

Large Motion Model for Unified Multi-Modal Motion Generation

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Project Page: <https://mingyuan-zhang.github.io/projects/LMM.html>

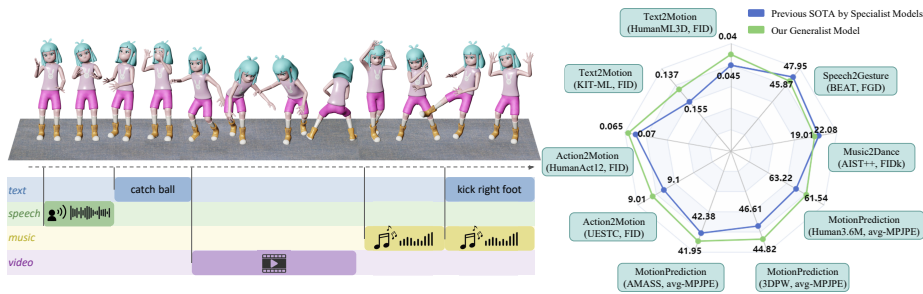


Fig. 1: We present Large Motion Model (LMM), the first generalist multi-modal motion generation model, that can perform multiple motion generation tasks simultaneously and achieve competitive performance across nine widely used benchmarks.

Abstract. Human motion generation, a cornerstone technique in animation and video production, has widespread applications in various tasks like text-to-motion and music-to-dance. Previous works focus on developing specialist models tailored for each task without scalability. In this work, we present **Large Motion Model (LMM)**, a motion-centric, multi-modal framework that unifies mainstream motion generation tasks into a generalist model. A unified motion model is appealing since it can leverage a wide range of motion data to achieve broad generalization beyond a single task. However, it is also challenging due to the heterogeneous nature of substantially different motion data and tasks. LMM tackles these challenges from three principled aspects: **1) Data:** We consolidate datasets with different modalities, formats and tasks into a comprehensive yet unified motion generation dataset, **MotionVerse**, comprising 10 tasks, 16 datasets, a total of 320k sequences, and 100 million frames. **2) Architecture:** We design an articulated attention mechanism **ArtAttention** that incorporates body part-aware modeling into Diffusion Transformer backbone. **3) Pre-Training:** We propose a novel pre-training strategy for LMM, which employs variable frame rates and masking forms, to better exploit knowledge from diverse training data. Extensive experiments demonstrate that our generalist LMM

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achieves competitive performance across various standard motion generation tasks over state-of-the-art specialist models. Notably, LMM exhibits strong generalization capabilities and emerging properties across many unseen tasks. Additionally, our ablation studies reveal valuable insights about training and scaling up large motion models for future research.

Keywords: Motion Generation · Unified Model · Multi-Modality

1 Introduction

Humans perform a variety of motions in response to environmental changes, personal thoughts, and emotions to achieve their goals. These intricate motions often serve as the most information-rich element within videos and animations that feature characters, making motion generation a critical component of Generative AI, significantly influencing visual experiences and content quality. Automated human motion generation, aimed at producing continuous, natural, and logical human movements based on specific commands and control conditions, has attracted considerable attention in the computer vision field.

These specific sub-tasks are characterized by their defined inputs and outputs, with clear objectives. For instance, action-to-motion generates movements based on the category of the motion [34, 102]; text-to-motion takes textual descriptions and produces corresponding movements [32, 155]; music-to-dance creates dance moves in tune with the style and beat of the music input [29, 121]. Dividing tasks allows for a more focused approach to each sub-task: constructing dedicated datasets and devising methods tailored to the task at hand. However, these approaches, when designed for a singular sub-task or modality, face challenges due to limited data quantity and a narrow data domain, which in turn can lead to models with restricted capabilities and poor generalization performance. In contrast, the objective of this work is to build a unified yet versatile foundation model for human motion generation, leveraging resources from a wide range of applications and achieving strong performance across the board.

Leveraging multi-modal and multi-task motion generation datasets presents significant challenges. First, disparate datasets feature varying motion formats and evaluation metrics, such as keypoint-based or rotation-based formats, and metrics assessing realism or diversity. Consequently, employing a single model to tackle multiple tasks and perform evaluations across different datasets is exceedingly difficult. Furthermore, transferring motion knowledge across tasks within these datasets is challenging, complicating the model’s ability to integrate useful knowledge from various data sources to enhance its capabilities. For instance, differences in frame rates and the number of keypoints (sometimes even missing parts of the body) make it hard to unify the learned knowledge. Although some studies attempt to address multiple tasks simultaneously [79, 166], they often utilize only two or three datasets with the same motion format, which limits their ability to achieve enhanced controllability and generalizability. In summary, integrated motion generation models for multi-modal and multi-task applications encounter the following problems: 1) Non-uniformity of motion data formats;

2) Different evaluation metrics due to varying task objectives; 3) Difficulty in transferring action knowledge across multiple tasks.

