer framework [6–10], by considering amateur dances as the source style and professional dances as the reference style. However, while style transfer algorithms provide a possible way to handle this problem, they do not address exactly the same problem. Professionalism is not a specific style, but closer to an evaluation metric. Dances with different styles might be seen as professional. Professional dance preparation, whatever the style, not only has specific anatomical and physical demands, but also requires artistic qualities, such as musicality, expression and distinct communication skills. On top of that, existing style-transfer methods face two technical challenges. Firstly, they mainly focus on motions with well-defined styles, while different styles of motions have explicit changes over the whole sequence. In contrast, dances often contain highly-dynamic and heterogeneous movements, and the professional and non-professional dances may share a large number of similar poses but with a limited number of local changes: see Figure 1. Therefore, it is difficult to learn mappings between unpaired professional and non-professional dances, as state-of-the-art motion style transfer methods do [8, 9]. Secondly, they mainly focus on music-free motions, with no explicit and deterministic control over the correlations between motion content and other external factors, such as musical rhythm. Even though existing methods may cause timing changes in motion based on the style differences hidden in the data, such changes are uniformly distributed over the temporal domain.

In this work, we propose a two-stage dance enhancement model that adds *professionalism* to existing dance motions, and release a new dataset with paired professional and amateur dances that enables the training on the model. We define *dance professionalism* term, and describe how it can be evaluated through various attributes, e.g. flow, amplitude and rhythm of a dance. In particular, we improve the quality of dance motions in both spatial and temporal domains, focusing on the following three professional properties: (i) the production of *fluent and smooth* movements; (ii) the *physical amplitude* of intense movements that is restricted by the poor physical condition of the amateur dancer; and (iii) the *temporal alignment* of the dance movements to a given musical rhythm. Firstly, our model estimates temporal correlations between dance motions and musical rhythm, followed by a temporal alignment and spatial motion enhancement process, under the guidance of the proposed professionalism metrics. The dance-to-music alignment stage consists of a network that learns the affinity matrix between dance and

music with attention mechanisms, and a classic dynamic time-warping module to infer an optimal temporal alignment path matrix. Secondly, the dance-enhancement-stage enables adjustment of the dance motion in both temporal and spatial domains, under the guidance of the optimal alignment path, a reconstruction loss, and a consistency loss. The reconstruction loss constraints the network to preserve the original motion content of the amateur dance, while adjusting it to be similar to the corresponding professional dance. The consistency loss preserves the temporal continuity of the enhanced dance motion and decreases temporal noise.

One of the most critical challenges we faced in this project was the lack of data for training our network. Professional and corresponding amateur dances may differ in various combinations of the above professionalism properties. Since the professionalism of a dance is independent of its choreography or style, the dances in a professional or amateur dance dataset may contain highly dynamic and heterogeneous movements. This makes it difficult to learn a homogeneous distribution for the professional or amateur dataset using existing methods, let alone a credible mapping between the two heterogeneous datasets. In addition, the mappings between professional dances and amateur ones are not deterministic. Therefore, before designing our network, we first introduce a key-pose based data augmentation scheme to generate amateur data from professional dances, taken from the AIST++ dataset [3]. The data augmentation scheme modifies the movements in all three professionalism metrics, and the constructed dataset contains many-to-one paired amateur and professional dances.

We demonstrate the effectiveness of our method by comparing it to two state-of-the-art motion transfer methods [6, 8] via thorough qualitative visual controls, quantitative metrics, and a perceptual study. Apart from using our synthesized amateur data, we additionally captured several dance sequences performed by amateur dancers, to further examine the generalizability of our method. User responses indicate that our method enhances amateur motion so that it cannot be easily distinguished from actual professional dance. In addition, we provide temporal and spatial module analysis via an ablation study to evaluate the mechanisms and necessity of key components of our framework.

The main scientific contributions of the paper are:

- The concept of enhancing professionalism in dance movements: we give a first definition of what dance professionalism is, and how a professional dance can be distinguished from an amateur one.
- A novel two-stage deep learning framework that extracts meaningful features from motion inputs, in terms of the newly defined professionalism criteria, to improve the quality of dance motions. It integrates a reconstruction loss, to preserve the original content of the dance, and a consistency loss, to maintain the temporal coherency of the reconstructed motion.
- A novel model designed to synchronize 3D dance motions with reference audio in the face of non-uniform and irregular misalignment.
- Thorough evaluation, and an ablation study to examine the efficiency and necessity of our methods.

2 Related Work

2.1 Dance Evaluation

Dance is an expressive form of performing art that consists of aesthetic movements of the body in a rhythmic way, usually to music, for the purpose of expressing an idea or emotion, releasing energy, or simply taking delight in the movement itself [5]. To professionally perform dance, performers regularly attend long routine training, and have extensive experience in dance studies, choreography, and musicality, along with excellent physical condition, which enables them to perform complex movements with extreme physical amplitude demands in some instances [11, 12]. Only a few works in the dance research community have identified qualitative indicators of professional dances. For example, Neave *et al.* [13] and Torrents *et al.* [14] have reported qualitative experiments showing that kinematic parameters related to the amplitude of movement are highly associated with perceived dance beauty and aesthetics, while Park [15] investigated the correlation between dance professionalism and motion smoothness (using jerk-based quantitative measures). However, no explicit quantitative metrics have been proposed so far to completely evaluate dance professionalism.

In computer graphics, several interactive dance systems have been proposed to enhance dance learning and teaching [16–18]. Basically, these methods export dance movement features to enable comparisons between dances performed by professional dancers (teachers) and amateurs (students). For example, Chan *et al.* [19] implemented a self-learning dance system by visually comparing motion accuracy through Euclidean distance between professional and amateur motions. Aristidou *et al.* [20] leveraged the well-known Laban movement analysis (LMA) theories [21] to introduce quantitative feature components that measure quality characteristics relating two dance motions. Although these movement measurements can be used to understand

motion qualities and to compare similarities between dance motions, no metrics have been developed so far that explicitly measure the professionalism of dance motions.

2.2 Motion Style Transfer

One obvious way to add professionalism to existing motion sequences is to use methods based on the concept of motion style transfer. These methods aim to transform the style of a reference motion to a source motion, while simultaneously preserving the original source motion content. Several approaches [22, 23] have been proposed in the literature to infer styles of motions using hand-crafted features. For example, Tenenbaum and Freeman [22] explicitly separate style and content using asymmetric bilinear models. Aristidou *et al.* [23] built statistical correlations between LMA features and emotions, and used such correlations to support interactive emotion-based motion transfer. However, those methods explicitly construct common mappings between hand-crafted features and motions, which are hard to generalize to heterogeneous or large-scale datasets.

Machine Learning Based Techniques. To avoid the disadvantages of selecting hand-crafted features, researchers started to extract style information from large-scale paired data using machine learning techniques [24–26]. Brand and Hertzmann [24] introduced a style hidden Markov model (HMM) and minimized information entropies to separate structure, style and accidental properties. Following their work, Hsu *et al.* [25] built dense correspondences between different motions with an iterative motion warping algorithm, and then proposed a linear time-invariant model to translate motion styles, while Xia *et al.* [26] proposed to learn local regression models. However, machine learning-based methods require explicit or implicit motion registration between the input and output motions, and are therefore limited to styles and content that exist in the training dataset; as a result, they do not generalize well to new styles of motion.

