





# SMooDi:Stylized Motion Diffusion Model

https://neuvi.github.io/SMooDi/

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## **Motivation**

#### **Text2Motion**

#### **Content Text:**

A person walks forward and then sits down.

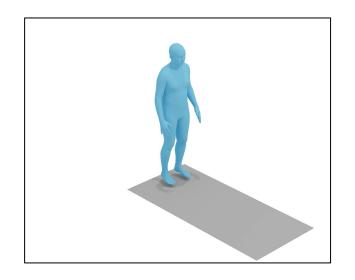


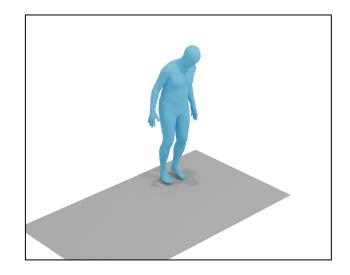
Text2Motion

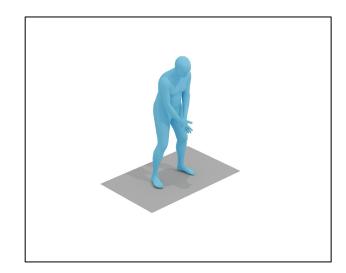
**Text2Motion** primarily focuses on translating content text into corresponding motions without considering the motion style.

## **HumanML3D dataset**

The HumanML3D dataset contains diverse motion content but limited motion styles.

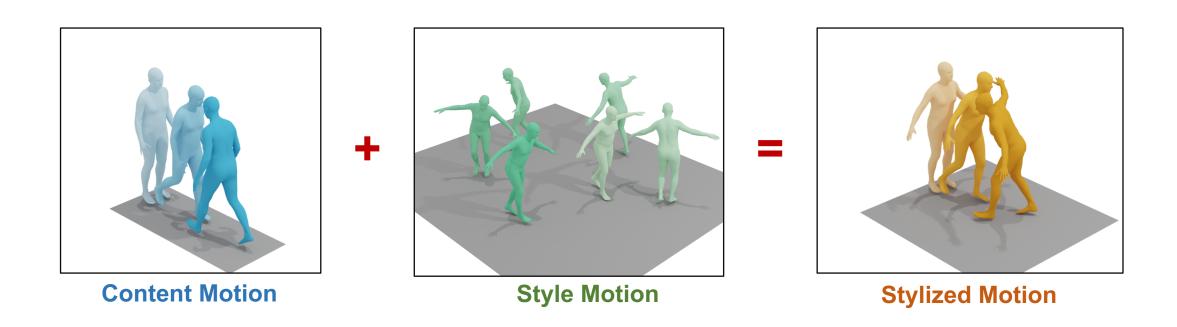






## **Motion Style Transfer**

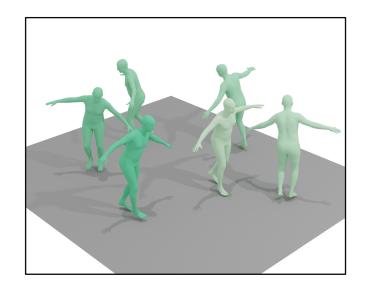
Giving a content text and a style motion, MST aim to generate a stylized motion that adheres to both content and style constraints

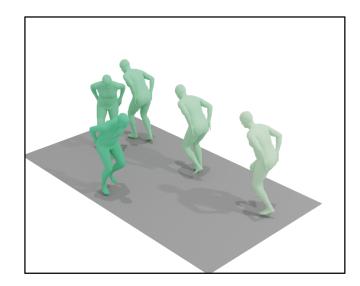


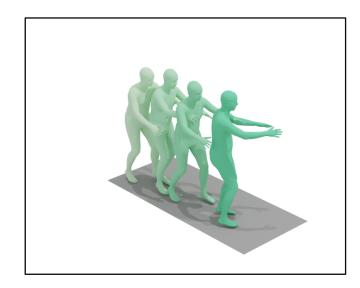
<sup>\*</sup> MST means motion style transfer.

### **100STYLE** dataset

The 100STYLE dataset contains up to 100 motion styles but only includes *locomotion-related* motion content.

