


Generative AI
Semester Project Presentation

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Contents

Introduction

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About this presentation

This presentation is a semester project for the course *Generative AI* and aims to explain the ***Adv-CPG: A Customized Portrait Generation Framework with Facial Adversarial Attacks*** paper, a novel approach to generating personalized portraits while protecting user privacy, published by Junying Wang, Hongyuan Zhang, and Yuan Yuan in 2025.

Key features:

- Customized Portrait Generation (CPG) creates personalized, high-fidelity portraits form a facial image and text prompts.
- Current CPG methods lack effective protection against malicious face recognition (FR) systems.
- Adv-CPG integrates facial adversarial attacks into CPG to protect user privacy.
- It generates visually consistent portraits that deceive FR systems while allowing fine-grained customization.
- Key innovation: Progressive two-layer privacy protection combined with multi-modal image customization.

Concept 1: Customized Portrait Generation (CPG)

What is CPG?

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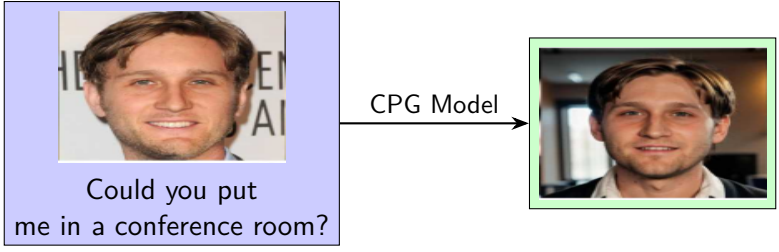

Figure: Customized Portrait Generation: From prompt to result. (Images from the paper)

CPG Types

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- **Recent methods**: do not require fine-tuning, allowing for real-time generation of customized portraits.

More specifically, the recent methods of CPG enable large-scale, high-fidelity, and flexible portrait generation for social media, art, and entertainment.

The Problem: A Privacy Risk

Problem Definition

Even though the exciting potential of CPG methods, they also pose significant privacy risks. Specifically, the high-fidelity portraits generated by CPG can be collected by malicious *face recognition (FR)* systems. Some of the most common risks include:

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The main reason why such things can happen is because current CPG methods lack built-in security mechanisms to protect users.

Concept 2: Adversarial Attacks

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- Recent unrestricted methods concentrate on learning perturbations in the semantic space, further improving transferability and stealthiness

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2. These alterations are often imperceptible to the human eye, maintaining "stealthiness."
3. Previous methods either add noise (less stealthy) or modify attributes like makeup (limited customization).

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Idea: Use adversarial attacks to protect privacy

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Goal: Give users the creative freedom of CPG without sacrificing their facial privacy.

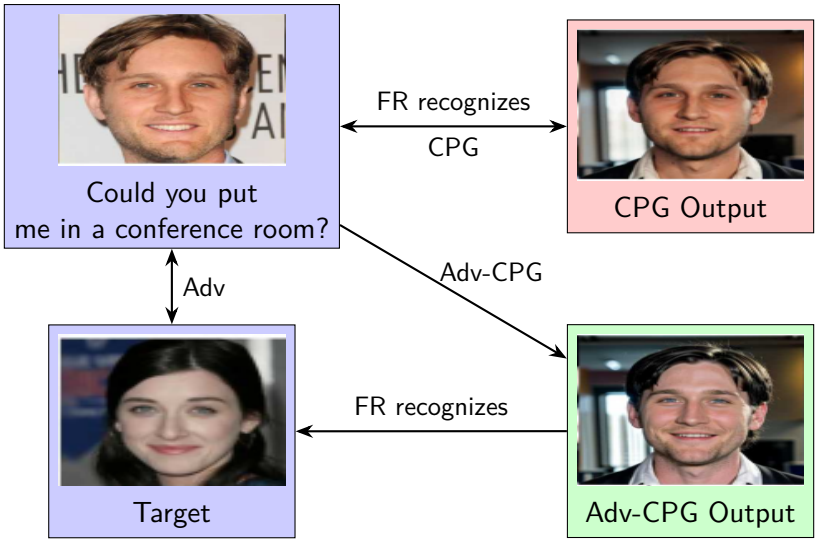

Figure: Adv-CPG: Combining CPG and Adversarial Attacks. (Images from the paper)

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Adv-CPG is built upon a pre-trained diffusion model (SDXL) and features three core modules:

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- **Encryption Enhancer (En 2)**: Adds additional identity guidance during denoising steps for enhanced local protection.

Generation Process

The generator process is divided into two steps, based on MMIC's operation:

- **Stage 1: Progressive Facial Privacy Protection**: *En 1* and *En 2* primary work with the initial text prompt to embed the adversarial target identity and introduce the background.