Deep Learning Based Techniques. In recent years, deep learning techniques have been widely adopted to transfer motion styles [6–10, 27–29], enabling more efficient and effective results for complex and even unpaired motions. For instance, Holden *et al.* [6] leveraged convolutional autoencoders [30] to learn hidden motion representations with paired input and output motions. The same authors in [7] further improved this model with an additional feed-forward neural network, and transformed motion style in the hidden motion space under the constraint of a *Gram matrix* [31]. Later, Aberman *et al.* [8] proposed a neural network to disentangle latent style and content codes, where the latent style code is used to modify the decoded motion content through an AdaIN [32] operator. By using a multi-style discriminator, this method can handle unpaired motions. Following their work, Wen *et al.* [10] recently proposed an unpaired and unsupervised motion style transfer method using a generative flow model. Despite their great progress, existing deep-learning-based methods mainly focus on locomotions with a limited number of motion structures, and have no explicit control over musical correlations. Unlike locomotions, dance performed by professional dancers may contain heterogeneous motions with various choreographies (e.g. different motion poses and ordering of poses) and are well-synchronized to temporal rhythmic patterns. Our method deals with these challenges by simultaneously learning the intrinsic motion attributes and the motion-rhythm correlations that commonly appear in professional dance.

2.3 Music-driven motion synthesis

Many scholars have worked on methods for music-driven dance synthesis. Typical solutions leverage a graph-based framework [33–36]. In pioneering work, Kim *et al.* [34] constructed a movement transition graph based on extracted motion beats and synthesized new motions under kinematic and rhythmic constraints. More recently, the use of machine learning to synthesize music-driven dance motions has witnessed impressive progress [4, 37–41]. For instance, Lee *et al.* [38] proposed a decomposition-to-composition framework to generate 2D movements conditioned on a given piece of music, under the guidance of learned correlations between musical beat and dance units. Chen *et al.* [4] proposed a choreomusical embedding module to learn stylistic and rhythmic music-dance correspondences, and incorporated the embedding distances into the traditional graph-based dance synthesis framework. More recently, Aristidou *et al.* [41] introduced a music-driven neural framework that generates rich and diverse dance motions that respect the overall choreographic structure of a dance genre. However, music-driven dance synthesis learning methods heavily rely on high-quality dance motion data synchronized to given audio for adequate training. Since access to dance data made by professionals is not always possible, our method can be used to enrich databases using data from amateurs that have been artificially enhanced to look more visually appealing; our work simultaneously learns music-to-dance correspondences and leverages them to learn dance-to-dance correlations.

2.4 Audio Alignment

To enhance non-professional dances, an essential goal is to align dance motions to reference audio. Motion-audio synchronization aims to temporally align human motion dynamics to audio rhythms, which is fundamental to synthesis of rhythmic human motions. Traditional motion-audio synchronization methods leverage hand-crafted 2D motion and rhythmic features, determine their correspondences, and warp motions under the guidance of motion-rhythm matches [35, 42–44]. Over the years, more attention has been devoted to the video-audio timing alignment problem. A common basic idea is to find optimal video-to-audio correspondences and use them to guide warping between visual and audio features, either using hand-crafted features [45, 46] or deep multi-modal features [47, 48]. Among such methods, Wang *et al.* [49] introduced two attention modules before the feature extraction stage to highlight important spatial and temporal regions. In contrast, instead of emphasizing specific features, we introduce an integrated attention module to map correspondences between spatial and temporal motion features, and audio rhythms, without hand-crafted elements or post-processing. Our model is the first to synchronize 3D dance motions with reference audio under irregular and non-uniform misalignment.

3 Data Augmentation

An important challenge that needs to be addressed in this work is the lack of training data. The limited existing dance motion datasets [2, 3, 39] typically contain high-quality professional dances, but lack corresponding non-professional ones. As a result, it is difficult to build correlations between paired professional and non-professional movements. Capturing realistic non-professional dances requires amateur dancers to learn the original professional choreography, which can be challenging and requires practice, and it may be difficult to cover the large variability of the movements of professional dancers. Instead, we propose a data augmentation scheme that artificially synthesizes random non-professional dances, by altering professional ones taken from the AIST++ dataset [3], both in the spatial and temporal domains.

3.1 The Definition of Dance Professionalism

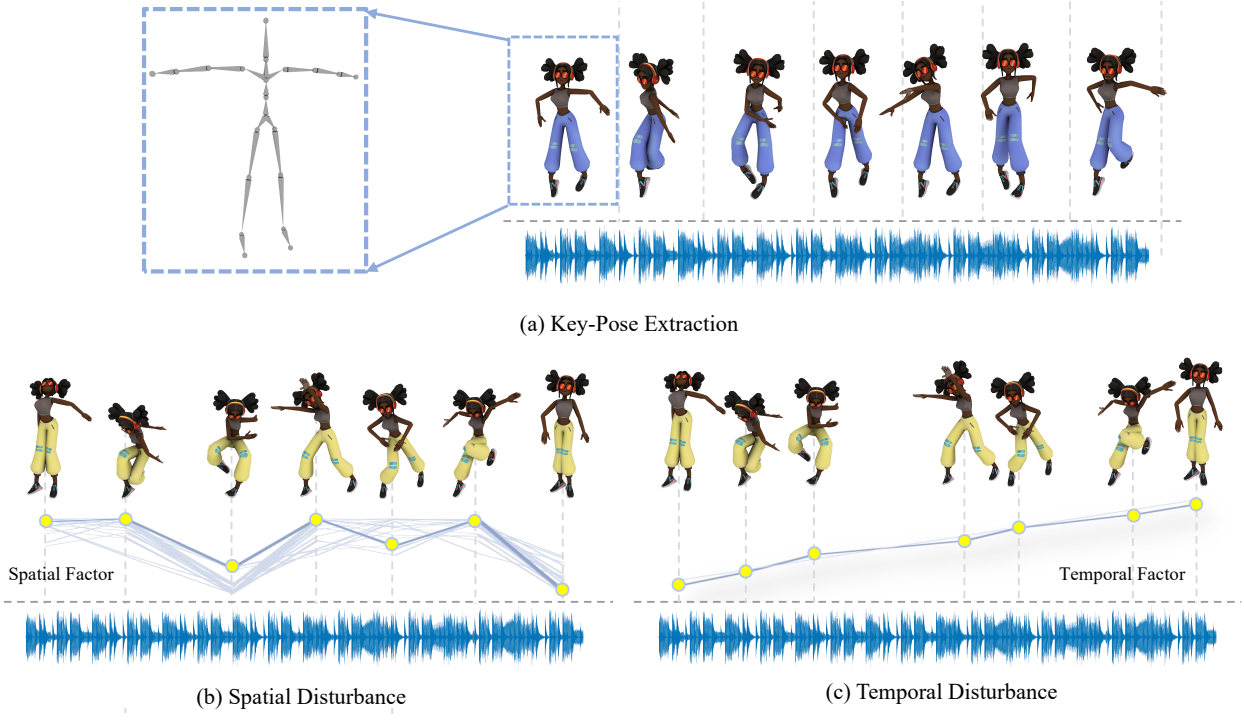
Before we present our data augmentation schema, it is important to define first the criteria that distinguish a professional dance movement from an amateur one. In that matter, we consulted expert choreographers, experienced dancers, and dance teachers, who pointed out the following key criteria:

- **Sense of rhythm** Professional dancers can perfectly follow the beat of the music, while amateur dancers often lose synchronization and have difficulty in following the rhythm of the music.
- **Physical amplitude** Professional dancers have excellent physical condition, which allows them to perform complex and dynamic movements, in some cases reaching the limits of the body. In contrast, non-professional dancers usually have difficulties in completing certain dance moves as they have limitations due to their poor physical condition (to extend their body to the limits, to perform the splits, etc.).
- **Motion quality** The movements of a professional dancer are elegant, smooth, and the movement cycle is nicely completed. In contrast, the movements of an amateur dancer are often not in balance, they abruptly start and end movements without fully completing the movement cycle (sharp movements), and may be shaky, lacking smoothness. All these result in amateurs requiring more effort than professionals because they do not control their movements as experts do.
- **Concentration and consistency** Amateur dancers usually focus on one part of the body (e.g. legs or arms) and may neglect the consistency of movements of other parts of the body (such as the head, and overall style). Note that our method does not take this feature into account.
- **Choreography** Professionals have a richer choreography in terms of the diversity of movements, compared to amateurs who usually repeat the same movements multiple times. Again note that changing dance choreography is outside the scope of this paper.