To deal with these challenges, we first amass multiple cross-modal motion datasets, encompassing 16 datasets with a total of 320k sequences and 100 million frames. These datasets span seven standard tasks: text-to-motion, action-to-motion, motion prediction, speech-to-gesture, music-to-dance, motion imitation, and motion in-betweening. Additionally, based on the standard tasks and multi-modal control signals, we introduce three new tasks: conditional motion prediction, conditional motion in-betweening, and multi-condition motion generation. Together, these datasets and tasks form our cross-modal motion benchmark, **MotionVerse**. To align the diverse formats of motion data, we employ a two-step approach: 1) We use the TOMATO representation [91] as a unified intermediary format, and then divide the entire representation into 10 parts. All kinds of motion representations are aligned to this format, with annotations indicating which body parts are present in each sequence; 2) We train a series of representation translators to convert the unified motion representation into the specific representations of each dataset during the testing phase. With MotionVerse, we can smoothly use training data from various tasks and modalities, and conduct tests across different datasets.

Building on MotionVerse, we introduce the multi-modal Large Motion Model (**LMM**), which is built on a transformer-based diffusion model. Addressing the motion format inconsistency, we developed a body part-aware motion generation model. This model divides the human body into 10 segments and employs a specialized attention mechanism **ArtAttention**, featuring multi-conditioning, spatial-temporal independence, and mask injection, allowing for distinct control over different body parts. Furthermore, body part-aware modeling decomposes motion data from various datasets into relatively independent segments, thereby enabling the model to more effectively leverage knowledge learned across different datasets. Lastly, we adopt learning strategies from large language models (LLM), proposing a training method for LMM that combines unsupervised and supervised learning. In unsupervised learning, we enhance model robustness to frame rates through random frame rate augmentation and improve control over the continuity of body part movements by applying random masks to sequences and body parts in various ways. This training approach significantly leverages large amounts of multi-modal data to bolster LMM’s capabilities. In supervised learning, we refine the capabilities of models to enhance their performance on specific tasks. Experimental results show that LMM achieves state-of-the-art results across various tasks, demonstrating its exceptional generalization performance, as shown in Fig. 1. Furthermore, LMM has the ability to process multi-modal inputs simultaneously, enabling it to accomplish unseen tasks.

In summary, our core contributions are as follows:

1. We present MotionVerse, a mega-scale, multi-modal, multi-task motion generation dataset that features a unified motion representation across a wide range of tasks and motion formats.

2. We introduce a Large Motion Model (LMM) that incorporates an advanced attention mechanism ArtAttention, allowing for precise and robust control, achieving finer results.

3. We devise a pre-training strategy for the LMM, including random frame rates and various masking techniques to fully leverage extensive motion datasets and enhance the model’s capabilities. Additionally, through ablation studies on our training approach, we explored certain characteristics inherent in LMM’s training process, laying a foundation for future research on the LMM.

2 Related Work

2.1 Motion Synthesis

Subtasks of motion generation are differentiated based on the types of control signals they utilize. Some tasks require the algorithm to synthesize motion sequences based on the given uncompleted motion sequences. For example, in the motion prediction task [1, 2, 8, 9, 14, 20, 30, 35, 48, 94, 123, 124, 133, 142], the control condition is the first several poses, and the generated motion must logically follow the preceding sequence to ensure the extended sequence appears natural and reasonable. There are also works focusing on recovering the whole body motion with the given sparse upper-body tracking signals [12, 21].

Action-to-motion [13, 34, 51, 59, 85, 102, 136, 161] is an inverse task derived from the motion recognition task. While the latter identifies the action category from a motion sequence, the former involves generating a corresponding action sequence from an input action category. In the music-to-dance task [22, 43, 61, 62, 65, 66, 99, 109, 121, 122, 129, 144, 147, 167], the control signal is music, and the motion sequence (dance) should be in accordance with the style and rhythm of the music. Bailando [121] addresses crucial spatial constraints and temporal coherence in dance generation by utilizing a codebook to store standardized dancing units, confining spatial constraints. It achieves temporal fluidity through a GPT designed to detect music beats. Another task based on audio is speech-to-gesture [4, 23, 57, 84, 141, 149, 150, 163], where the input is the speaker’s audio and the output is the corresponding gestures of the speaker, taking into account the speech’s pauses, emotional fluctuations, etc. GestureDiffuCLIP [4] utilizes CLIP to extract style information from the input and then employs a diffusion model to generate gestures. Text-to-motion is one of the most attracting topic in conditional motion generation [3, 5–7, 15, 18, 24, 25, 28, 29, 31, 33, 36, 38, 40, 42, 47, 49, 50, 52, 55, 56, 67, 74, 76, 77, 79, 80, 82, 90, 91, 103, 104, 106, 110–114, 116, 118, 127, 128, 130, 132, 134, 137, 139, 140, 145, 146, 148, 151–157, 159, 160, 164–166], where motions are generated based on textual descriptions. This requires the model to comprehend the meaning of the text and produce a corresponding sequence of motions. Previous works attempted to apply advanced generative model [128, 155, 159] to improve performance. While some other works focused on enhancing controllability [6, 110, 157]. Physical reality [113, 151] and out-of-domain performance [41, 82, 127] are also vital topics in this field.

In addition, some works focus on human-scene interaction generation [44,73,86,138], human-object interaction generation [19,37,60,63,64,78,101,105,119,126,135,158] and human-human interaction generation [11,16,26,71,87,120,125,162]. These tasks greatly expanded the scope of motion generation applications.

However, action generation targeting a single task often struggles with limited data volume and a singular data domain, leading to models with restricted capabilities and poor generalization. Our paper integrates various motion generation tasks, designing the Large Motion Model (LMM) to utilize multi-modality data from different tasks for model training. This enables the model to learn from various domains, enhancing its generalization capabilities.

