Diffusion-Based Garment Synthesis via Knowledge Graph-Driven Structural Cross-Modal Semantic Alignment

Miao-Yin Chen, Shu-Han Chuang
Department of Data Science, Soochow University, Taipei, Taiwan

OVERVIEW

AI-driven garment synthesis transforms fashion design.

Challenges

- Semantic drift
- Attribute confusion
- Regional inconsistencies

Our solution

- **Knowledge graph**-driven diffusion model for enhanced control and alignment.

Objective

- Improve semantic fidelity and structural precision in garment synthesis.

Text Prompt

Generate New Image

Problems

Challenges in Garment Synthesis

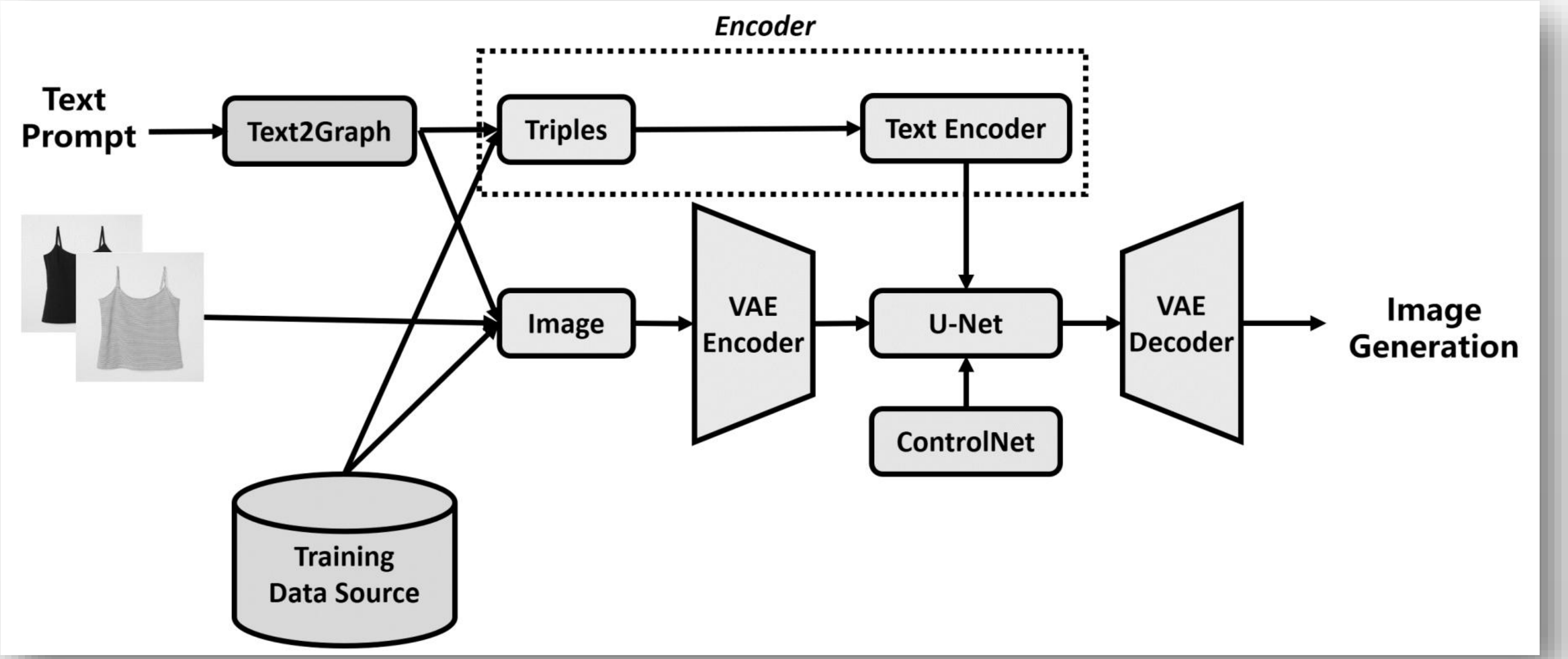
- Semantic drift — **Misalignment** between text prompts and visual outputs.
- Attribute confusion — **Incorrect assignment** of colors, patterns, or styles.
- Regional inconsistencies — Unintended modifications to garment **regions**.

Limitations of Existing Models

- Generative Adversarial Networks — Unstable training, model collapse, limited structural control.

Proposed Approach

We propose a **knowledge graph-driven diffusion model** to enhance control and alignment in garment synthesis



01. Text2Graph Module

Converts natural language into **semantic triples**
Use LLM to encode triples into text embedding

"a navy blue jacket with a red straight-point collar and a blue belted waist."