3.2 Generating Amateur Dance Movements

Amateur dancers have, in general, difficulties in synchronizing their movements to the musical beat, to achieve certain physical amplitudes, and to perform controlled and smooth movements. Therefore, to enrich our database, we introduce a method that artificially alters professional dance movements, through random disturbances, to generate corresponding amateur counterparts. It is important to note that our approach needs to meet the following three conditions: (a) to keep the choreography of the professional dances unchanged, (b) *temporal disturbance*: to alter the temporal alignment between motion, and music and rhythm; (c) *spatial disturbance*: to change the physical amplitudes of motions.

In this manner, we propose a key-pose-based scheme that first extracts key poses based on the motion beat; then,



(a) Key-Pose Extraction

(b) Spatial Disturbance

(c) Temporal Disturbance

Fig. 2 Data augmentation: the process for generating amateur dance movements. (a) Key-poses rendered on a girl's avatar. Our skeleton structure (top left) is highlighted within a dashed rectangle. (b) The key-poses are spatially modified based on the spatial disturbance curves. We highlight one curve for a specific joint with the spatial factors on key-poses (indicated by *yellow* dots). (c) The temporally modified key-poses and accompanying temporal disturbance curves.

it randomly generates spatial disturbance factors to limit or exaggerate the physical amplitudes of movements, and temporal disturbance factors to disrupt the music-motion synchronization. Finally, it computes the spatial and temporal disturbances in between those key-poses using piece-wise linear interpolation [50]. These are later used to modify the professional dances. Figure 2 overviews our data augmentation method.

Motion Representation. We represent a dance motion $\mathbf{M}$ as a sequence of T skeleton poses. Each skeleton pose $\mathbf{P}$ is represented by $J = 21$ joint rotations that are organized in a hierarchical order and depicted by unit local positions [51] between parent-child joints, denoted as $\mathbf{P} \in \mathbb{R}^{(J-1)\times 3}$. Therefore, a dance motion can be represented by $\mathbf{M} \in \mathbb{R}^{T\times(J-1)\times 3}$, where $T = 426$ to $2,878$ frames without being trimmed into short clips. Poses are then translated back to rotations via a Jacobian-based inverse kinematics solver [52]. Note that the root rotations and translations are discarded in the motion representation to avoid significant changes to the choreography.

Key-Pose Extraction. When learning to dance, it is usually easier for students to identify prominent changes of movements (such as pausing and turning). Based on this observation, we define the representative poses to be those with changes of velocity direction [46]. To facilitate key-pose extraction, we first uniformly sample several poses over a certain time duration t. The time duration t is set to three seconds in our implementation. We then search for the nearest motion beats as the corresponding key-poses, where the motion beat is found using the minimum of all joint speeds in a certain frame. Since some neighboring key-poses may bring about rapid direction changes, we filter out key-poses that have neighboring motion beats within 1 second.

Spatial Disturbance. The spatial disturbance aims to disrupt physical amplitudes of the movements, limiting or exaggerating their intensity. Thus, we define the spatial factor $\mathbf{S}' \in \mathbb{R}^{N\times J}$ for the N selected key-poses to control the spatial disturbance of all skeleton joints, and randomly generate corresponding values through an approximately inverse normal distribution:

$$S'_n = \tanh(s'_n d)\alpha + \beta, \tag{1}$$

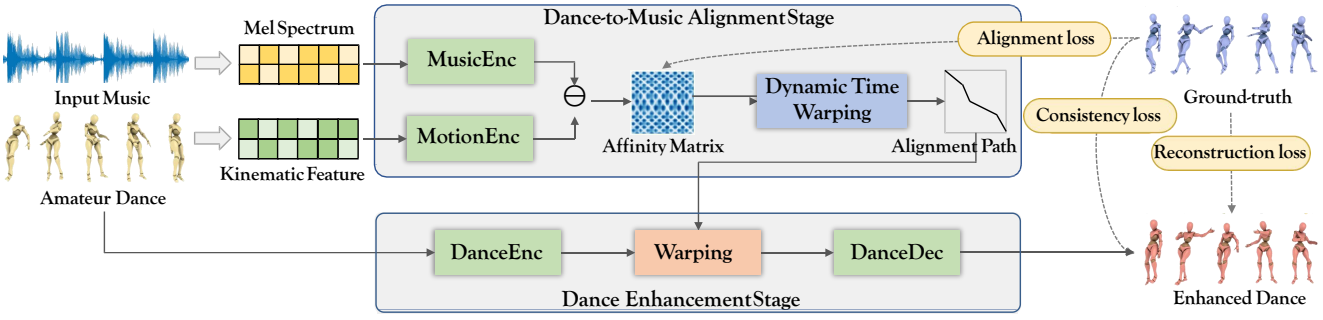


Fig. 3 Our two-stage dance professionalism architecture. The dance-to-music alignment stage learns the temporal alignment of the input dance motion to the corresponding music, through a dynamic-time-warping operation on the encoded deep features of dance motion and music. In the dance enhancement stage, we first extract the hidden dance motion features to express the original motion content, which are then modified under the guidance of the temporal alignment matrix, and further decoded into the enhanced dance motion under the constraints of a reconstruction and consistency loss.

where s'_n is the randomly generated spatial disturbance value for key-pose n. α and β are used to control the shape of the inverse normal distribution; in our implementation they equal 1.1 and 1.3 respectively. d is a randomly generated binary parameter that enables ($d = 1$) or disables ($d = 0$) exaggeration of the pose. All joints in a specific frame share the same d value. S'_n is then propagated to each frame of the entire sequence as $\mathbf{S} \in \mathbb{R}^{T\times J}$ ($T > N$) via linear interpolation.

A straightforward way to apply the aforementioned spatial factor for motion disturbance is to directly multiply the rotations or positions of each joint by it. However, this may produce infeasible poses that violate physical or bone constraints. Instead, we interpolate the new pose (local position) between the current and a standard standing pose, guided by the spatial factor, as follows:

$$\mathbf{p}'_{t,j} = |\mathbf{p}_{t,j}| \left(\frac{\mathbf{p}_{t,j}}{|\mathbf{p}_{t,j}|} S_{t,j} + \mathbf{u}_j (1 - S_{t,j}) \right), \qquad (2)$$

where $\mathbf{p}_{t,j}$ denotes the local position of the j-th joint in the t-th frame, and $\mathbf{u}_j$ is the pre-defined direction for joint j of the standard standing pose. To simplify the process, we define three key interpolation directions for the standing pose: up ($\mathbf{u}_j = (0, 0, 1)$) for joints on the spine, no modification for the shoulder and waist joints, and down ($\mathbf{u}_j = (0, 0, -1)$) for the other joints.

Temporal Disturbance. The temporal disturbance aims to disrupt the mappings between the dance motion and the corresponding musical rhythm. We define the temporal factor $\mathbf{Q} \in \mathbb{R}^N$ to control the temporal disturbance at the N key-poses, and randomly generate values to warp the original dance motion sequence according to Eq. 1. The parameters α and β are set to 50 and 0 respectively. We then move the key-poses to new positions by shifting them $\mathbf{Q}$ frames,

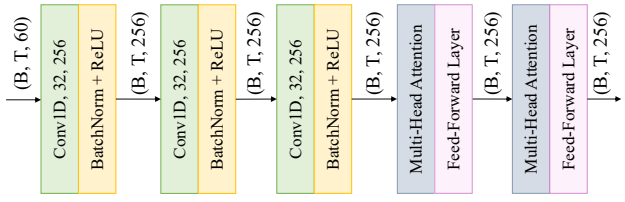


Fig. 4 Network architecture of the *MusicEnc*. The input music feature sequence is processed by three temporal convolution blocks, each containing a 1D-convolution layer, batch normalization and ReLu layer. Then it goes through two transformer blocks containing the multi-head self-attention and feed-forward layers to obtain the encoded feature sequence. The *MotionEnc* and *DanceEnc* share the same network architecture.

where negative Q_n means shifting backward and positive Q_n indicates shifting forward. Note that in this process we need to check time crossings between key-poses and preserve motion monotonicity. Finally we calculate the movements of the intermediate poses between adjacent key-poses by linear interpolation.

