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Few-shot exemplar-driven inpainting with parameter-efficient diffusion fine-tuning

Key words: Diffusion model; Image inpainting; Exemplar-driven; Few-shot fine-tuning

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Motivation

- Text-to-image diffusion models excel at inpainting but struggle to replicate specific objects with high fidelity from text prompts alone. As the saying goes, “a picture is worth a thousand words.”
- Users often need to inpaint a customized object using a reference (exemplar) image, but existing methods lack high fidelity.

Fig. 1 Text-driven inpainting (top) struggles to accurately describe the object’s details, while exemplar-driven inpainting (bottom) can make it easier. References to color refer to the online version of this figure

Existing Limitations

- **Textual Inversion (TxtInv)** learns a textual embedding from exemplars, but this contains limited parameters and is less expressive. It often produces boundary artifacts from its background blending technique.

- **Paint by Example (PbE)** relies on large-scale datasets, which cannot cover all personalized exemplars and fails to produce high-fidelity results for out-of-dataset objects. Training is also labor-intensive.

Main Idea

To achieve high-fidelity, customized inpainting, this work enhances a pretrained text-driven inpainting model with a lightweight, plug-and-play module that learns a specific object's appearance from just a few examples. To achieve this, we introduce:

- **Lightweight Fine-tuning**, which employs a plug-and-play low-rank adaptation (LoRA) module to efficiently learn an exemplar's concept into model weights, enabling powerful customization while preserving the base model's integrity.
- **GPT-4V Prompting**, which leverages the GPT-4V model to generate expressive text prompts from the exemplar image, guiding the model to better preserve key object details.
- **Prior Noise Initialization**, which initiates the generation process from a "prior noise" containing exemplar information instead of from random noise, significantly improving the final result's fidelity.