2.2 Diffusion Model for Multiple Tasks

As diffusion models have made remarkable strides in image generation tasks, researchers have extended their application to a broader array of fields, including video generation [54,131,143], image editing [10,17,39,53,98], and motion generation [18,128,155,157,165], etc. Moreover, given the limited functionality and control over generation provided by single-modal conditions, multi-modal inputs have been introduced into diffusion models to enhance their versatility and control capabilities. In the realm of image generation, UNIMO-G [70] takes both images and text as inputs, utilizing the subjects in pictures and textual prompts to generate realistic images that match complex semantics. For video generation, MM-Diffusion [115] incorporates audio and video in a multi-modal manner, enabling the harmonious adaptation of audio and visuals to produce realistic videos with sound. In image editing tasks, the integration of multi-modal inputs with diffusion models has made image editing more flexible and convenient. Control-color [72] combines text, strokes, exemplars, and other conditions to achieve interactive, multi-modal controlled image coloring. InstructAny2pix [68] uses similar conditions for multi-modal control over inpainting. Likewise, in the field of motion generation, works like MotionDiffuse [155] and MDM [128] have tackled text-to-motion and action-to-motion. MCM [79], UDE [166] has addressed text-to-motion and music-to-dance. MoFusion [92] attempted to learn a better motion prior. In summary, across different domains, multi-modal diffusion models enrich the content and enable more precise control of generation tasks. Previous dual-modal motion generation methods often utilize similar annotation formats, such as SMPL [88], facilitating easy data alignment. However, the multi-modal datasets we collected cover a broader domain span, and the formats for motion annotation are extremely diverse. Thus we propose a comprehensive benchmark, MotionVerse, to unify the motion representation, ultimately leading to the development of LMM.

3 MotionVerse: Unified Motion Generation Datasets

3.1 Motivation

Large models have been extensively studied in fields such as language, image, and video. These models, by absorbing common knowledge from vast amounts of

data and leveraging a unified task format, demonstrate outstanding performance across multiple tasks. However, on the path towards large motion models, a significant challenge lies ahead: the inconsistent motion formats across datasets. Specifically, there are three types of inconsistencies:

1. **Inconsistent pose representations:** For instance, the UESTC [46] benchmark adopts a 6D rotation representation based on SMPL [89], while the Human3.6M [45] motion prediction benchmark uses keypoint coordinates.
2. **Inconsistent number of keypoints:** For example, TED-Gesture++ [150] only includes upper body keypoints, while NTU-RGBD 120 [83, 117] lacks fine-grained keypoints for the hands.
3. **Inconsistent frame rates:** KIT-ML [107] operates at 12.5 fps, whereas Motion-X [75] runs at 30 fps.

Such differences not only demand models capable of handling diverse data formats but also pose significant challenges in acquiring common knowledge.

To address this challenge, we introduce the first unified and comprehensive motion-centric benchmark **MotionVerse**, the workflow of which is shown in Fig. 2. MotionVerse possesses three advantages:

1. **Unified Problem Formulation:** we describe mainstream tasks within a unified framework, reducing the need to consider task-specific properties during model design.
2. **Unified Motion Representation:** we convert the motion formats of various datasets into a unified intermediate representation, enabling the model to acquire common knowledge from the originally diverse data formats and to be evaluated on different datasets smoothly.
3. **Systematicness and Comprehensiveness:** we encompass 10 tasks across 16 datasets, comprising 320K sequences and nearly 100M frames of motion data, as shown in Tab. 2, which enables us to explore large motion models.

Task	Mask	Condition
T2M	None	Text
A2M	None	Action
M2D	None	Music
S2G	None	Speech
MIm	None	Video
MP	$m = \begin{cases} 0 & \text{if } x > k \\ 1 & \text{Otherwise} \end{cases}$	None
MIn	$m = \begin{cases} 0 & \text{if } k_1 < x \leq k_2 \\ 1 & \text{Otherwise} \end{cases}$	None
CMP	$m = \begin{cases} 0 & \text{if } x > k \\ 1 & \text{Otherwise} \end{cases}$	Any single modal
CMI	$m = \begin{cases} 0 & \text{if } k_1 < x \leq k_2 \\ 1 & \text{Otherwise} \end{cases}$	Any single modal
MMG	None	Multi-modal

Table 1: Task definitions. x and k_* are the frame indices, and k_* represents the boundary of the mask.

Dataset	#Seq	#Frames	Repr	Condition
HumanML3D [32]	14614	2M	H3D	Text
KIT-ML [107]	2485	245K	H3D	Text
Motion-X [75]	50863	9M	SMPLX	Text
BABEL [108]	5123	7M	SMPLX	Text
UESTC [46]	25600	10M	SMPL	Action
HumanAct12 [34]	1191	90K	Kpt3D	Action
NTU-RGB-D 120 [83, 117]	139656	10M	Kpt3D	Action
AMASS [93]	14244	20M	SMPLX	-
3DPW [96]	81	140K	SMPL	Video
Human3.6M [45]	210	530K	Kpt3D	Video
TED-Gesture++ [150]	34491	10M	Kpt3D	Speech
TED-Expressive [84]	27221	8M	Kpt3D	Speech
Speech2Gesture-3D [58]	1047	1M	Kpt3D	Speech
BEAT [81]	1639	18M	Kpt3D	Speech
AIST++ [66]	1408	1M	SMPL	Music
MPL-INF-3DHP [97]	16	1M	Kpt3D	Video
Total	320K	100M	-	-

Table 2: Dataset information. We collect 16 widely used dataset, process all motion data into our intermediate format.

