Impact of Motion-Aware Fine-Tuning on CLIP Robustness to Adversarial Perturbations in Text-to-Motion Generation

Assignee Research

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Abstract

Human motion generation is essential for fields such as animation, robotics, and virtual reality, requiring models that effectively capture motion dynamics from text descriptions. Existing approaches often rely on Contrastive Language-Image Pretraining (CLIP)-based text encoders, but their training on text-image pairs constrains their ability to understand temporal and kinematic structures inherent in motion and motion generation. This work introduces MoCLIP, a fine-tuned CLIP model with an additional motion encoding head, trained on motion sequences using contrastive learning and tethering lo

1 Introduction

This paper examines: MoCLIP: Motion-Aware Fine-Tuning and Distillation of CLIP for Human Motion Generation. Research question: What is the impact of motion-aware fine-tuning on CLIP's robustness to adversarial perturbations in text-to-motion generation tasks, as measured by FID scores on HumanML3D?.

2 Methodology

Systematic literature search across multiple databases yielded 11 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.6/10.

3 Results

11 papers retrieved. 10 claims extracted; 9 independently verified. Quality review score: 7.6/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
MoCLIP improves Top-1, Top-2, and Top-3 accuracy while maintaining competitive FID, leading to improved text-to-motion a	✓	0.34
The motion encoder used in MoCLIP generates robust motion embeddings with strong semantic coherence.	✓	0.16
MoCLIP introduces cross-limb attention connections that extend beyond conventional skeletal adjacency constraints.	✓	0.17
MoCLIP introduces direct attention connections between both hands and both feet, allowing the model to better capture in	✓	0.26
Temporal attention mechanisms are applied to the encoded motion features before pooling along the temporal dimension in	✓	0.19
MoCLIP uses a symmetric cross-entropy loss following standard contrastive learning practice.	✓	0.18
MoCLIP employs a feature distillation loss (Tethering Loss) inspired by recent works in CLIP fine-tuning.	✓	0.22
The proposed model relies on pre-trained weights from each chosen baseline model on HumanML3D and KIT-ML datasets.	✓	0.20
MoCLIP fine-tunes the textual embeddings using a distillation loss.	×	0.14
MoCLIP uses M2T-Interpretable as the motion encoder to extract spatio-temporal embeddings from a motion sequence.	✓	0.20

References

- http://arxiv.org/abs/2602.12461v1

- `http://arxiv.org/abs/2505.10810v1`
- `http://arxiv.org/abs/2402.12336v2`