Method

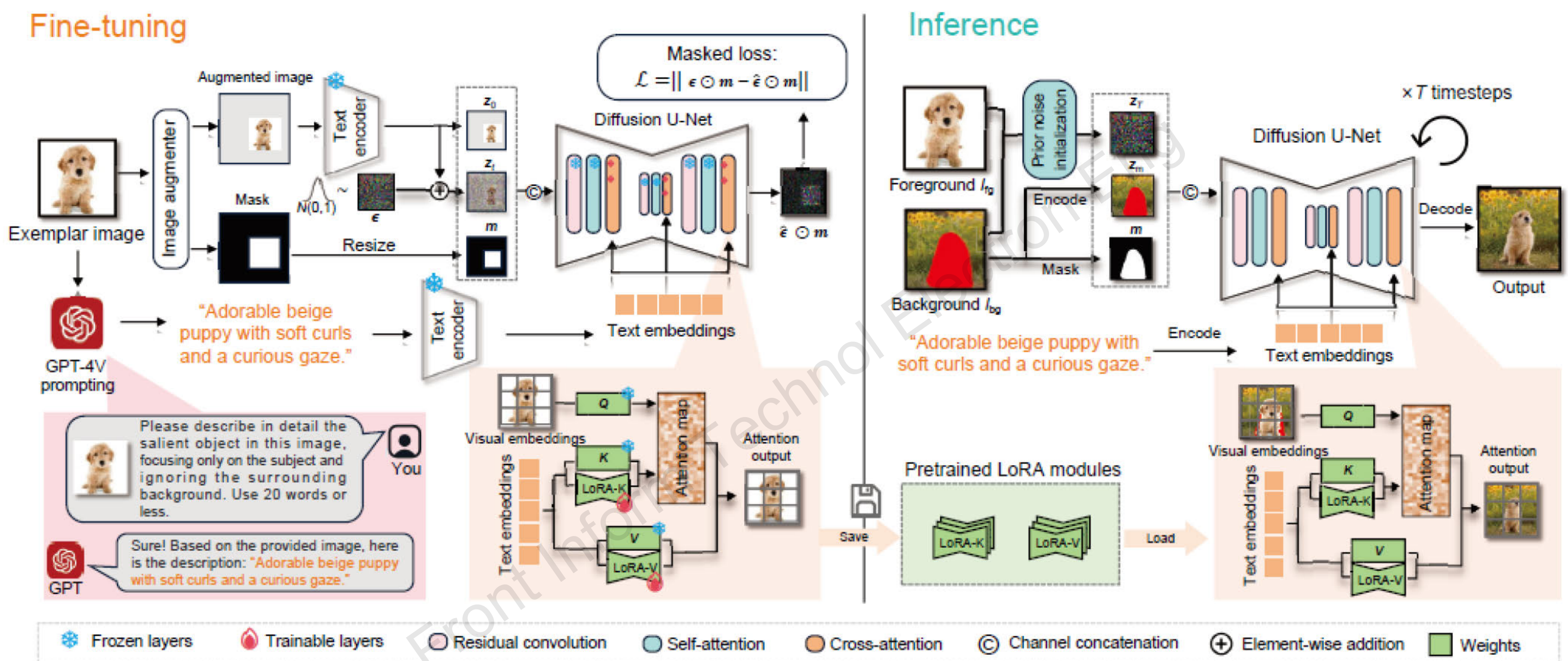


Fig. 2 Pipeline overview of our method. Based on frozen SD-inpaint model, the fine-tuning stage (left) involves fine-tuning learnable LoRA modules on a given exemplar image with GPT-4V generated prompt. The inference stage (right) first loads exemplar-specific pretrained LoRA modules and then samples from the prior noise initialization to facilitate high-fidelity exemplar-driven inpainting within the masked region of the provided background image. References to color refer to the online version of this figure

Method

Two-Stage Pipeline:

Fine-tuning Stage (Few-Shot Learning):

1. A LoRA module is added to a frozen, pretrained Stable Diffusion (SD) inpainting model.
2. The LoRA module learns the specific concept from a few user-provided exemplar images.
3. A detailed text prompt for the exemplar is generated using GPT-4V to improve detail preservation.

Inference Stage:

1. The fine-tuned, exemplar-specific LoRA module is loaded.
2. The denoising process starts from a “prior noise initialization” derived from a composite image (exemplar pasted into the background) instead of random noise.
3. The model inpaints the object into the masked region, guided by the GPT-4V prompt.

Technical Details

1. Parameter-Efficient Fine-tuning with LoRA:

• The LoRA module is lightweight and is added only to the cross-attention layers of the U-Net, learning the exemplar concept directly into the model weights.
• This provides a larger parameter space and stronger fitting capability compared to just optimizing text embeddings (like TxtInv).
• Base model weights remain frozen, preserving original text-driven inpainting capabilities.