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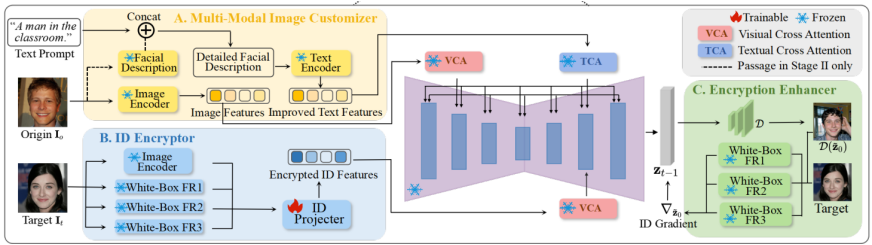

How It's Trained and Generated

Training and Generation Process

In order to achieve the model's goals, two phases were introduce and it is really important to analyze them:

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2. Inference Phase:
   - All of the modules are involved (MMIC, En 1, and En 2).
   - Uses the two-stage generation process described earlier (see slide "Generation Process p*18*").
   - Switches from original text features to augmented text features after a certain diffusion timestep to balance privacy and customization.

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The following slides will showcase the effectiveness of Adv-CPG in generating adversarial portraits.

Face Verification

Method	Dataset ASR% on FR Model ↑	FFHQ IR152	FFHQ IRSE50	FFHQ FaceNet	FFHQ MF	CelebA-HQ IR152	CelebA-HQ IRSE50	CelebA-HQ FaceNet	CelebA-HQ MF	Average
Clean	—	3.14	4.73	1.49	8.96	4.64	5.74	1.06	13.27	5.38
Noise-Based	FGSM (ICLR'15) [9]	9.86	48.53	4.23	51.48	12.07	45.81	1.35	53.02	28.29
	MI-FGSM (CVPR'18) [6]	46.31	69.24	20.62	69.26	46.53	70.57	27.09	58.94	51.07
	PGD (ICLR'18) [33]	31.64	75.38	18.59	63.12	41.87	63.23	19.62	57.34	46.35
	TI-DIM (CVPR'19) [7]	43.57	65.89	14.72	53.31	35.13	62.38	13.68	52.84	42.69
	TIP-IM (ICCV'21) [54]	46.25	67.38	59.82	52.03	41.26	57.29	39.07	49.56	51.58
Makeup-Based	Adv-Hat (ICPR'21) [25]	13.77	15.36	5.26	9.83	5.04	16.88	4.91	12.64	10.46
	Adv-Makeup (IJCAI'21) [56]	10.03	25.57	1.08	20.38	12.68	19.95	1.37	22.11	14.15
	AMT-GAN (CVPR'22) [17]	11.52	56.02	9.74	41.32	12.09	53.26	4.87	47.95	29.60
	Clip2Protect (CVPR'23) [43]	52.12	86.53	45.01	76.29	47.63	80.96	42.57	73.64	63.09
	GIFT (ACMMM'24) [27]	69.72	87.64	54.49	82.93	73.84	83.72	56.48	86.37	74.40
	DFPP (arXiv'24) [44]	54.25	90.63	52.13	80.09	46.38	80.59	45.37	72.13	69.20
	DiffAM (CVPR'24) [47]	67.24	90.30	**64.96**	89.56	65.09	**89.66**	62.99	84.51	76.79
Facial Semantic Invariant	DiffProtect (arXiv'23) [31]	57.62	60.14	49.38	67.52	58.64	79.34	24.69	75.91	59.16
	DPG (arXiv'24) [60]	34.87	76.82	36.57	69.03	42.89	62.47	35.83	66.42	53.11
	SD4Privacy (ICME'24) [1]	51.31	79.94	43.57	71.55	66.89	79.96	53.49	74.58	65.16
	Adv-Diffusion(AAAI'24) [29]	50.93	81.76	30.84	67.52	52.84	81.67	34.95	70.78	58.91
	P3-Mask (ECCV'25) [3]	73.18	85.35	57.92	70.69	73.47	83.40	60.24	69.64	71.74
Portraits	Adv-CPG (Ours)	**75.26**↑2.1	**91.03**↑0.4	63.84↓1.1	**89.94**↑0.4	**76.96**↑3.1	88.72↓0.9	**63.50**↑0.5	**87.95**↑1.6	**79.65**↑2.9

Figure: Face Verification Attack Success Rate (ASR) of Adv-CPG compared to other adversarial attacks. (Image from the paper Table 3)

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Average ASR is 28.1% higher than the best noise-based attacks and 2.86% higher than the best unrestricted attacks.

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Demonstrates strong transferability across diverse FR models including IR152, IRSE50, FaceNet, and MobileFace.