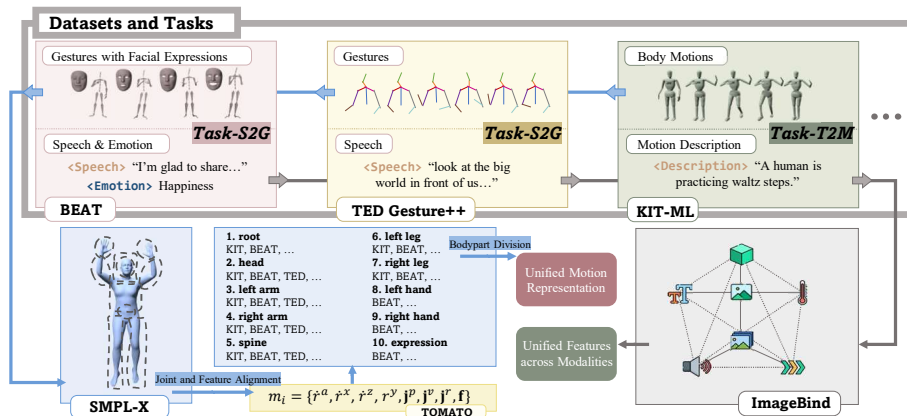


Fig. 2: MotionVerse. We preprocess distinct motion-centric datasets into a unified format. As for motion sequences, we initially convert them to the TOMATO [91] representation and then further divide them into 10 independent body parts, serving as our unified motion representation. To tackle multi-modal condition signals, we employ ImageBind [27] to transform them into unified features across modalities.

3.2 Unified Problem Formulation

Motion generation encompasses a variety of sub-tasks with differing objectives. To standardize the data for these tasks, we first formalize the problem for motion generation tasks as:

$$\Theta = M(\mathbf{x}, \mathbf{m}, \mathbf{c}), \quad (1)$$

where $\mathbf{x} \in \mathbb{R}^{F \times D}$ represents the motion data, $\mathbf{m} \in \{0, 1\}^{F \times D}$ defines the model’s visibility scope, which is used in motion completion tasks, such as motion prediction and motion in-betweening. Here F is the number of frames of the target motion sequence. D is the dimensionality of each pose state. \mathbf{c} is a set of condition control signals, including text, speech, music, and video.

We have included seven standard tasks: action-to-motion (A2M), text-to-motion (T2M), music-to-dance (M2D), speech-to-gesture (S2G), motion prediction (MP), motion in-betweening (MIn) and motion imitation (MIm), along with three multi-modal tasks: conditional motion prediction (CMP), conditional motion in-betweening (CMI), and multi-condition motion generation (MMG). For each specific task, we can align their inputs using Eq.(1). Tab. 1 lists the details of these ten tasks.

3.3 Unified Motion Representation

For data formats with varying inputs and outputs across different tasks, we preprocess to ensure format consistency. The basic unit of general motion datasets can be defined as <input-output> pairs. For inputs, we consider multi-modalities including text, speech, music, and video. To align these modalities, we employ Imagebind [27] to encode different inputs into unified features of the same dimension, which ensures semantic consistency across modalities.

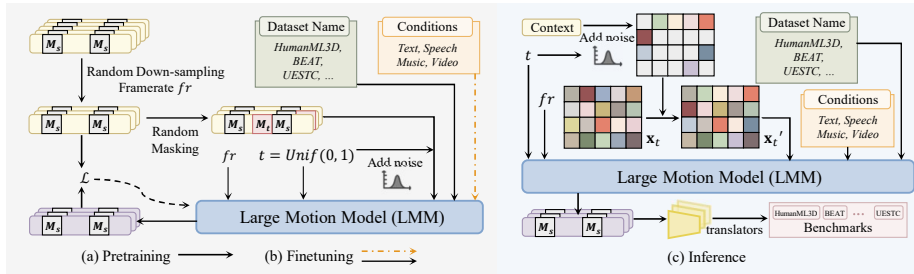


Fig. 3: Overall pipeline of LMM. **Left:** Our two-stage training procedure, including unsupervised pretraining and supervised fine-tuning. Random down-sampling and random mask strategies are applied to enhance knowledge absorption. **Right:** The generic inference process of LMM. The noised motion sequence and the given context are initially merged before being input into the network. LMM will then synthesize motion sequences, consistent with the provided multi-modal condition signals.

As for the output, it encompasses motion sequences in various formats, such as keypoints and SMPL [89]. To standardize motion representation, we define a unified format similar to TOMATO [91], where we remove foot contact from TOMATO. Our representation is described as:

$$m_i = \{r^a, r^x, r^z, r^y, \mathbf{j}^p, \mathbf{j}^v, \mathbf{j}^r, \mathbf{f}\}, \quad (2)$$

where r denotes information related to the root. Specifically, $r^a \in \mathbb{R}$ is the angular velocity along the Y-axis, $(r^x, r^z \in \mathbb{R})$ represent linear velocities on the XZ-plane, and r^y indicates the root’s height. $\mathbf{j}^p \in \mathbb{R}^{3(J-1)}$, $\mathbf{j}^v \in \mathbb{R}^{3J}$, and $\mathbf{j}^r \in \mathbb{R}^{6(J-1)}$ correspond to the position, velocity, and rotation of local keypoints relative to the root, with J denoting the number of joints ($J-1$ means all joints without the root joint). Here we follow SMPL-X [100] and consider 22 main body joints and 30 hand joints. Lastly, \mathbf{f} denotes facial expression [69].