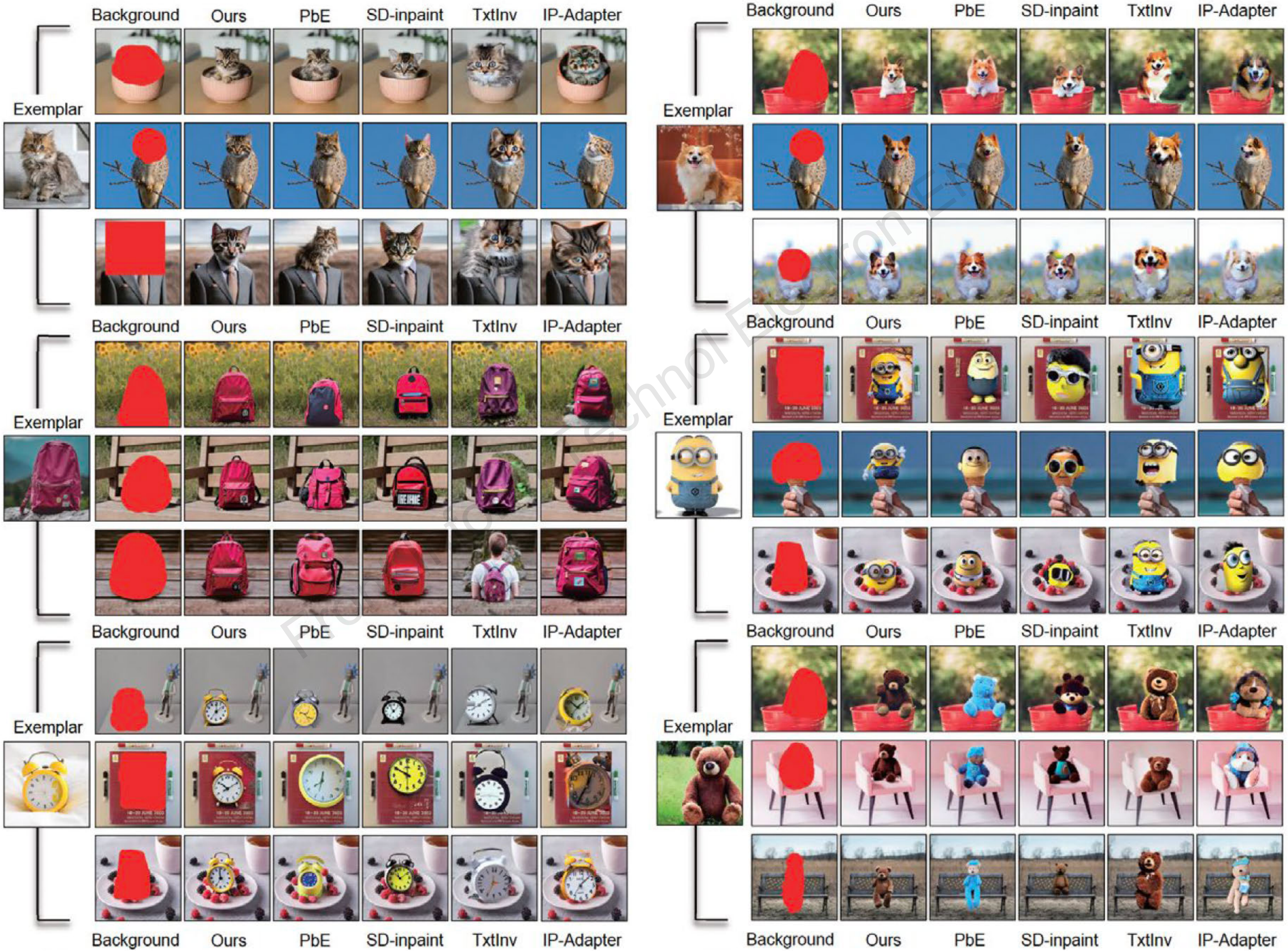
2. GPT-4V Prompting:

• Instead of simple prompts (e.g., “a photo of <x>”), we use the GPT-4V model to generate expressive, detailed descriptions of the exemplar image.
• High-quality prompts are crucial for model performance and help retain more details from the exemplar.

3. Prior Noise Initialization:

• Standard diffusion models start inference from random Gaussian noise.
• Our method applies one-step forward noising to a composite image, where the exemplar is pasted onto the masked background.
• This ensures that the initial latent input retains prior information from the exemplar, bridging the gap between training and inference and improving the fidelity.