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Method	Dataset	FFHQ				CelebA-HQ				Average
	ASR% on FR Model ↑	IR152	IRSE50	FaceNet	MF	IR152	IRSE50	FaceNet	MF	
Clean	——	3.14	4.73	1.49	8.96	4.64	5.74	1.06	13.27	5.38
Noise-Based	FGSM (ICLR'15) [9]	9.86	48.53	4.23	51.48	12.07	45.81	1.35	53.02	28.29
	MI-FGSM (CVPR'18) [6]	46.31	69.24	20.62	69.26	46.53	70.57	27.09	58.94	51.07
	PGD (ICLR'18) [33]	31.64	75.38	18.59	63.12	41.87	63.23	19.62	57.34	46.35
	TI-DIM (CVPR'19) [7]	43.57	65.89	14.72	53.31	35.13	62.38	13.68	52.84	42.69
	TIP-IM (ICCV'21) [54]	46.25	67.38	59.82	52.03	41.26	57.29	39.07	49.56	51.58
Makeup-Based	Adv-Hat (ICPR'21) [25]	13.77	15.36	5.26	9.83	5.04	16.88	4.91	12.64	10.46
	Adv-Makeup (IJCAI'21) [56]	10.03	25.57	1.08	20.38	12.68	19.95	1.37	22.11	14.15
	AMT-GAN (CVPR'22) [17]	11.52	56.02	9.74	41.32	12.09	53.26	4.87	47.95	29.60
	Clip2Protect (CVPR'23) [43]	52.12	86.53	45.01	76.29	47.63	80.96	42.57	73.64	63.09
	GIFT (ACMMM'24) [27]	69.72	87.64	54.49	82.93	73.84	83.72	56.48	86.37	74.40
	DFPP (arXiv'24) [44]	54.25	90.63	52.13	80.09	46.38	80.59	45.37	72.13	69.20
	DiffAM (CVPR'24) [47]	67.24	90.30	**64.96**	89.56	65.09	**89.66**	62.99	84.51	76.79
Facial Semantic Invariant	DiffProtect (arXiv'23) [31]	57.62	60.14	49.38	67.52	58.64	79.34	24.69	75.91	59.16
	DPG (arXiv'24) [60]	34.87	76.82	36.57	69.03	42.89	62.47	35.83	66.42	53.11
	SD4Privacy (ICME'24) [1]	51.31	79.94	43.57	71.55	66.89	79.96	53.49	74.58	65.16
	Adv-Diffusion(AAAI'24) [29]	50.93	81.76	30.84	67.52	52.84	81.67	34.95	70.78	58.91
	P3-Mask (ECCV'25) [3]	73.18	85.35	57.92	70.69	73.47	83.40	60.24	69.64	71.74
Portraits	Adv-CPG (Ours)	**75.26**↑2.1	**91.03**↑0.4	63.84↓1.1	**89.94**↑0.4	**76.96**↑3.1	88.72↓0.9	**63.50**↑0.5	**87.95**↑1.6	**79.65**↑2.9

Outperforms 17 benchmark methods on FFHQ and CelebA-HQ datasets.

Face Identification

Method	FR Model	IR152		IRSE50		FaceNet		MobileFace		Average	
	ASR% ↑	R1-T	R5-T	R1-T	R5-T	R1-T	R5-T	R1-T	R5-T	R1-T	R5-T
Noise-based	MI-FGSM (CVPR'18)	3.0	13.2	3.8	12.6	8.4	22.0	7.8	20.6	5.75	17.10
	TI-DIM (CVPR'19)	8.2	14.2	4.2	13.8	17.8	32.2	21.4	43.8	12.90	26.00
	TIP-IM (ICCV'21)	9.8	29.8	7.4	27.8	25.8	55.8	31.8	52.6	18.70	41.50
Unrestricted	Clip2Protect (CVPR'23)	17.8	51.8	10.6	35.2	27.2	54.4	39.0	67.8	23.65	52.30
	GIFT (ACMMM'24)	21.2	**57.2**	**34.6**	49.4	33.2	65.6	41.2	67.6	32.55	59.95
	DFPP (arXiv'24)	14.8	41.4	13.6	37.2	25.2	53.8	36.6	60.4	22.55	48.20
	SD4Privacy (ICME'24)	15.6	26.8	23.4	41.2	33.6	53.8	31.8	49.8	26.10	42.90
	Adv-CPG (Ours)	**24.4**↑3.2	56.4↓0.8	33.8↓0.8	**51.2**↑1.8	**36.6**↑3.0	**67.4**↑1.8	**43.4**↑2.2	**70.4**↑2.6	**34.55**↑2.0	**61.35**↑1.4

Figure: Face Identification Attack Success Rate (ASR) of Adv-CPG compared to other adversarial attacks. (Image from the paper Table 3)

In most cases, the results of the proposed Adv-CPG are superior to recent approaches under Rank-1 and Rank-5 settings.

