Uniform Text-Motion Generation and Editing via Diffusion Model

<u>Ruoyu Wang, Xiang Li, Tengjiao Sun, Yangfan He, TIANYU SHI, yitingxie</u> Genfun.ai <u>https://genlab3d.genfun.ai/</u> <u>ty.shi@mail.utoronto.ca</u> Method

Motivation

Limited to unimodal inputs and outputs

Insufficient Guidance by Textual Instruction

• Rely solely on textual instructions for guidance, lacking the capability to process motion or multimodal inputs.

• Textual instructions are often brief and ambiguous, making them insufficient to achieve the desired outcomes in many scenarios.

Restricted to motion generation

• Prevent them from performing related tasks such as motion annotation or generating text-based descriptions of motions.



CTMV CTMV Diffusion Model Denoising Diffusion CTMV BART T CTMV BART Text ncode CLIP Motion CTMV CTMV Text Encoder Adapter Motion Motion Decoder Encoder text motion MCRE Train stage2 Train stage Train stage? Multimodal Conditional Representation and Editing (MCRE) • Designs a motion adapter to align motion with CLIP's text representations, leveraging its rich semantic understanding. Lossali Sample From $\mathcal{N}_m(\mu_m, \sigma_m^2)$ Sample From $\mathcal{N}_t(\mu_t, \sigma_t^2)$ * * * * * * … * $(\mu_t) (\sigma_m^2)$ $(\mu_t) (\sigma_t^2)$ Text Decoder Motion Decoder Text Encoder Motion Encoder (*) *) (* Input Text Output Tex Output Motio Loss_{re} Lossred

Contrastive Text-Motion Variational Autoencoder (CTMV)

- Aligns text-motion pairs into a shared latent space via transformer-based encoders leveraging contrastive learning.
- Offloads the task of generating high-frequency details of different modalities to the autoencoder
- Enables the diffusion to focus on the high-level semantics generation.





Uniform Text-Motion Generation and Editing via Diffusion Model

Experiments

Training Data--HumanML3D dataset

•Comprising 14,616 motions and 44,970 descriptions.

- •Data span various domains daily activities, exercise, and artistic performances.
- •With an average duration of 7.1 seconds per action and an average description length of 12 words.



Training Strategy

• Jointly training by training losses, which is composed of reconstruction and alignment losses.

Reconstruction Loss:

- Cross-Entropy Loss for Text
- L2 loss for Motion
- Alignment Losses
 - Cosine loss
 - KL Loss.



Demonstrate advanced effectiveness and generalization across multiple tasks

• Text-to-Motion



Table 2. Quantitative results of motion-to-text task on the HumanML3D and Motion-X test set

Method	R-Prec Top1	Top3	MM-Dist↓	$Length_{avg}\uparrow$	Bleu@1↑	Bleu@4†	Rouge↑	Cider↑	BertScore↑
"HumanML3D Test set"									
Real	0.523	0.828	2.901	12.750	-	-	-	-	-
TM2T	0.516	0.823	2.935	10.670	48.900	7.000	38.100	16.800	32.200
MotionGPT	0.543	0.827	2.821	13.040	48.200	12.470	37.400	29.200	32.400
Ours	<u>0.520</u>	<u>0.825</u>	<u>2.878</u>	13.000	49.300	<u>11.700</u>	35.000	30.300	32.800
"Motion-X Test set"									
Real	0.520	0.821	2.892	17.250	-	-	-	-	-
TM2T	0.484	0.803	2.975	11.901	46.500	6.781	35.903	15.201	29.909
MotionGPT	0.518	0.817	2.858	14.340	47.800	11.890	36.202	27.601	31.009
Ours	<u>0.510</u>	0.820	2.886	13.890	48.302	11.025	<u>34.800</u>	28.998	31.198

• Motion Completion • Multimodal Motion Editing 1) motion based · · · · · waving lking with holding onto t 2) multimodal based

Table 4. Quantitative results of motion completion task on the HumanML3D and Motion-X test set

thed		Motion Pro	Motion-In-between				
ethod	FID↓	$\text{Diversity} \rightarrow$	ADE↓	FDE↓	FID↓	Diversity [↑]	ADE↓
umanML3D Test set"							
al	0.002	9.503	-	-	0.002	9.503	-
DM	6.031	7.813	5.446	8.561	2.698	8.420	3.787
irs	1.702	9.001	4.740	6.670	1.203	9.600	3.669
lotion-X Test set"							
al	0.003	9.508	-	-	0.003	9.508	-
DM	8.931	7.783	7.846	10.021	4.398	8.150	2.987
irs	2.102	8.901	5.940	7.970	1.583	9.230	3.042