Results



Results

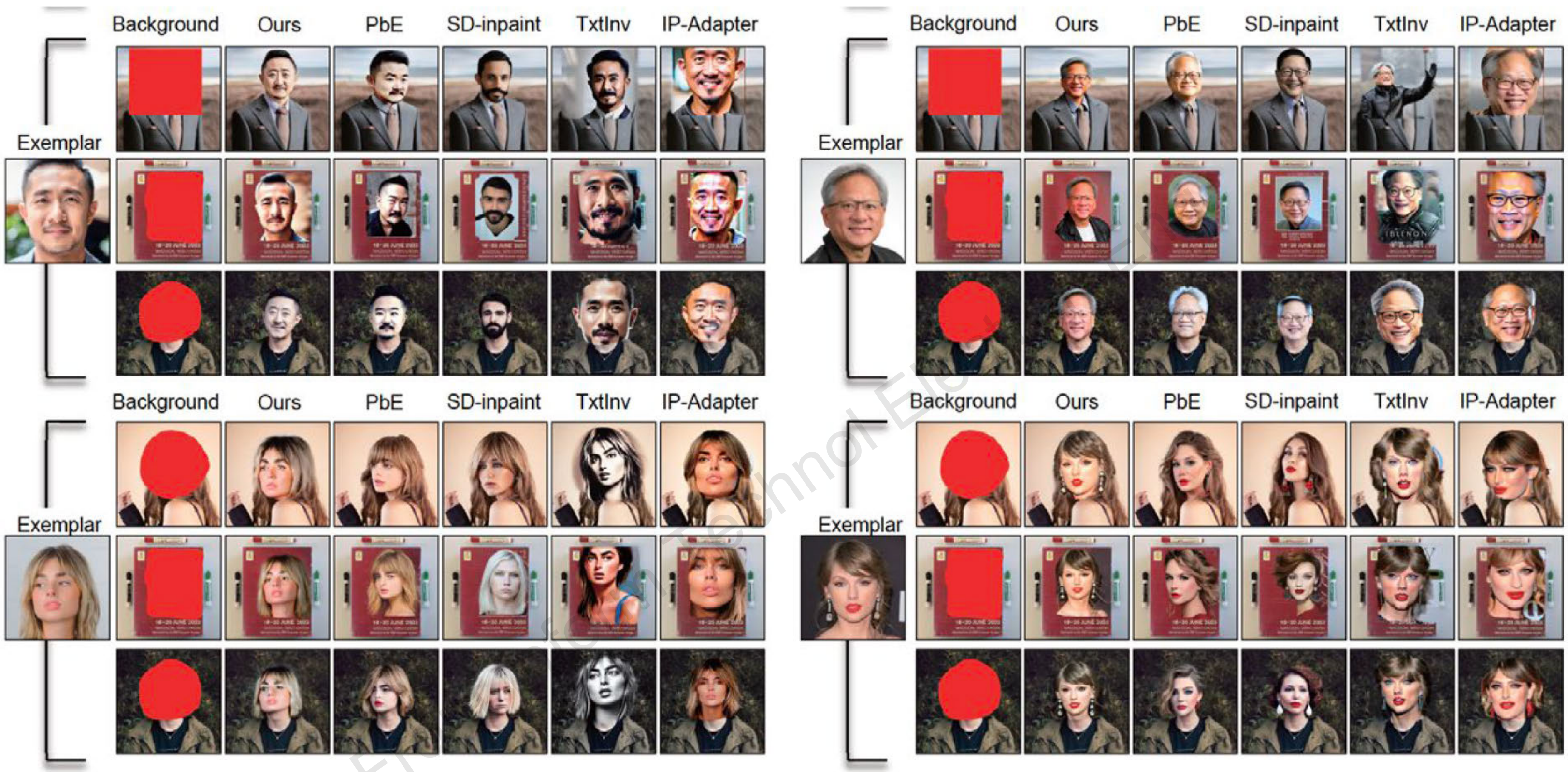


Table 1 Qualitative comparison with baselines

Method	I2I score	T2I score	FID score	Aesthetic score
SD-Inpaint (Rombach et al., 2022)	65.59	28.10	149.62	5.0836
TxtInv (Gal et al., 2022)	70.86	**29.45**	146.89	5.0765
PbE (Yang BX et al., 2023)	69.47	28.79	150.45	**5.0864**
IP-Adapter (Ye et al., 2023)	64.77	27.74	152.45	4.9558
Ours	**72.05**	29.31	**146.14**	5.0854

The best results are in bold

Ablations

GPT-4V Prompting: Using detailed GPT-4V prompts significantly improves the retention of object details.

Fig. 5 Visual comparison between using plain prompting (blue box) vs. GPT-4V prompting (orange box). References to color refer to the online version of this figure

Prior Noise Initialization: Sampling from prior noise leads to more stable and consistent outputs.

Fig. 6 Batched visual comparison between sampling with (w/) or without (w/o) prior noise initialization

Conclusions

We presented a novel approach for few-shot exemplar-driven inpainting using a parameter-efficient fine-tuned diffusion model.

- Our method upgrades a pretrained SD-inpaint model with a lightweight LoRA module to learn customized concepts efficiently.
- We introduced GPT-4V prompting and prior noise initialization to significantly enhance the fidelity and detail preservation of the inpainting results.
- The method outperforms state-of-the-art baselines both qualitatively and quantitatively, offering a more adaptable and effective solution for customized image editing.

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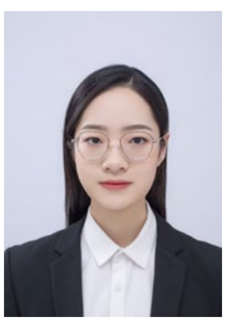

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