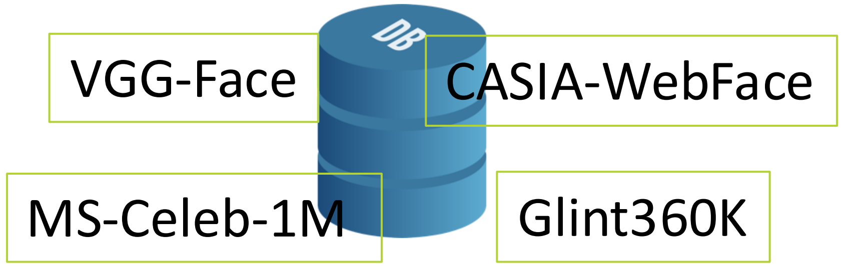
IDPERTURB: Enhancing Variation in Synthetic Face Generation via Angular Perturbations

Fadi Boutros[1],Eduarda Caldeira[1,2],Tahar Chettaoui[1],Naser Damer[1,2]
[1]Fraunhofer IGD
[2]TU Darmstadt

Motivation

Synthetic data for face recognition development

- ❑ There is technical limitation in collecting, large, diverse and representative real data
- ❑ Real biometric datasets face increasing privacy, legal, and ethical restrictions.



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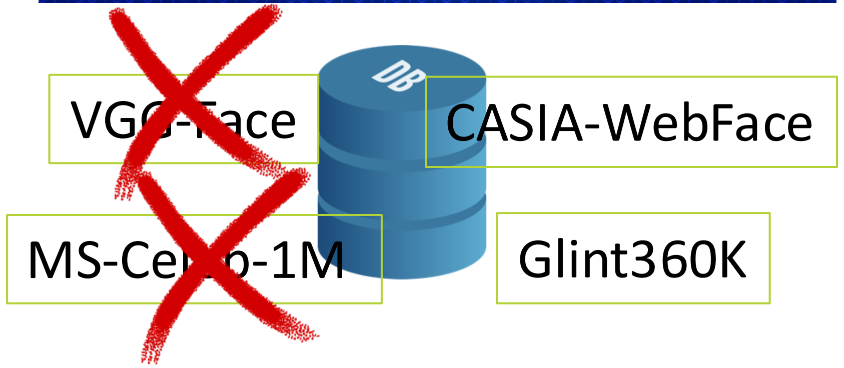

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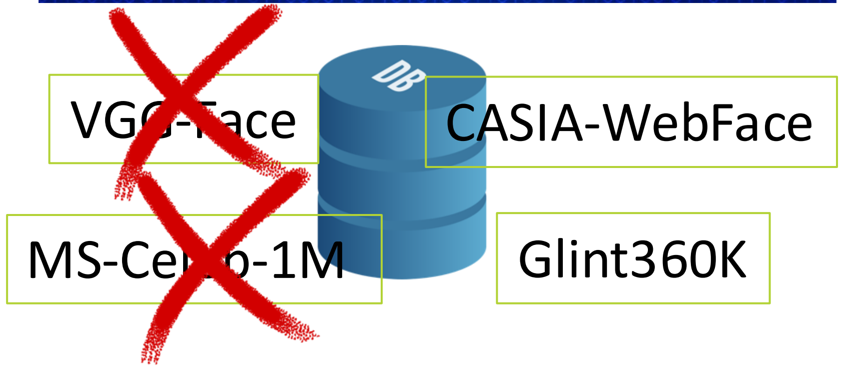