Augmented Data. Using the above approach, we constructed a large, highly variable, non-professional dataset of dances paired to professional ones. We repeated the temporal and spatial disturbance four times, creating many-to-one paired amateur and professional dances, in a dataset 4 times the size of the original AIST++ database.

4 Dance Professionalism Framework

Our framework, by taking as input a dance motion sequence performed by an amateur dancer, and its corresponding audio file, aims to enhance professionalism by considering the following three conditions: *retention of the original choreographic content, generation of fluid movements, and amplification of physical amplitudes*. Enhancement is made in

both temporal and spatial domains. In the temporal domain, our framework aligns the amateur dance motion to music to achieve fluid and consistent motions, while in the spatial domain, it increases the physical amplitudes of the input motions to match those of a professional dancer, while preserving the original content of the dance's choreography. To do so, we have designed a two-stage deep framework: a dance-to-music alignment stage, and a dance enhancement stage. The dance-to-music alignment stage estimates the temporal mapping of the amateur dance required to match the input music; these estimates are later integrated into the dance enhancement stage to enable temporal warping of the encoded dance content features, which are later decoded to reconstruct a professional dance with the same choreographic content. Figure 3 shows the two-stage architecture of our framework, whose details will be described in the following sections.

4.1 Dance-to-Music Alignment Stage

The main goal of the dance-to-music alignment stage is to find the optimal alignment between the input music and dance sequences. Taking into account the highly complex correspondences between a dance motion and music, we use auto-encoders to learn the cross-modal frame-to-frame mapping between the high-level motion and the music features extracted from the raw data.

High-Level Feature Extractor. For an input music signal with T frames, we compute the mel-scaled spectrogram using the well-known *librosa* [53] audio analysis library, depicted as $\mathbf{G} \in \mathbb{R}^{T\times B}$ where B is the number of frequency bins. For the input T-frame dance motion given by position offset vectors $\mathbf{M} \in \mathbb{R}^{T\times(J-1)\times 3}$, we first calculate the corresponding joint positions, and then estimate the velocities and accelerations of each joint in x, y, z directions per frame, denoted $\mathbf{K} \in \mathbb{R}^{T\times C}$; $C = J \times (3+3)$ where $J = 21$ joints in the human skeleton.

Dance-to-Music Alignment Network. The dance-to-music alignment network is composed of two encoders, *MusicEnc* and *MotionEnc*, to map the music feature G and dance motion feature K to the corresponding latent feature sequences f_G and f_K, respectively. The two encoders share the same network architecture but have different weights. Following the two encoders, we compute the Euclidean distance between the frames of the two latent feature sequences to form a $T \times T$ affinity matrix, defined as:

$$F(i,j) = \|f_G(i) - f_K(j)\|_2^2 \tag{3}$$

where i is the index of the music frame, and j is that of the motion frame. Figure 4 shows the structure of our dance-to-music alignment network.

Specifically, for each encoder, the input sequence is first processed by three temporal 1D-convolution layers sequentially, and each is followed by batch normalization and a ReLU layer. Considering the complex correlations between dance choreographies and their musical correspondences, we use the attention mechanisms in a transformer network to learn contextualized dance-to-music information, providing adaptive local neighbors for both the dance and music encoders. In particular, we add a shallow transformer with two multi-head self-attention and feed-forward layers on the basis of the 1D-convolution layers, and thus obtain latent feature sequences f_G or f_K encoding temporal context information. Note that the self-attention layers in the transformer are biased towards the local neighbors of each frame by setting the attention mask matrix B_a as follows:

$$B_a(i,j) = \begin{cases} 0, & |i-j| < \delta, \\ -\infty, & \text{otherwise}, \end{cases} \tag{4}$$

where δ is a parameter to control the neighborhood size and is set to 50 in our implementation.

Dynamic Time Warping. The target now is to find the optimal alignment between the input dance and music, so that each dance frame can be matched to the music frame with minimal alignment distance. Under the guidance of the affinity matrix deduced from the dance-to-music alignment network, we perform dynamic programming [54, 55] to obtain an optimal alignment path matrix $\mathbb{W}$ between the latent dance and music features.

4.2 Dance Enhancement Network

The enhancement stage aims to modify amateur dances so as to look more professional in terms of physical amplitudes and dance-to-music synchronization. To achieve this goal, we leverage an auto-encoder network to modify the non-professional dances in latent feature space. Specifically, the non-professional dance sequence given by unit local positions is used to extract corresponding latent features via an encoder, *DanceEnc*. The latent dance features are then temporally warped under the guidance of the optimal dance-to-music alignment path, followed by a decoder to output the corresponding professional dance sequence.

DanceEnc has similar implementation details to the *MusicEnc* and *MotionEnc* networks. We warp the encoded feature sequence f_D by calculating the dot-product between f_D and the alignment path matrix $\mathbb{W}$ obtained from the dynamic time

warping module. The decoder is implemented as a three-layer MLP network to project the feature sequence to the final enhanced dance.

4.3 Training and Loss

The two stages in our framework are trained separately with different loss functions. In particular, the dance-to-music alignment network is trained using an *alignment* loss, while the dance enhancement network is trained with a *reconstruction* and a *consistency* loss. In this process, we leverage the optimal alignment path as a condition to modify the latent dance features; we use the ground-truth alignment path as an initial warping condition, and then fine-tune the network with the estimated alignment path. Note that the lengths of the input dance motions during training and testing can be arbitrary.

Alignment loss. We assume that the dance sequences and their corresponding music sequence are well-synchronized: a motion frame is well matched with its paired music frame. Therefore, we design the temporal alignment loss on the affinity matrix in a contrastive learning manner. To be more specific, for each music frame, we select the corresponding dance frame as the positive sample and a randomly selected frame as the negative one. Then, we compute the triplet loss on the latent features of the three frames as the alignment loss:

$$L_{\text{triplet}} = \sum_{t}^{T} \left[\left\| f_G(t) - f_K(\hat{\phi}(t)) \right\|_2^2 - \| f_G(t) - f_K(r) \|_2^2 + a \right]_+, \tag{5}$$

where f_G, f_K are the music feature and dance feature respectively, r is a randomly sampled frame index, $\hat{\phi}(t)$ is the index of the corresponding dance frame for the music frame t.

Reconstruction loss. To improve the physical amplitudes of the movements in amateur dances so that they look more professional, we trained our network using paired amateur and professional data; our target is to force the enhanced amateur movements to be as close as possible to the corresponding professional ones. Therefore, we define a reconstruction loss that minimizes the local position error between the enhanced motion and the ground truth, given by the equation:

$$L_{\text{recon}} = \sum_{t}^{T} \sum_{j}^{J} |p_{t,j} - \hat{p}_{t,j}|, \tag{6}$$

where $p_{t,j}$ is the local position of joint j at frame t in the enhanced dance motion, and $\hat{p}_{t,j}$ is the corresponding local position in the ground-truth professional dance motion.