We further divide this representation into ten independent parts: global orientation and trajectory, face expression, head, spine, left arm, right arm, left leg, right leg, left hand, and right hand. When processing raw data, we allow for missing body parts and annotate them in the metadata. For missing keypoints, we manually estimate the missing points from known ones for completion, while extra keypoints are discarded in this process. We then train a series of motion translators to map our unified motion representation to each dataset’s specific one. Thus, in the testing process of different tasks, once the model outputs in our unified format, we can map the output to the corresponding motion format through the translator, facilitating smooth metric evaluation.

4 Large Motion Model

Our model architecture closely follows the literature [128, 155], built upon a transformer-based diffusion model. We primarily reference the FineMoGen [157] as our baseline and extend it to support various condition signals, multi-tasking,

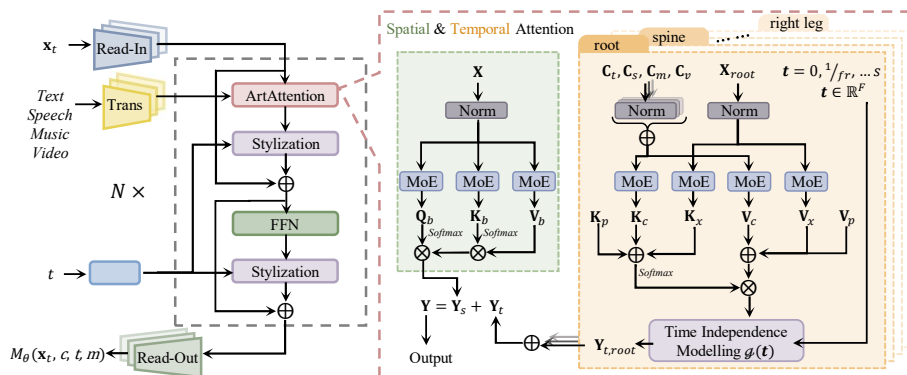


Fig. 4: Architecture of LMM. LMM is a transformer-based diffusion model. Dataset-dependent Read-In layers and Read-Out layers facilitate the conversion of the motion sequence between our intermediate representation and the latent feature space. In the stem of LMM, ArtAttention refines the feature representations through the spatial and temporal attention branches.

multiple frame rates, and various mask forms. The overall workflow is illustrated in Fig. 3 while the detailed architecture is shown in Fig. 4.

4.1 Transformer-based Diffusion Model

Diffusion models are powerful generative models, capable of producing high-quality, diverse outcomes, garnering widespread attention, and demonstrating formidable generative capabilities in many fields. Its essence lies in two intertwined processes: the forward diffusion process and the reverse diffusion process. More details are provided in the supplementary materials.

4.2 Read-In Layer and Read-Out Layer

The read-in layer is responsible for transforming noised motion data into feature representations of the form $F \times H \times D$, while the read-out layer generates clean motion data from the feature space. Here, the first dimension represents the number of frames in the motion sequence, and the second dimension represents the number of body parts. Although we standardize all motion data into a unified motion format, the differences in distribution among various datasets cannot be completely ignored. Therefore, in the backbone network’s read-in and read-out stages, we employ dataset-dependent motion encoders and decoders. Additionally, to obtain more comprehensive knowledge for practical applications, during training, there is a 10% probability of replacing the original dataset name with “all”. Consequently, the corresponding read-in and read-out layers can be better applied in real-world application scenarios.

4.3 ArtAttention

To achieve outstanding zero-shot continuous generation capability, our model builds upon the SAMI module from FineMoGen [157], incorporating upgrades to address three new requirements: multi-modal condition, various frame rates, and allowance for missing body parts, as shown in Fig. 4.

For multi-modal signals, we preprocess all signals into token sequences using the ImageBind [27] model. To better integrate these features into our network, we further refine them with two learnable transformer encoder layers. This process transforms text, speech, music, and video into feature sequences $\mathbf{C}_t \in \mathbb{R}^{L_t \times (H \cdot D)}$, $\mathbf{C}_s \in \mathbb{R}^{L_s \times (H \cdot D)}$, $\mathbf{C}_m \in \mathbb{R}^{L_m \times (H \cdot D)}$, $\mathbf{C}_v \in \mathbb{R}^{L_v \times (H \cdot D)}$, where L_t, L_s, L_m, L_v represent the lengths of the corresponding condition sequences, and $H \cdot D$ denotes the feature length of each element.

Our attention mechanism can be divided into two main components: body-part attention (spatial attention) and temporal attention. Assuming the feature representation of our motion sequence is $\mathbf{X} \in \mathbb{R}^{F \times H \times D}$. In the body-part attention section, due to the presence of inherent missing body parts in our data and the masked body parts introduced artificially during pre-training, we cannot utilize a fixed set of coefficients to determine the mutual contributions among body parts. Therefore, unlike the design in FineMoGen, for each frame, we opt to use an attention structure to obtain a set of refined features $\mathbf{Y}_s \in \mathbb{R}^{F \times H \times D}$.