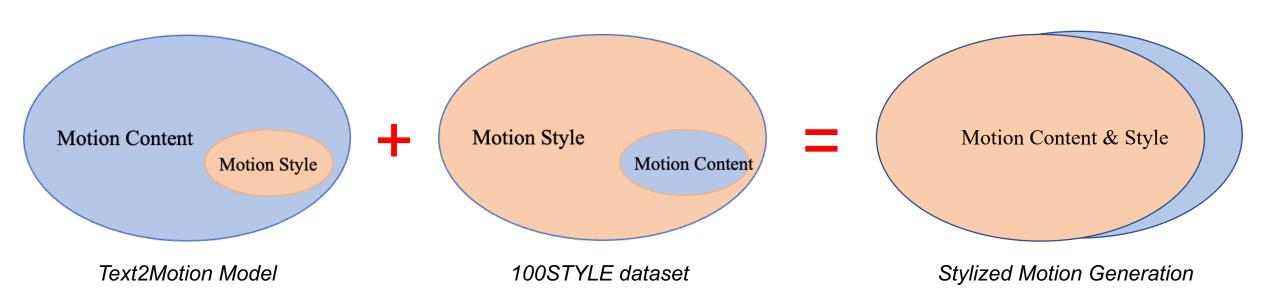




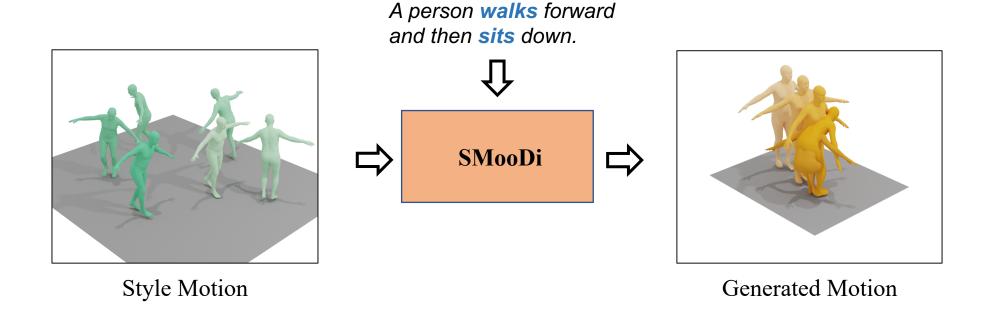


### **Motivation**

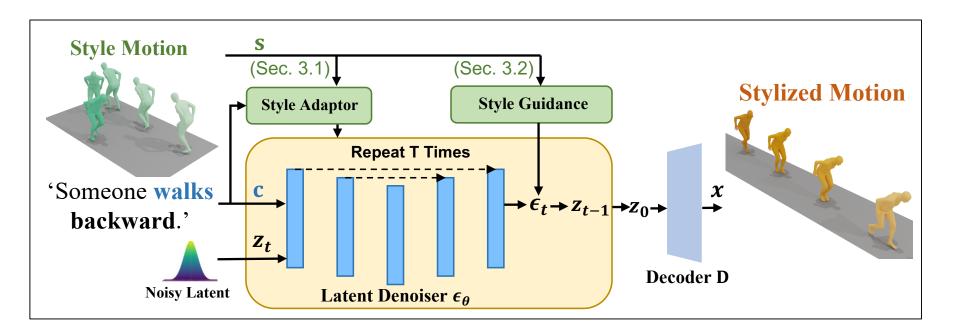
Could we apply **locomotion-style** to the existing **Text2Motion** model?



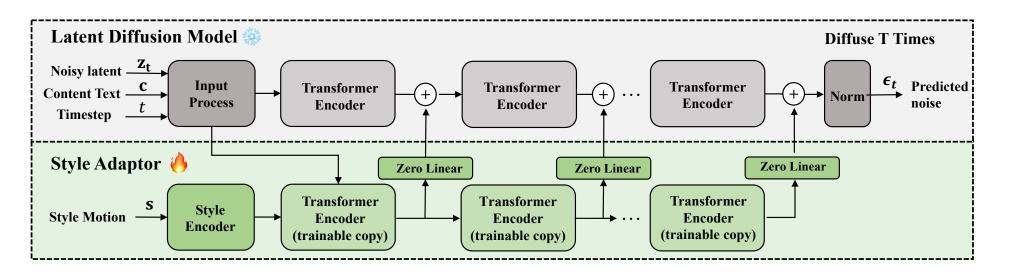
Giving a content text and a style motion, **SMooDi** can generate a stylized motion that adheres to both content and style constraints



Giving a content text and a style motion, **SMooDi** leverages **a style adaptor** and **style guidance** to enable stylized motion generation.



Style Adaptor is a trainable copy of the Transformer encoder in the motion diffusion model to learn to enforce the style constraints.



#### Pseudo Code

#### Algorithm 1 SMooDi's inference

```
Require: A motion diffusion model M with parameters \theta_M, a style adaptor model A with parameters \theta_A, style motion sequence s (if any), content texts c (if any).

1: z_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I}) \# \text{Sample from pure Gaussian distribution}

2: for all t from T to 1 do

3: \{r\} \leftarrow A(z_t, t, c, s; \theta_A) \# \text{Style Adaptor model}

4: \epsilon_t \leftarrow M(x_t, t, c, \{r\}; \theta_M) \# \text{Model diffusion model}

5: for all k from 1 to K do \# \text{Classifier-based style guidance}

6: \epsilon_t = \epsilon_t + \tau \nabla_{z_t} G(z_t, t, \mathbf{s})

7: end for

8: z_{t-1} \sim \mathcal{S}(z_t, \epsilon_t, t) \# S(\cdot, \cdot, \cdot) represents the DDIM sampling method [10].

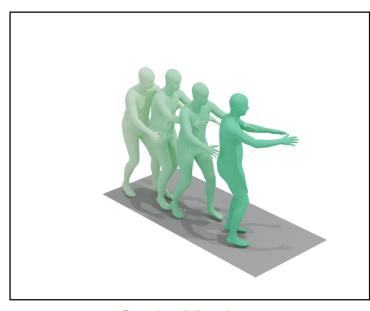
9: end for

10: x_0 = \mathbf{D}(z_0)

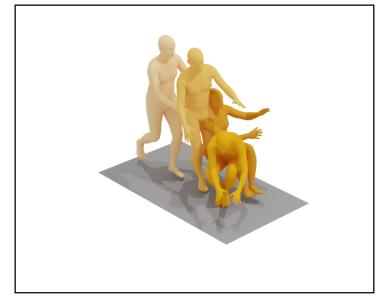
11: return x_0
```

## **Content Text:**

A person walks forward and then sits down.