Consistency loss. To enforce temporal coherence in the enhanced dance, we introduce a consistency loss by measuring the error between the velocity of the enhanced dance and that of the corresponding ground-truth. Our consistency loss is:

$$L_{\text{cons}} = \sum_{t}^{T} \sum_{j}^{J} |v_{t,j} - \hat{v}_{t,j}|, \tag{7}$$

where v and $\hat{v}$ are the velocities of the enhanced and ground-truth dance motion, respectively.

5 Results and Discussion

In this section, we present the dataset used for training and testing our method, implementation details, and evaluation metrics. We also demonstrate the efficiency of our framework in several experiments, a perceptual survey that evaluates its performance in terms of professionalism, realism, and dance-to-music synchronization, and an ablation study. Figure 1 shows a gallery of selected frames extracted from the input amateur motion (yellow), our result (red), and the ground-truth professional dance (blue). It can be observed that our method enhances professionalism so that the input's temporal and spatial features better match those of the ground-truth dance sequence. The quality of our enhanced dance animations may be examined in the supplementary video.

Dataset. The original AIST++ dataset [3] contains 1,408 sequences of 3D human dance motion represented as joint rotations along with root trajectories. Each sequence of dance motion is accompanied by corresponding music well-synchronized to the animation. Overall, the dataset includes 10 dance genres with hundreds of different choreographies, providing rich and varied dance content. We follow the music-choreography data splits used in the original paper [3] for network training and testing/validation. For each professional music-dance pair in the AIST++ dataset, we produced multiple amateur dance counterparts using our key-pose based dance synthesis algorithm (see Section 3), by controlling their temporal and spatial disturbance factors. In total, we generated $3,680$ non-professional dances for training, 80 for testing and 80 for validation.

Implementation Details. We implemented our framework in PyTorch and tested it on a 6-core PC with a 3.7 GHz Intel i7 CPU, 16 GB RAM, and an NVIDIA Tesla P100 GPU. All

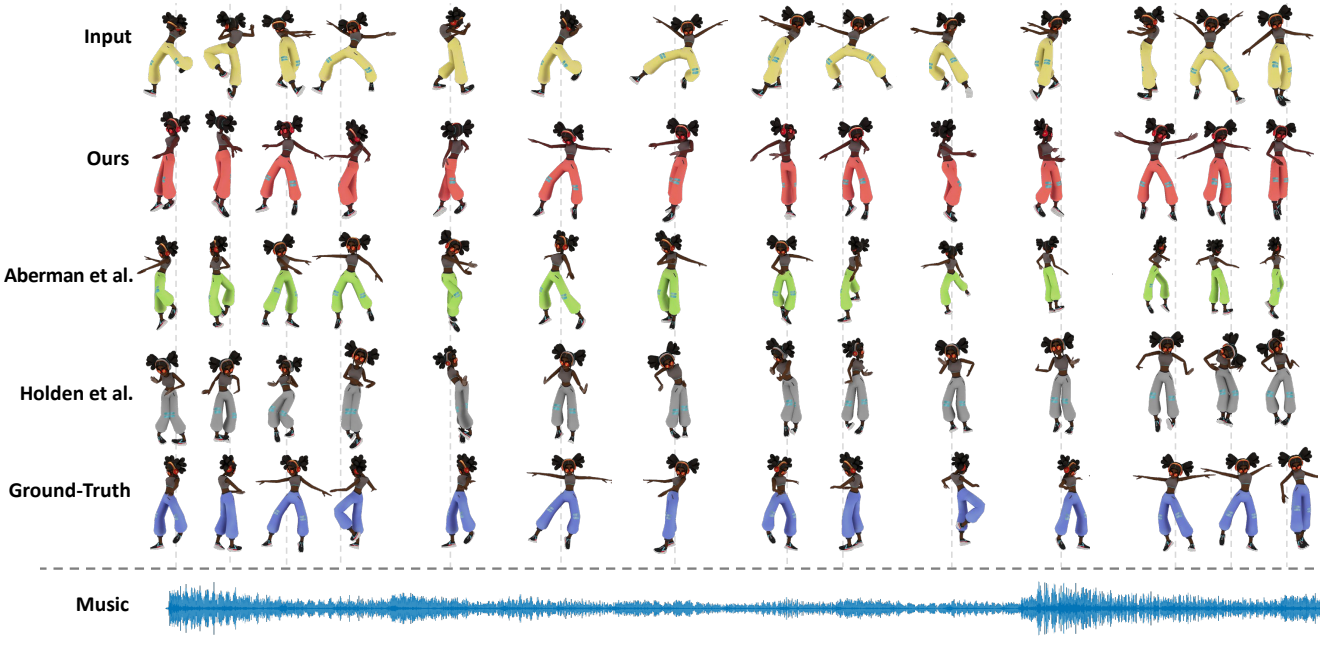


Fig. 5 Qualitative comparison of our method to baseline methods [7, 8]. Each row shows a set of frames selected from the same music beat. It can be observed that our results are closer to the ground-truth than the two alternatives, in terms of dance-to-music alignment and pose reconstruction. For an animated version, please refer to our supplementary video.

networks in our framework were trained with a batch size of 64 and learning rate of 10^{-4}, and optimized by the Adam optimizer [56]. In total, it took about 12 training hours for the dance-to-music alignment network and 6 training hours for the dance enhancement network, on 4 NVIDIA Tesla P100 GPUs.

Evaluation Metrics. To the best of our knowledge, no quantitative metrics currently exist to evaluate the professionalism of dances. Therefore, we used the *temporal alignment error* (time error), the *pose error* (PE) and the *Fréchet inception distance* (FID), as evaluation metrics, and observed the temporal and spatial differences between the input motions, our enhanced dance motions, and the corresponding ground-truth professional dances. The three evaluation metrics are defined as follows:

- *Temporal alignment error* is the average distance between the indices of motion poses per music frame, in the optimal dance-to-music alignment path and the ground-truth alignment path.
- *Pose error* measures the average Euclidean distance between joint positions for specific poses in two motions sequences to be compared.
- *Fréchet inception distance* measures how far the distribution of the enhanced dance is to that of the ground-truth professional one [4, 57]. We calculate FID based on the extracted kinematic features [3] of the enhanced and ground-truth professional dances.

5.1 Evaluation

In this section, we evaluate the performance of our method with two baseline methods – the Holden's *et al.* [7] and the Aberman's *et al.* [8] methods – using the three aforementioned evaluation metrics. In addition, we conducted three perceptual studies to qualitatively evaluate: (a) the quality and realism of our artificially generated amateur dance motions; the quality and realism of our experimental results in enhancing professionalism on amateur movements using (b) our synthetically generated amateur dataset, and (c) real, motion-captured amateur dances. More details about our perceptual study can be found in our supplementary materials.

5.1.1 Comparisons

Baseline Methods. As far as we know, there are no other methods in the literature that deal with the dance enhancement problem. Thus, we compare the results of our approach with two state-of-the-art motion style transfer methods due to Holden *et al.* [7] and Aberman *et al.* [8], which also use auto-encoders as a backbone network. Unlike our problem, these methods take a content motion and a target style motion as input, and then generate an output motion by preserving the same but desired style of input content with the target motion. Note that, these methods do not take music into consideration.

To adapt the two baseline methods to our problem, we made the following modifications. (1) Since they require motions

Table 1 Quantitative evaluation of our results and the motion style transfer methods on the test set.

Method	Pose Error↓	FID ↓
Holden *et al.* [7]	4.323	322.327
Aberman *et al.* [8]	3.156	36.456
Ours	**1.951**	**14.817**

to have the same length, we down-sampled our dataset to the same length (400 frames). (2) We used our synthesized amateur dance together with the accompanying music as the input, and randomly selected another professional dance of the same genre as the target motion style for their network. (3) As Aberman's *et al.* [8] network is trained using unpaired motion data with a consistency loss, minimizing a reconstruction error between the input and output content when the input content sequence and the style sequence have the same style. To make their method applicable to paired motion data, we use the consistency loss to calculate the reconstruction error between the output of the network and the ground-truth professional dance. Holden's *et al.* [7] method was trained with its original loss functions.