(jacket, has-color, navy blue),
(jacket, has-feature, collar),
(collar, has-style, straight-point),
(collar, has-color, red),
(jacket, has-feature, waist),
(waist, has-color, blue)

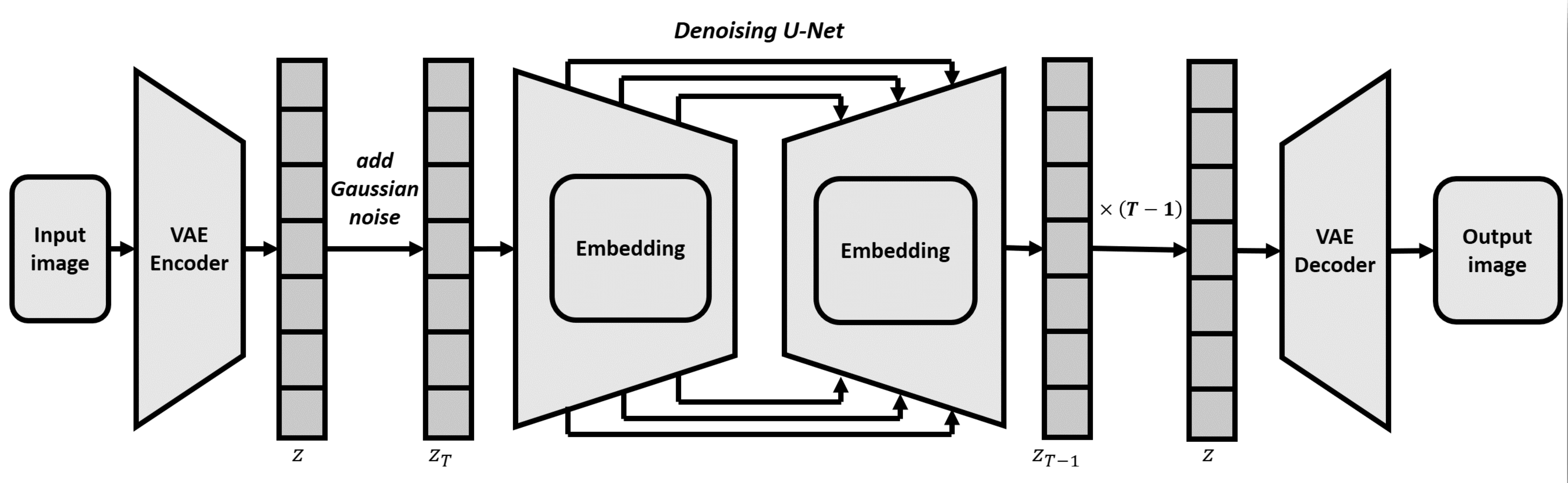
02. Stable Diffusion

Fine-tuned with **LoRA** for fashion-specific tasks.

03. ControlNet

Incorporates structural inputs (pose, sketches) to ensure the generated images maintain **spatial** association.

Diffusion-Based Garment Synthesis



- Forward phase:
  Adds Gaussian noise to images.
- Reverse phase:
  U-Net iteratively removes noise to reconstruct images.
- VAE:
  Compresses images into latent space for efficiency.

High-fidelity garment images with accurate textures, shapes, and colors.

Experiments

01. Datasets

H&M Personalized Fashion Recommendations dataset from Kaggle competition (approx. 105,000 images)

02. Parameters Setting

- Fine-tuned Stable Diffusion v1.4 with LoRA
- *AdamW* optimizer, learning rate of 1×10^{-6}, over 200,000 iterations
- Conducted on a single NVIDIA A6000 GPU
- Images resized to 512×512

03. Evaluation Metrics

CLIP Score → Text-image semantic alignment.

Fréchet Inception Distance (FID) → Visual realism

Inception Score (IS) → Image quality and diversity.

Results

Model	CLIP Score	FID Score	Inception Score
Stable diffusion	31.54	290.15	1.76
Fine-tuned Stable diffusion	28.56	275.35	1.89
KG-driven Stable diffusion	29.28	255.90	1.86

Higher CLIP Score = Better Text-Image Alignment

Lower FID = Better Visual Realism

Higher IS = Better Quality & Diversity

CLIP Score

- ✓ Our approach shows a modest improvement over the fine-tuned model, but lower than base model.
- ✓ Knowledge graph-driven text triple prompt are structurally concise but semantically sparse.

→ The original pretrained CLIP model was not trained on structured triples, it fails to fully understand input triples, even if the image is semantically correct.

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FID Score

Our approach achieves a notably lower FID, indicating a closer alignment with the distribution of real images and reflecting superior visual realism.

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Inception Score

Our approach attains a higher Inception Score, demonstrating improved image quality and greater intra-class diversity.
Both fine-tuned model and our approach achieve better IS than the original Stable Diffusion v1.4 baseline → Fine-tuning process may lead to better results.