Comparison on Image Quality

Method (Metric)	PGD	TIP-IM	Adv-Makeup	AMT-GAN	CLIP2Protect	DiffAM	SD4Privacy	Adv-Diffusion	**Adv-CPG**
FID ↓	78.92	38.7325	4.2282	34.5703	26.1272	26.1015	26.4078	22.5751	26.0758
PSNR ↑	27.96	33.2106	34.5152	19.5048	19.3542	20.5260	26.8864	28.8501	29.9996
SSIM↑	0.8573	0.9236	0.9850	0.7924	0.6025	0.8861	0.8092	0.8046	0.8978

Figure: Comparison of image quality metrics for Adv-CPG and other methods. (Image from the paper Table 4)

- In contrast to the noise-based method TIP-IM, the adversarial examples of Adv-CPG are more natural, with no obvious noise patterns.

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Figure: Comparison of image quality metrics for Adv-CPG and other methods. (Image from the paper Table 4)

- In contrast to the noise-based method TIP-IM, the adversarial examples of Adv-CPG are more natural, with no obvious noise patterns.
- In terms of unrestricted makeup-based approaches, CLIP2Protect generates reasonable and high-quality makeup, and DiffAM achieves outstanding performance in terms of precision and refinement

Comparison on Image Quality

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1. Among all quantitative evaluations, Adv-Makeup performs the best. The reason is that Adv-makeup only generates eye shadow, not full-face makeup, which makes minimal modifications to the image. Also, Adv-Makeup had a really low ASR.
2. In summary, Adv-CPG obtains comparatively low FID scores and high PSNR and SSIM scores, indicating that the images generated by Adv-CPG are relatively natural.

Results (Part 2): It works on Real-World Systems

Commercial APIs Testing

For benchmarking, recent methods are chosen, including 4 unrestricted makeup- based methods and 5 unrestricted facial semantical invariant methods.

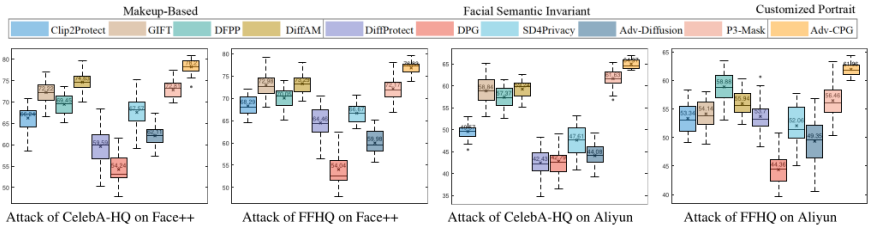

Figure: The confidence scores (↑) returned from commercial APIs, Face++ and Aliyun. (Images from the paper)

The results demonstrate that the average confidence scores of Adv-CPG on each API are about 77.5 and 63.0, respectively, which is superior to current SOTA methods, and the attack effectiveness is comparatively stable.

Commercial APIs Testing

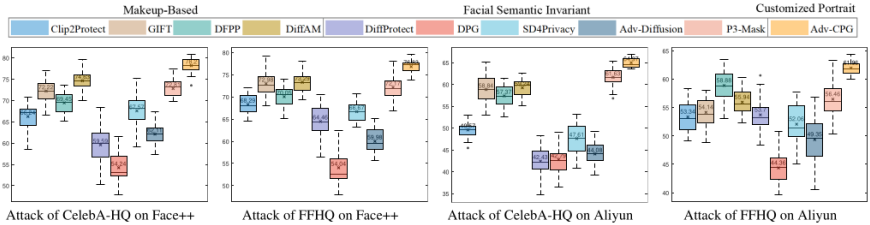

Figure: The confidence scores (↑) returned from commercial APIs, Face++ and Aliyun. (Images from the paper)

Adv-CPG has higher and more stable confidence scores than state-of-the-art noise-based and makeup-based facial privacy protection methods.

Conclusions

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Adv-CPG Overview

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Adv-CPG Overview

- Adv-CPG is the first framework to integrate facial adversarial attacks into customized portrait generation.
- It achieves progressive two-layer facial privacy protection by injecting a target identity and adding identity guidance.
- The multi-modal image customizer enables fine-grained, high-fidelity, and personalized portrait generation.

Conclusions

Experimental results show Adv-CPG outperforms state-of-the-art methods in:

- Robust black-box attacks against diverse face recognition models and commercial APIs.
- Maintaining high image quality and customization.

Future work could explore the application of this facial privacy protection paradigm to other facial manipulation tasks, such as face editing and face swapping, to fully protect facial privacy in the age of artificial intelligence.

References


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Thank you!

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