**Style Motion** 

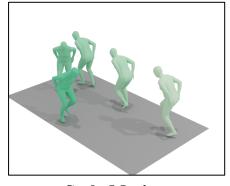


**SMooDi** 

- The straightforward baselines involve applying motion style transfer methods to the motion sequences generated by the text2motion model.
- SMooDi achieves better performance both quantity and quality.

'A person walks

backward.



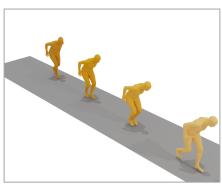
**Style Motion** Content Text



(a) MLD+Motion Puzzle



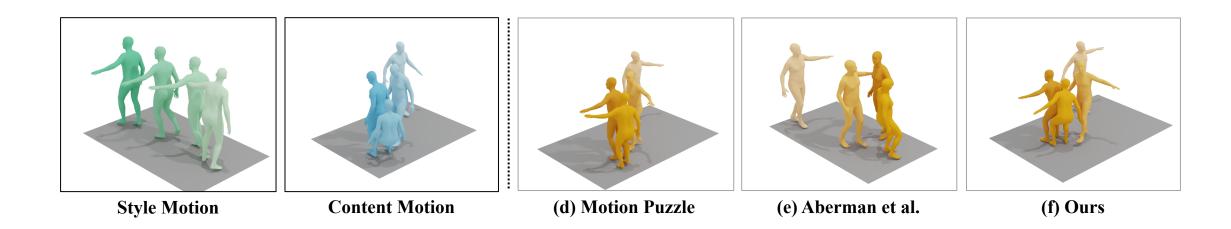
(b) MLD+Aberman et al.



(c) Ours

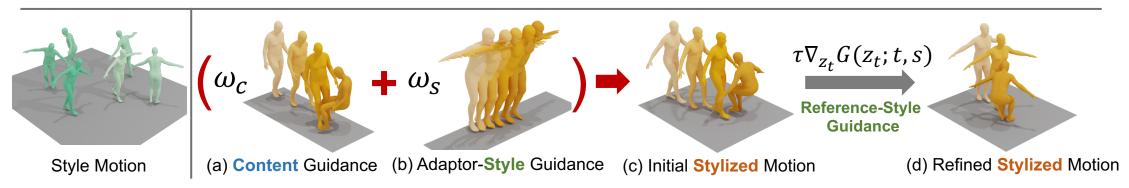
# **Motion Style Transfer**

Through DDIM inversion, **SMooDi** enables motion style transfer and achieves performance comparable to existing methods.



## **Visualize Style Guidance**

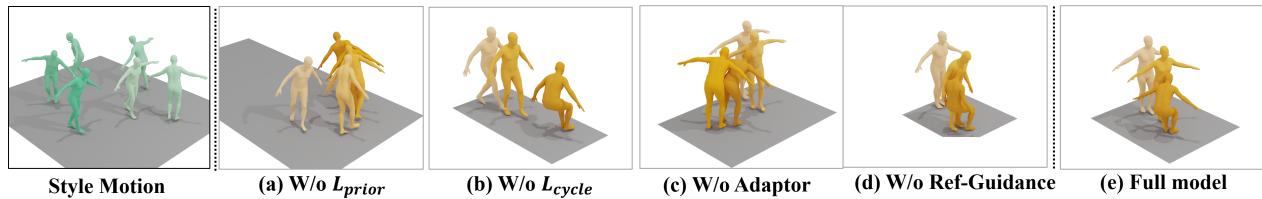
**Text**: A person walks forward and then sits down.



## **Ablation Studies**

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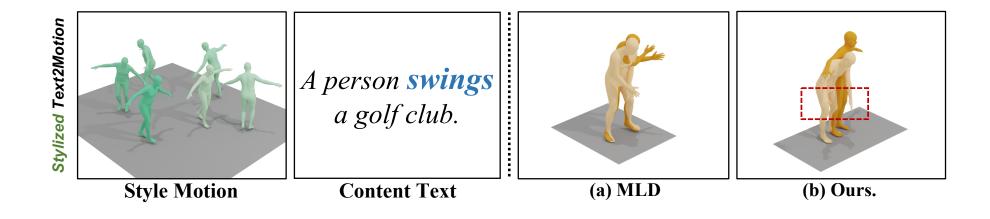
Text: A person walks forward and then sits down.



## **Failure Cases**

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When there are conflicts between the **content text** and the **style motion** in a specific body part, **SMooDi** may generate unrealistic motions.



# **Thanks**