Results

Input prompt:

“A navy blue jacket with red straight-point collar and blue belted waist”

(a)

Stable diffusion	Navy blue jacket ✓	Red straight-point collar ✗	Blue belted waist ✗
Fine-tuned Stable diffusion	Navy blue jacket ✓	Red straight-point collar ✗	Blue belted waist ✗
KG-driven Stable diffusion	Navy blue jacket ✓	Red straight-point collar △	Blue belted waist ✓

Results

Input prompt:

"a blue shirt with brown collar"


(b)

Stable diffusion	Blue shirt	Brown collar
Fine-tuned Stable diffusion	Blue shirt	Brown collar
KG-driven Stable diffusion	Blue shirt	Brown collar

Results

Input prompt:

"Black cotton shirt with chest patch pocket, round neck, and featuring logo patch at the chest,"

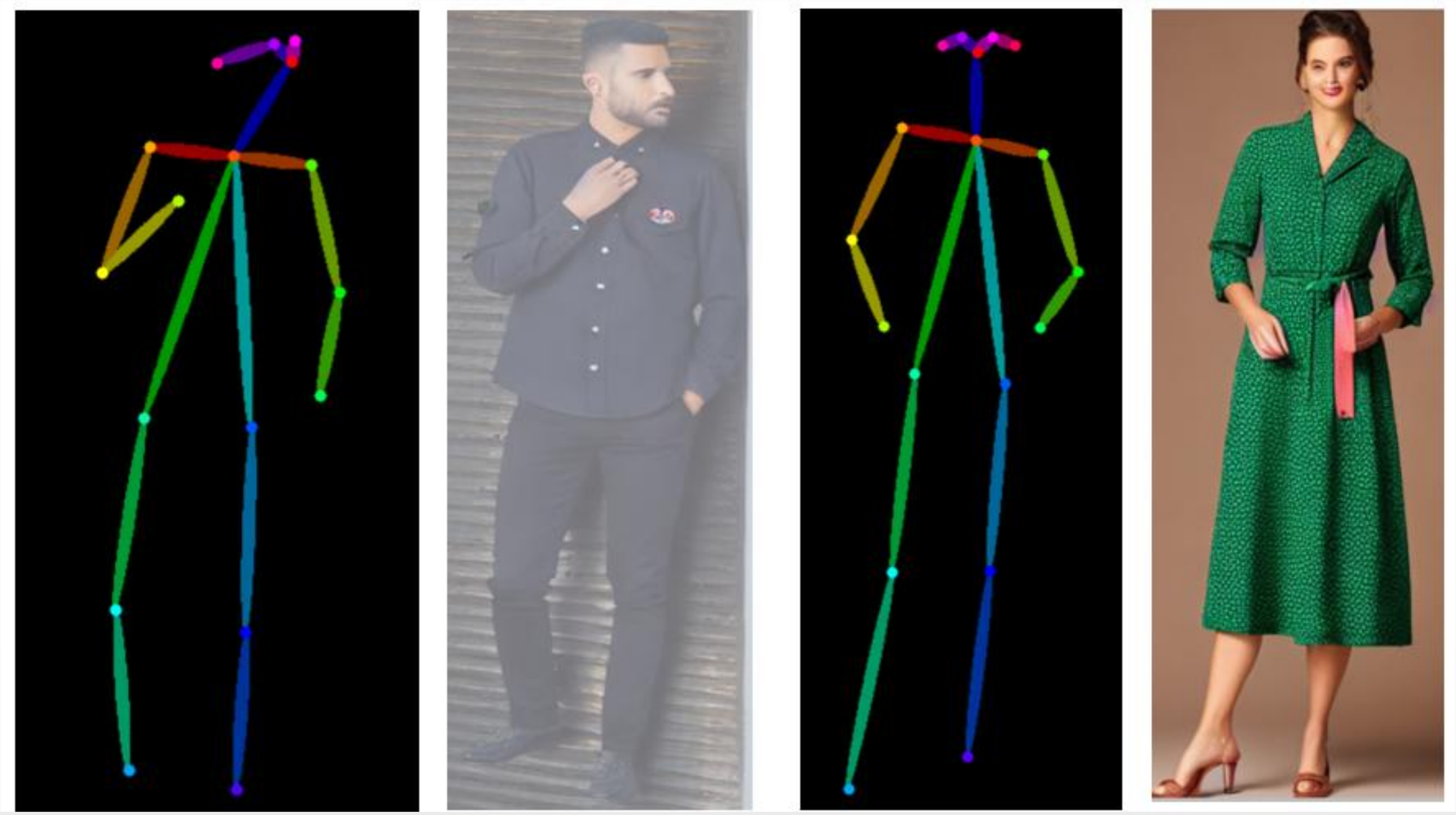
Stable diffusion		Black cotton shirt ✓	Chest patch pocket ✗	Round neck ✗	Logo patch ✓
Fine-tuned Stable diffusion		Black cotton shirt ✓	Chest patch pocket △	Round neck ✓	Logo patch ✓
KG-driven Stable diffusion		Black cotton shirt ✓	Chest patch pocket ✓	Round neck ✓	Logo patch ✓

(c)

Pose-controlled garment synthesis

Our approach combines ***OpenPose*** with knowledge graphs for precise pose and attribute alignment.

By using ***OpenPose***, it can accurately replicate the exact body pose of the input image.



Conclusion

Key Achievements

Knowledge graph-driven framework enhances semantic fidelity and controllability.

Superior performance in visual realism and text-image alignment.

Limitations

Sensitivity to noisy text inputs.

Challenges with long, ambiguous prompts.

Thank you