Qualitative Comparison. Figure 5 illustrates selected poses from the input dance motion sequence (yellow), our method (red), Aberman's method (green), Holden's method (gray), and the ground truth (blue). The music beat [53] is marked with a gray dotted line to indicate the temporal coherence. It can be observed that our method successfully produces good correspondences to the professional dance sequences, with satisfactory temporal alignment and spatial amplitudes. In contrast to our method, the two alternatives are not synchronized to the beat (since they are not designed for aligning dance-to-music), and their reconstructed poses are further than ours from the ground-truth movement.

Quantitative Comparison. Table 1 quantitatively reports the pose error and the FID metric. These metrics confirm our observations; the two baseline methods produce worse results than our method, having larger pose error and FID score. Since they are not designed to compute an explicit temporal alignment between dance and music, we do not consider the time error metric in this evaluation.

In addition, we use a professional dance sequence as input to the network to further evaluate the naturalness and realism of the output motion. As Figure 6 shows, the results confirm the ability of our method to generate natural movements, returning a movement that is realistic and well aligned to the music beat.

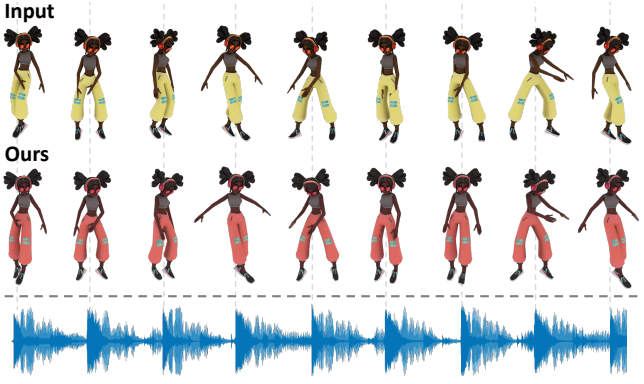


Fig. 6 In this example, we tested our network by inputting a dance sequence performed by a professional dancer. It can be observed that the output motion remains natural and realistic, and similar to the input.

5.1.2 Perceptual Study

Evaluation of our synthetic amateur dance dataset. We first conducted a perceptual study to evaluate the quality and realism of our synthetic amateur motions, and whether they resemble true amateur dances. For this task, we recruited, in total, 20 participants, 11 female and 9 male. Each participant watched 28 pairs of side-by-side dance motions; on the right side, we showed amateur motions, which were either selected from our synthetic dataset (16 samples), or captured by amateur dancers who imitated professional dance moves (12 samples); on the left side of the video, we showed the corresponding ground-truth dance expert motions, so that the participants could use the professional motion as a reference to examine the quality of the amateur and synthetic motions.

The participants were asked to rate on a Likert scale whether the presented motion on the right side was captured from an amateur dancer, or generated by a computer algorithm. The scale was 0: the motion was not performed by an amateur, there is too much computer-generated noise, 2: it is hard to decide, 4: the participant is strongly confident that the motion was performed by an amateur dancer. The scores were statistically analyzed to compare our synthetic motions and the true amateur motions. Figure 7 shows box-plots of the average score for the synthetic and true amateur motions. Both cases have an average score between two and three, which indicates that it is hard for participants to discriminate whether the motions are computer-generated or not. However, it is important to mention here that our synthetic dataset may have some differences compared to the true, motion-captured data. Our synthetic amateur motions are generated by randomly setting disturbances in spatial and temporal spaces to imitate the amplitude and music synchronization of amateur dances, so some motions may exist with too exaggerated or limited

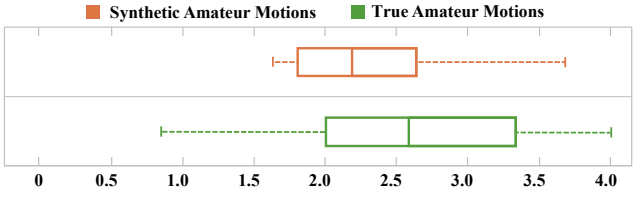
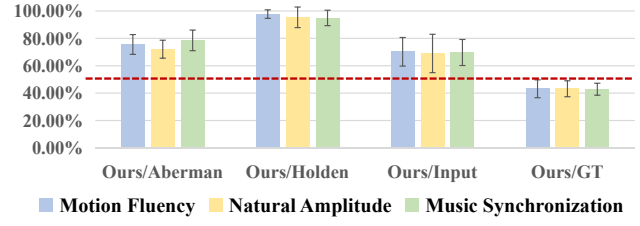
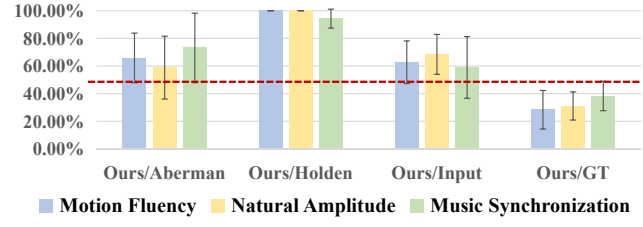


Fig. 7 Average scores evaluating whether dance motions were captured from amateur dancers or algorithmically synthesized. Red: score for all synthetic amateur motions. Green: score for real, motion-captured, amateur motions.



(a) Results from amateur participants.



(b) Results from dance expert participants

Fig. 8 Professionalism evaluation for synthetic dance motions. Each group of bars indicates the average percentage of participants that preferred our results, with 95% confidence intervals. Blue bars: motion fluidity, yellow bars: naturalness of amplitudes, green bars: dance-to-music synchronization. Bars higher than the red dotted line indicate cases when our results were preferred by a majority of users.

movements. In addition, dances performed by amateurs may have lower consistency of the body parts and contain different choreographies compared to those performed by experts; these differences have not been considered in our synthetic data generation process. Therefore, as expected, our synthetic amateur motions got a slightly lower score than the true amateur motions.

Professionalism Evaluation on Synthetic Data. We conducted a perceptual survey to evaluate the quality of our results when the synthetic dataset was used. We compared the results of our method with two baselines [7, 8], the input, and the ground truth, considering the following three aspects of professionalism: (i) the *smoothness and fluency* of the dance motions; (ii) the *naturalism of the dance physical amplitudes*; and (iii) *the dance-to-music synchronization*. For this evaluation, we randomly selected seven motions, each

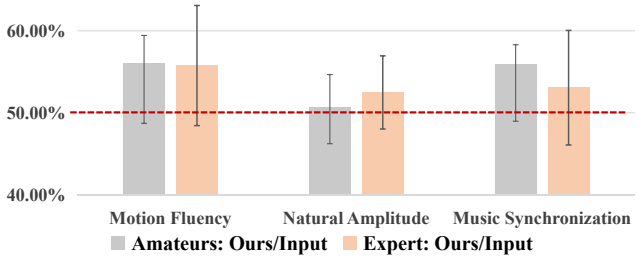


Fig. 9 Professionalism evaluation on true amateur dance motions. Each group of bars indicates the average percentage of participants that preferred our results, with 95% confidence intervals. Gray bars: votes of amateur users, orange bars: votes of expert users.