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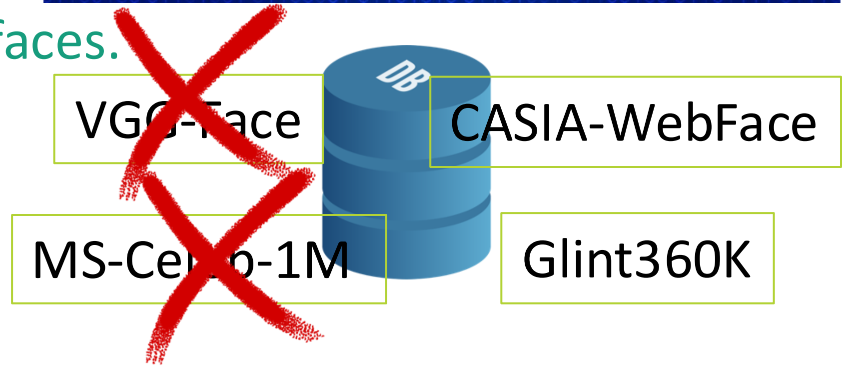
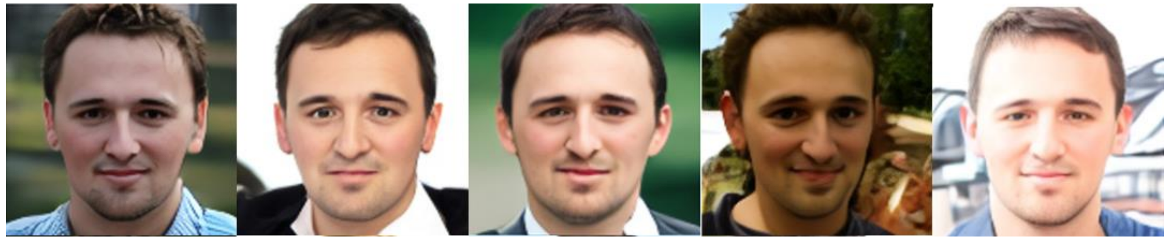
- Identity-conditioned diffusion models can synthesize realistic, identity-consistent faces.



IDPERTURB

Synthetic data for face recognition development

Challenge: Synthetic face datasets often preserve identity but lack intra-class variation.