In the temporal attention section, we aim to leverage the self-correlation inherent in the motion features \mathbf{X} and guidance obtained from the condition signals $\mathbf{C}_t, \mathbf{C}_s, \mathbf{C}_m, \mathbf{C}_v$ to generate higher-quality features for each body part in every frame. Here, we employ a Multi-head Attention mechanism, with each head focusing on a specific body part, emphasizing the utilization of temporal correlations to optimize features. We begin by utilizing Mixture-of-Expert to obtain a set of features $\mathbf{K} \in \mathbb{R}^{L \times D}$ from these condition features, where L represents the sequence length of the corresponding feature source.

Empirically, we found that directly concatenating motion sequences and condition sequences like FineMoGen and then applying Softmax processing hinders the modeling of self-correlation in multi-condition scenarios, resulting in lower motion quality, especially when the condition feature sequence is much longer than the motion sequence. Therefore, we independently normalize the motion feature $\mathbf{K}_x \in \mathbb{R}^{F \times D}$ obtained and then normalize condition features. To support unconditional generation, we introduce 64 learnable tokens \mathbf{K}_p and \mathbf{V}_p as placeholders. These tokens are concatenated with all condition signals for normalization, resulting in $\mathbf{K}_c \in \mathbb{R}^{(64+L_t+L_s+L_m+L_v) \times D}$. This approach also facilitates better blending of the model across different conditions. The remaining processing is similar to FineMoGen. After obtaining a series of time-varying signals, for each frame’s pose, we use time as the sole query feature to calculate the correlation between each frame and each time-varying signal, as well as the values at each signal point. Unlike FineMoGen, which uses frame indices to represent time, we use real time to support different frame rates. More details are introduced in the supplementary material. Suppose the output of the temporal

attention section is $\mathbf{Y}_t \in \mathbb{R}^{F \times H \times D}$, then the output of the entire ArtAttention is $\mathbf{Y} = \mathbf{Y}_s + \mathbf{Y}_t$.

4.4 Pre-Training and Fine-Tuning

Leveraging MotionVerse, we have collected a vast array of <input-motion> data pairs. Disregarding the inputs, the abundant motion data inherently contains valuable information, which can enable the model to comprehend numerous characteristics of human motion, such as coherence, balance, and joint-based rotations, among others. To enable the model to better acquire common knowledge across datasets, we divide the entire training process into two main parts: **Unsupervised Pre-Training** and **Supervised Fine-Tuning**. In the first stage, we require our model to learn motion priors independent of conditions. While in the second stage, the model is supposed to learn the correlation between condition signals and motion sequences.

As illustrated in Fig. 3, in the unsupervised pretraining phase, to enrich the model’s prior knowledge from these motion sequences, we employ random downsampling and random masking strategies for data augmentation. Since our representation includes terms related to velocity, when downsampling, we need to recalculate the velocity values to match the downsampling rate, while the terms related to states remain unchanged. This approach enables the model to better learn from data with different original frame rates. As mentioned earlier in the data preprocessing part, some body parts in the sequences are masked out, such as the detailed keypoints of the left and right hands in the KIT dataset. We denote this original mask as $\mathbf{M}_s \in \{0, 1\}^{F \times H}$. Based on this, we additionally apply masking with a certain probability to obtain a new mask $\mathbf{M}_t \in \{0, 1\}^{F \times H}$. After the model performs the read-in operation, we replace the body parts marked as 1 in \mathbf{M}_t with learnable empty tokens. When calculating the loss, we only ignore the parts marked by \mathbf{M}_s . This means that the model not only needs to restore the noised sequence to its clean parts but also utilize the visible part to infer the rest. With this modeling, the knowledge embedded in the data with missing body parts can be better absorbed by the model.

In the supervised fine-tuning phase, our goal is to enable the model to learn the relationship between condition signals and motion sequences. Here, we pass the preprocessed condition token sequences as additional inputs to the model. To support classifier-free guidance, during training, we randomly mask out the condition signals with a probability of 10%.

5 Experiments

5.1 Implementation Details

We designed four variants: LMM-Tiny, LMM-Small, LMM-Base, and LMM-Large, which have 90M, 160M, 410M, 760M parameters respectively. We use all data in MotionVerse for both pretraining and finetuning, except for the sequences used in evaluation. We maintained a fixed total batch size of 512. For

Table 3: Quantitative results of text-to-motion generation on the HumanML3D test set. ‘↑’(‘↓’) indicates that the values are better if the metric is larger (smaller). We run all the evaluations 20 times and report the average metric and 95% confidence interval. “MM” is MultiModality. The best scores are bold, and the second-best results are underlined.