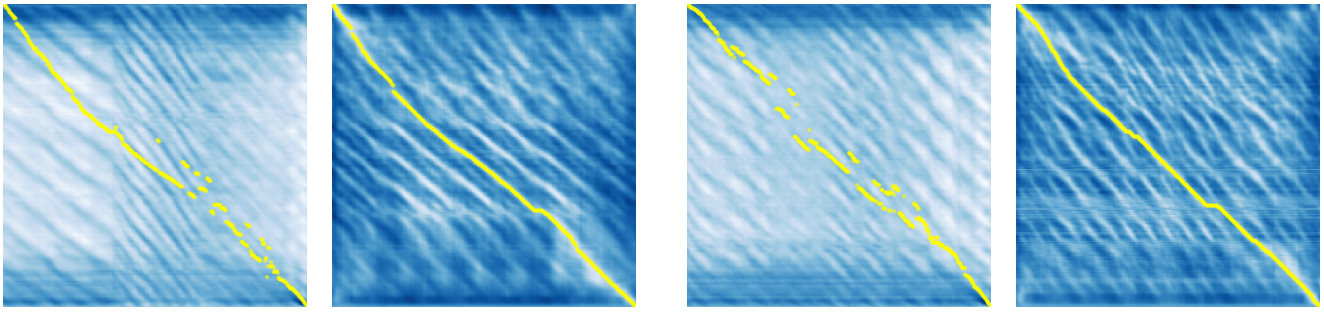
from a different dance genre.

We recruited 20 participants, 15 amateur dancers with less than one year of dance experience and 5 expert dancers with more than eight years of experience. Each participant was shown, in total, 28 pairs of dance motions; each pair included one generated by our approach, and the other from the ground-truth dataset or generated using one of the two baselines. For each pair, in three independent questions, the participants were asked to select the dance motion that: (i) is smoother and more fluid, (ii) has more natural physical amplitudes, and (iii) is better synchronized to the music. All experimental dance motions were randomly ordered to avoid learning effects.

The answers were gathered to quantify the overall professionalism of the dance motions. Results of the perceptual study are shown in Figure 8, which lists the average percentage of participants who preferred our results over the results of the two baseline methods, the input, and the ground-truth. It can be observed that our method received higher scores than the two baselines and the input for all three aspects of professionalism, in the votes of both amateur and expert participants. Apart from smoother and more natural motion, we believe that the better dance-to-music alignment plays an important role in these results. As expected, both the amateur and dance expert participants gave higher scores to the ground-truth motions than to ours.

Professionalism Evaluation on Real Motions. Finally, we used the 12 motion-captured dance sequences performed by amateur dancers to further evaluate our method on real amateur data. The motion-captured dances were performed by amateur dancers, who imitated 12 ground-truth professional dances chosen from our testing dataset.

In this survey, we recruited 20 participants, 15 amateur dancers, and 5 expert dancers. As in the previous study, each participant was shown pairs in random order of true amateur motions and our enhanced results, and asked to



(a) Case 1 (b) Case 2

Fig. 10 Visualization of temporal alignment results. The temporal affinity matrix is encoded by a *Blue* colormap with *white* as low values and *blue* as high values. The optimal alignment path is illustrated as a *yellow* curve.

select the motion that: (i) is smoother and more fluid, (ii) has more natural physical amplitudes, and (iii) has better synchronization to the given music. Figure 9 presents the results of this study. Compared to the input amateur dances, our enhanced results were preferred by most amateur and expert participants; our results scored significantly higher with respect to motion fluency and music synchronization. As expected, our method performs worse on the true amateur dataset than the synthetic dataset, because our network has been explicitly trained using synthetic amateur data. An interesting future problem is to enrich our training dataset with true amateur dances or to better simulate synthetic data so that they can better execute real amateur dance motions.

5.2 Ablation Study

To evaluate the contribution of the dance-to-music alignment stage and the necessity of each of its components, we conducted an ablation study which evaluated several variations of the proposed network, by removing or replacing key components with other alternatives. In detail, we assessed our network: (i) without integrating the dynamic time warping module (W/O DTW); and (ii) without combining the dance-to-music alignment stage (W/O Alignment). Table 2 reports the results of the ablation study; for visual comparisons, please refer to our supplementary material.

Temporal-Alignment Stage. If the temporal alignment stage is not integrated into our framework (W/O Alignment), we concatenate the input music and amateur dance, and provide them as input to the dance encoder during the dance enhancement stage. The encoded latent features are directly fed into the decoder without warping. Table 2 lists results using this setup; we can easily observe the necessity of having the temporal alignment stage: the network cannot implicitly learn the temporal warping from the convolutional layers.

Table 2 Temporal alignment analysis and spatial enhancement analysis results.

Method	Time Error↓	Pose Error ↓	FID↓
Input	24.433	3.081	29.973
W/O Alignment	-	2.479	31.324
W/O DTW	21.177	2.366	20.392
ConvNet	18.547	1.998	13.595
Transformer	18.547	3.371	77,317
Conv.+Trans. (Ours)	18.547	1.951	14.817

Dynamic-Time-Warping Component. To evaluate the effect of the dynamic-time-warping component, we use temporal attention mechanisms as an alternative to our learning alignment method. Without the dynamic-time-warping component, we built the optimal temporal alignment path for each music frame by selecting the motion frame with the maximum attention value in the affinity matrix. More details of how we have built and trained the affinity matrix can be found in the supplementary material. The results in Table 2 confirm that the performance of the attention-based implementation (W/O DTW) is worse than the original implementation. To better demonstrate the results, we show alignment results of our method and the attention-based implementation in Figure 10. In each case, the blue background gives the $T \times T$ temporal affinity matrix (rows are motion frames, columns are music frames), and it is overdrawn by the optimal alignment path (yellow curve). A white color indicates low alignment correspondence between the motion and music frame. It can be observed that the optimal alignment path produced by the W/O DTW approach is scattered: aligned poses between neighboring frames may have large changes, causing motion jitters. Instead, our optimal alignment path is continuous and monotonic. This validates the necessity for a separate dynamic time warping component to give temporal alignment.

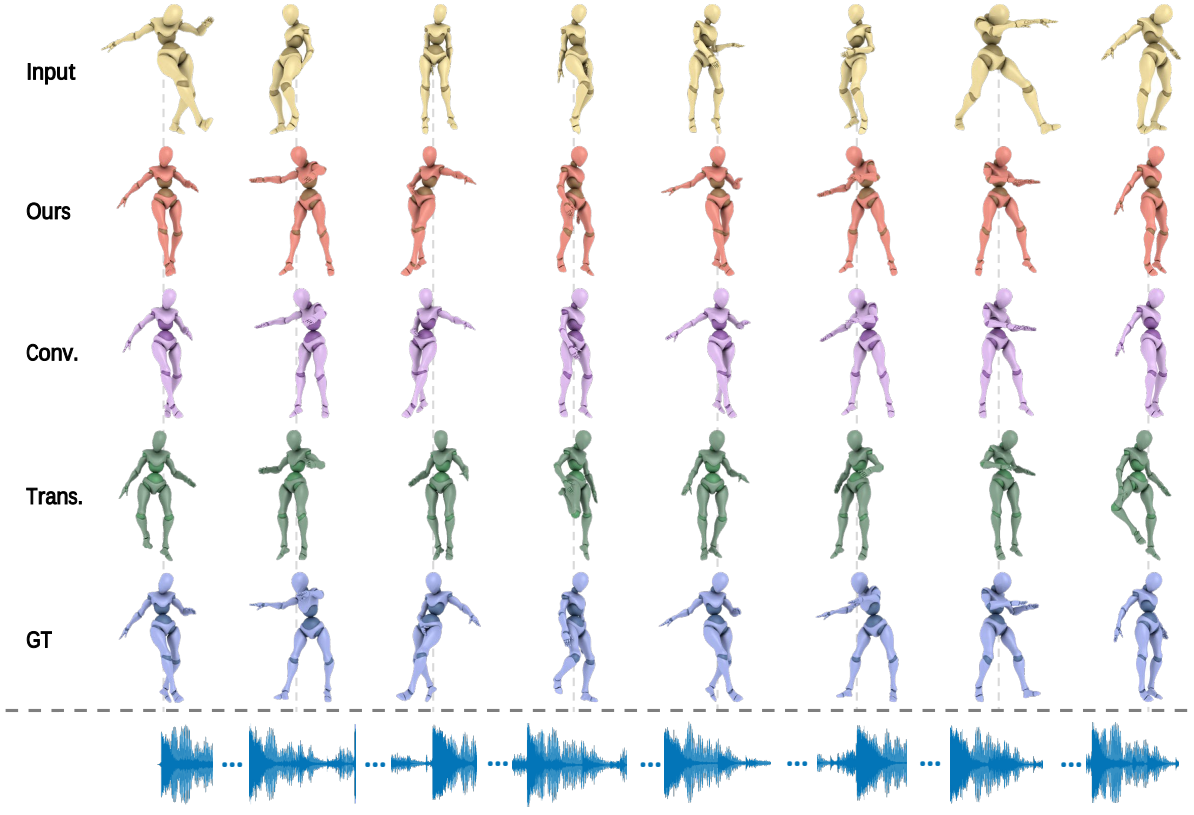


Fig. 11 Ablation study: visual comparison between our final configuration, and when using only *ConvNet* or *Transformer*. Our final structure produces dance poses closest to the ground-truth.

Dance Enhancement Stage. To examine the impact of our deep neural architectures, we reimplemented the dance enhancement network with two baseline structures, *ConvNet* and *Transformer*. The *ConvNet* encoder is composed of three Conv-BN-ReLU blocks. The encoder of *Transformer* is implemented as a shallow network with two attention-forward blocks, while our method (*ConvNet with a Transformer*) concatenates three Conv-BN-ReLU blocks and two attention-forward blocks. The decoder for all three structures is implemented as the three-layer MLP. In this experiment we kept the same parameters, for the dance-to-music alignment stage, for all three structures.

The last three rows in Table 2 show that our network's structure performs better than *Transformer*. Compared to *ConvNet*, our performance is slightly better in pose error, but a little worse in FID. Since pose error measures pose similarity to the ground-truth per frame while FID measures overall kinematic feature distribution, we believe that the pose error metric is more important when evaluating visual effects. As Figure 11 shows, the enhanced poses produced by our structure are visually closer to the ground-truth than when using *ConvNet* or *Transformer* alone. This evaluation indicates that the convolution layers are essential for encoding dance features with temporal contextual information.

5.3 Application: Dance-to-Music Synchronization

One of the main features of our method is that it aligns 3D motion data with audio files in the presence of non-uniform and irregular misalignment. This feature enables some very interesting applications, where the same dance can be reused with audio files with different beats. Figure 12 shows an example of such dance-to-music synchronization. It can be observed that the input and output dance sequences share similar poses, but are temporally misaligned since they are artificially synchronized to music files played at different beats. To the best of our knowledge, there are no other works in the literature that do dance-to-music synchronization in 3D motion. Our approach enables data reuse, and puts the foundations to facilitate future development in this important application area.

6 Limitations and Future Work

Our study mainly focuses on two attributes of dance professionalism, extending specific physical amplitudes via spatial amplitude enhancement, and making dances fluid by temporal motion-rhythm synchronization. However,

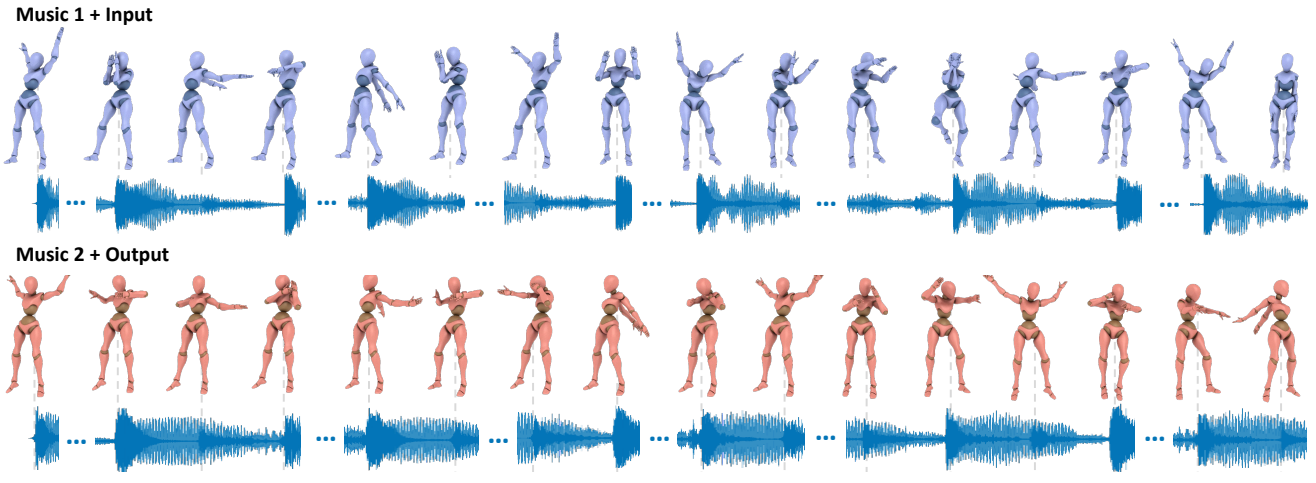


Fig. 12 Synchronizing the same dance to different audio files. Above: the dance and its original music rhythm. Below: dance motion synchronized to a new audio file. Our method can align a dance motion to audio files with different rhythms and beats, enabling data reuse. See our supplementary video for animated results.

dance professionalism is also correlated with other semantic attributes, such as *smoothness*, *energy*, *balance*, and *aesthetics*. In future work, it would be interesting to investigate these attributes, and design algorithms that emphasize semantics in dances, e.g. to enhance the aesthetics of the input dance. Furthermore, our framework modifies input amateur dances based on their original content. No additional constraints have been considered for adding or deleting poses in the original amateur dances. Therefore, when choreographic errors exist in the input amateur dances, or their choreography is not rich or diverse enough, our method cannot improve it. A possible future direction is to use motion motifs [58] to learn fine-grained mappings between professional and non-professional dances, and to build a knowledge code-book for dance enhancement, similar to the concept of [41]. Last but not least, our framework is built on a paired professional and synthetic non-professional dance motion dataset. When the input amateur dance contains poses far away from the distribution of dances in the dataset, our method may produce unsatisfactory results. A future improvement would be to enrich the synthetic non-professional dataset with real captured amateur dance motions, or to design an unpaired dance enhancement approach by leveraging characteristics of different dance genres. We would also like to experiment with other pose representations, e.g. see [59, 60], to avoid the use of inverse kinematics to restore joint rotations, and avert potential rotation discontinuities caused by the network. Finally, our method can be used to improve e-learning applications e.g. for XR systems when users try to learn dance with a virtual avatar.

7 Conclusions

In this paper, we have presented a deep learning framework that enhances professionalism of amateur dances, satisfying three main professionalism properties: *fluid dance movements*, *physical amplitudes*, and *temporal alignment of dance and music*, without changing the content of the original choreography. The framework consists of a dance-to-music alignment stage and a dance-enhancement-stage, the first learning an optimal temporal alignment path between the input dance and the accompanying music, and the second enhancing the dance motion in both spatial and temporal domains. We have also presented a key-pose based dance augmentation scheme that artificially generates non-professional dance data from the AIST++ [3] dataset. We demonstrate the effectiveness of our framework by comparing it to two baseline style transfer methods [7, 8] via a qualitative visual survey, quantitative metrics, and a perceptual study. We have also presented a useful application that reuses existing dance motion files by synchronizing them with audio files with a different rhythm.

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suggestions.

Declaration of competing interest

The authors have no competing interests to declare relevant to the content of this article.

Electronic Supplementary Material

We provide a supplementary document describing details of our implementation and the perceptual study. We also provide an accompanying video with visual comparisons of our method and the baseline methods.

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