Methods	R Precision↑			FID↓	MM Dist↓	Diversity↑	MM↑
	Top 1	Top 2	Top 3				
Real motions	0.511±.003	0.703±.003	0.797±.002	0.002±.000	2.974±.008	9.503±.065	-
T2M-GPT [153]	0.491±.003	0.680±.003	0.775±.002	0.116±.004	3.118±.011	<u>9.761±.081</u>	1.856±.011
MDM [128]	-	-	0.611±.007	0.544±.044	5.566±.027	9.559±.086	2.799±.072
FineMoGen [157]	0.504±.002	0.690±.002	0.784±.002	0.151±.008	2.998±.008	9.263±.094	<u>2.696±.079</u>
MoMask [31]	<u>0.521±.002</u>	<u>0.713±.002</u>	<u>0.807±.002</u>	<u>0.045±.002</u>	<u>2.958±.008</u>	-	1.241±.040
LMM-Tiny	0.496±.002	0.685±.002	0.785±.002	0.415±.002	3.087±.012	9.176±.074	1.465±.048
LMM-Small	0.505±.002	0.693±.002	0.789±.002	0.227±.002	3.051±.012	9.295±.076	1.761±.049
LMM-Base	0.511±.002	0.710±.002	0.802±.002	0.138±.002	2.971±.012	9.573±.076	2.426±.054
LMM-Large	0.525±.002	0.719±.002	0.811±.002	0.040±.002	2.943±.012	9.814±.076	2.683±.054

Table 4: Quantitative results of motion prediction on the AMASS and 3DPW test set for different time steps (ms). We report the MPJPE error in *mm*.

Method	AMASS-BMLrub								3DPW							
	80	160	320	400	560	720	880	1000	80	160	320	400	560	720	880	1000
LTD-10-10 [95]	<u>10.3</u>	19.3	36.6	44.6	61.5	75.9	86.2	91.2	<u>12.0</u>	22.0	38.9	46.2	59.1	69.1	76.5	81.1
SIMLPE [35]	10.8	<u>19.6</u>	34.3	40.5	<u>50.5</u>	57.3	62.4	65.7	12.1	<u>22.1</u>	38.1	44.5	54.9	62.4	68.2	72.2
GCNext [133]	10.2	19.3	34.1	<u>40.3</u>	50.6	<u>57.3</u>	<u>62.0</u>	<u>65.3</u>	11.8	22.0	<u>37.9</u>	44.2	<u>55.1</u>	<u>62.1</u>	<u>67.8</u>	<u>72.0</u>
LMM-Tiny	15.9	24.1	38.2	45.9	61.2	73.4	80.3	87.2	17.3	26.2	40.1	47.3	62.8	74.8	82.5	87.0
LMM-Small	14.7	23.2	37.5	43.8	58.3	69.2	75.2	81.9	16.2	25.7	39.4	45.9	60.7	71.5	79.5	82.8
LMM-Base	13.1	21.5	35.9	41.1	53.6	60.8	66.9	70.3	14.1	23.9	38.2	<u>44.1</u>	55.3	64.8	70.3	73.6
LMM-Large	12.8	20.9	<u>34.3</u>	39.6	49.1	55.3	60.5	63.1	13.1	22.6	37.1	42.4	52.4	59.2	63.8	68.0

the Tiny model, we conducted training directly on 8 NVIDIA V100 GPUs with 32GB memory each, with a batch size of 64 per GPU. For larger models, we use FP16 and gradient accumulation to achieve training effects equivalent to a batch size of 512 without exceeding 32 V100 GPUs. During the pre-training phase, we employed the Adam optimizer with a fixed learning rate of 2×10^{-4} for 80K iterations. In the fine-tuning phase, we used the same optimizer, initially iterating for 20K steps with a learning rate of 2×10^{-4} , followed by 20K steps with a learning rate of 2×10^{-5} . For more details, please refer to the supplementary material.

5.2 Quantitative Results

We evaluate our LMM variants on three tasks: text-to-motion, music-to-dance, motion prediction, and four datasets: HumanML3D [32], 3DPW [96], AMASS [93], and AIST++ [66], as shown in Tab. 3, Tab. 4 and Tab. 5. More experimental results are reported in the supplementary material.

Text-to-Motion. Tab. 3 demonstrates that our LMM-Large surpasses other existing works in terms of accuracy and fidelity while maintaining comparable diversity. On the other hand, LMM-Tiny, which shares a similar structure with FineMoGen, performs worse than it. This discrepancy can be attributed to the significant challenges posed by the large amounts of diverse data and the trade-offs across different tasks during model training, especially for smaller models like LMM-Tiny.

Motion Prediction. Tab. 4 reports the performance on AMASS and 3DPW test splits. The superior performance of LMM-Large can be attributed to its robust motion prior, which is obtained from the mega-scale data. It is worth noting

Table 5: Quantitative results for Music-conditioned Dance Generation. Quantitative results on AIST++ test set.

Methods	Motion Quality		Motion Diversity		Freezing		Best Align Score \uparrow
	FID $_k$ \downarrow	FID $_g$ \downarrow	Div $_k$ \uparrow	FID $_g$ \uparrow	PPF \downarrow	AUC $_f$ \downarrow	
Ground-truth	17.10	10.60	8.19	7.45	0.00	0.00	0.2374
DanceNet [167]	69.18	25.49	2.86	2.85	0.00	0.98	0.1430
DanceRevolution [43]	73.42	25.52	3.52	4.87	11.01	12.22	0.1950
Bailando [121]	28.16	9.62	7.83	6.34	14.91	13.25	0.2332
TM2D [29]	19.01	20.09	9.45	6.36	0.00	0.00	0.2049
LMM-Tiny	37.62	28.95	6.92	5.94	0.00	0.00	0.1736
LMM-Small	34.18	27.53	7.46	6.17	0.00	0.00	0.1791
LMM-Base	25.43	24.18	9.05	6.55	0.00	0.00	0.2084
LMM-Large	22.08	21.97	9.85	6.72	0.00	0.00	0.2249

that due to the errors introduced by the motion translation step, the accuracy of LMM-Large is still lower than other methods in short-distance prediction. However, it exhibits a significant advantage in long-distance prediction. Furthermore, we observed that the advantage of LMM-Large is more pronounced on 3DPW. This is because the 3DPW benchmark demands higher generalization ability from the model. After extensive learning of motion priors, our LMM-Large exhibits a more prominent performance on out-of-distribution tests.

Music-to-Dance. Our Large model achieves comparable performance to the current state-of-the-art, as shown in Tab. 5. In terms of diversity-related metrics, our approach demonstrates a significant advantage. Our performance in the metrics FID_k and FID_g did not surpass existing methods. One possible reason could be the relatively small proportion of the music2dance dataset in the current dataset composition.

5.3 Ablation Study

Table 6: Ablation of the pretraining strategy. All experiments utilized LMM-Base as the base model.

	Downsample	Random Mask	Attention	HumanML3D			3DPW		
				Top 1	FID	MModality	80	400	1000
1)	-	-	ArtAttention	0.031 \pm .001	32.814 \pm .176	5.293 \pm .129	17.3	48.4	89.3
2)	\checkmark	-	ArtAttention	0.028 \pm .001	31.365 \pm .171	5.714 \pm .147	16.2	46.5	78.4
3)	-	\checkmark	ArtAttention	0.515 \pm .002	0.151 \pm .002	2.214 \pm .051	14.5	45.5	76.1
4)	\checkmark	\checkmark	SAMI [157]	0.400 \pm .009	1.866 \pm .009	2.983 \pm .071	15.9	47.2	80.9
5)	\checkmark	\checkmark	ArtAttention	0.511 \pm .002	0.138 \pm .002	2.426 \pm .054	14.1	44.1	73.6

Tab. 6 shows the ablation results. We observed that random masking is a necessary component. When the model’s expressive power is strong enough, it can directly recover the clean motion sequence from the noised motion sequence. Consequently, during the fine-tuning stage, our condition signal may not play its expected role. Introducing random masking during training will make it more difficult for the model to solely restore the original sequence from the motion sequence, leading it to rely more on the additional information provided by the condition signal. Additionally, we found that both downsampling and random masking strategies are beneficial for improving the multimodality metrics in the text-to-motion task. This implies that the model can better absorb knowledge from different datasets with the help of these two strategies. These strategies also

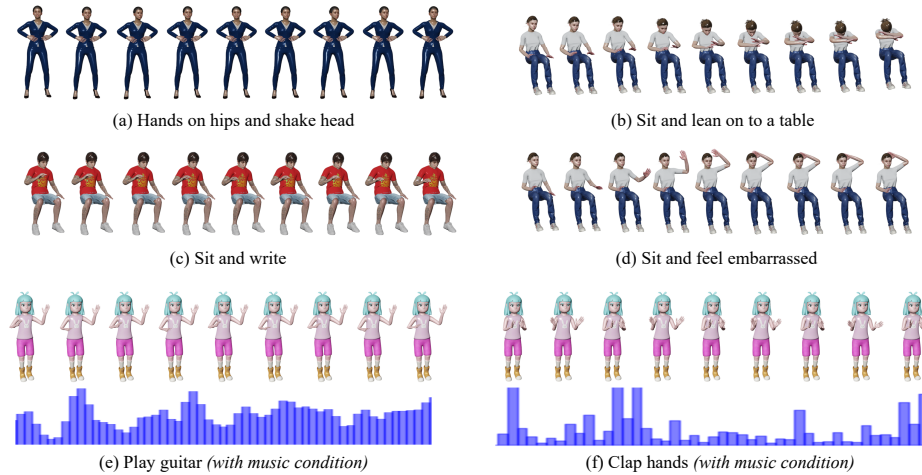


Fig. 5: Visualization results of LMM-Large. Figure a)-d) show examples of text-driven motion generation. Figure e) and f) show synthesized motion sequences under both textual and musical constraints.

significantly impact the effectiveness of motion prediction. Finally, we compared our proposed ArtAttention with the original SAMI and found that our proposed method is more suitable for the scenario of large motion models.

5.4 Qualitative Results

As shown in Fig. 5 (a)-(d), LMM-Large can respond to diverse textual descriptions with fine-grained control, which benefits from the large-scale training data and the well-designed architecture. In addition, Fig. 5 (e)-(f) provide examples for motion generation under both text description and music rhythms. Our generated motions successfully execute the given commands and follow the music beats simultaneously. For more visualization results, please kindly refer to the demo video in our homepage.

6 Conclusion and Discussion

In this paper, we establish a comprehensive motion-centric benchmark, MotionVerse, comprising then conditional motion generation and motion completion tasks. We align all motion data to a unified intermediate format and convert all condition signals into token sequences that are closer in feature space. Building upon this foundation, we introduce the first large motion model, LMM, capable of generating high-quality actions under multi-condition guidance. We identify and address three challenges encountered in constructing large motion models through careful model structure design, especially our used novel attention module, ArtAttention. Our proposed LMM model achieves comparable performance and even surpasses existing state-of-the-art methods.

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