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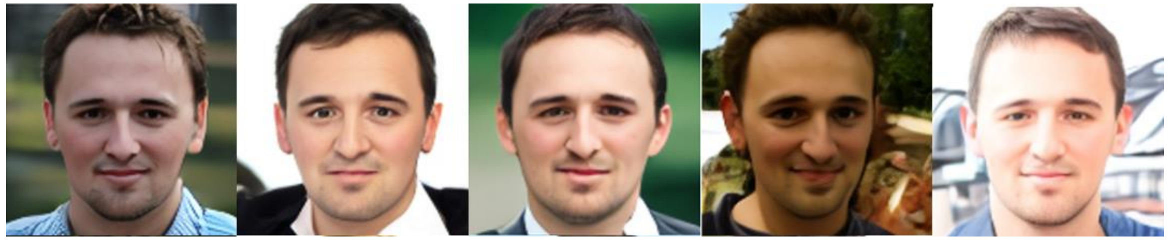
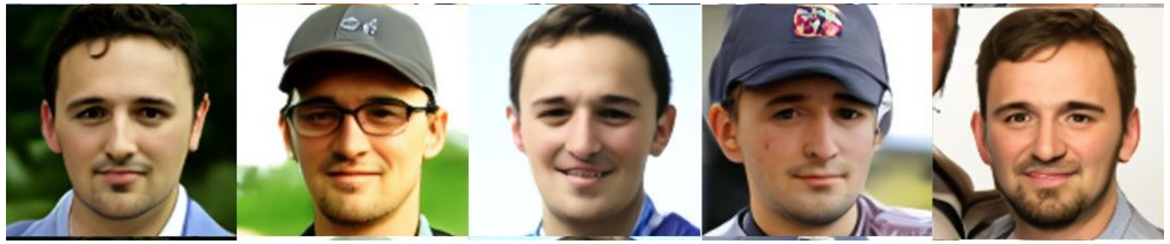
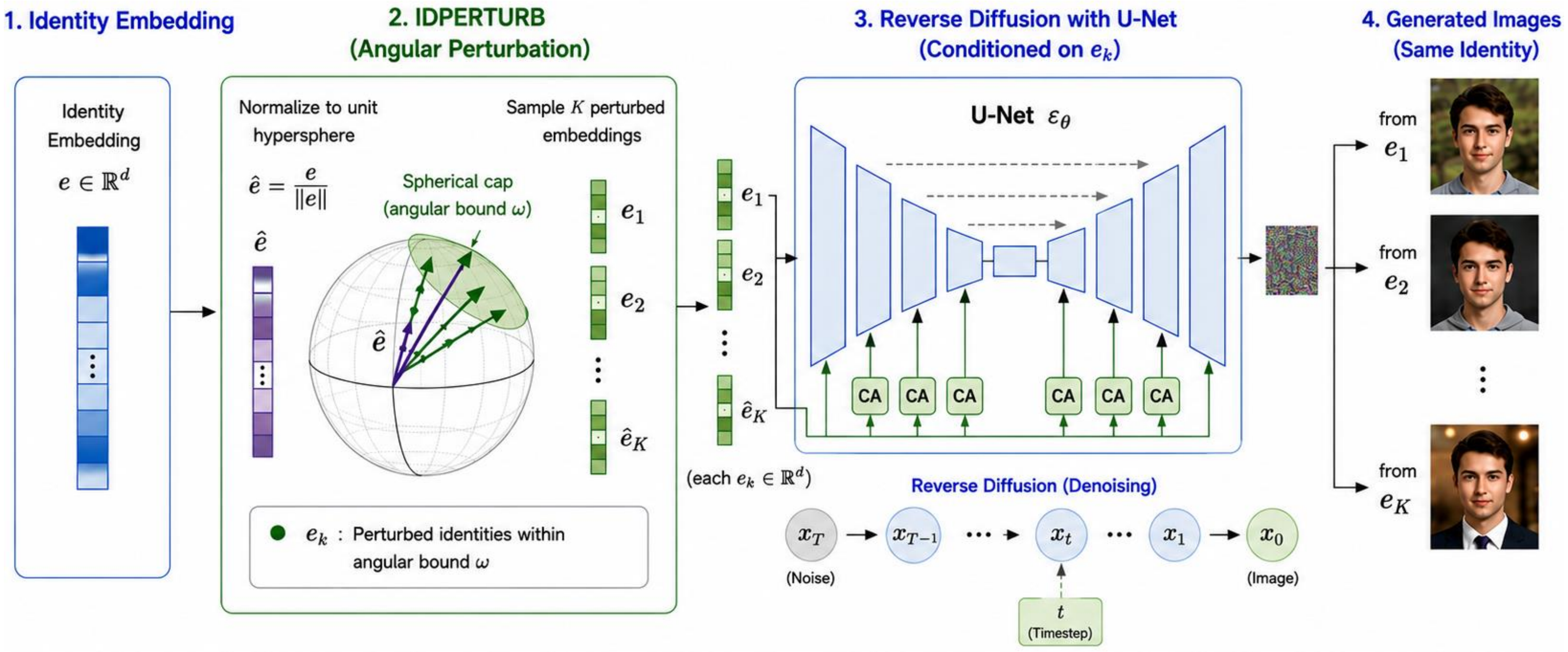


Goal: generate diverse yet identity-consistent synthetic faces for robust face recognition.



IDPERTURB

Enhancing Variation in Synthetic Face Generation via Angular Perturbations



Impact of IDPERTURB on intra-class variations

Lb: lower bound of the cone boundary

Impact of IDPERTURB on intra-class diversity and FR performances

Dataset	lb	Age ↑	Yaw ↑	Pitch ↑	Roll ↑	Exp. ↑	D-Intra ↑	C-Intra	FR ↑
C-WF	-	*0.354*	*23.479*	*9.069*	*5.154*	*0.589*	*0.423*	*0.948*	*94.63*
Baseline	-	0.283	18.881	7.992	3.230	0.429	0.366	0.999	91.25
IDPERTURB	0.9	0.325	19.907	8.384	3.606	0.492	0.393	0.998	92.68
	0.8	0.369	20.899	8.727	4.029	0.538	0.417	0.994	93.31
	0.7	0.416	21.816	9.117	4.551	0.574	0.439	0.978	93.44
	0.6	0.461	22.735	9.467	5.124	0.603	0.458	0.939	93.62
	0.5	0.501	23.611	9.724	5.602	0.621	0.474	0.875	93.56
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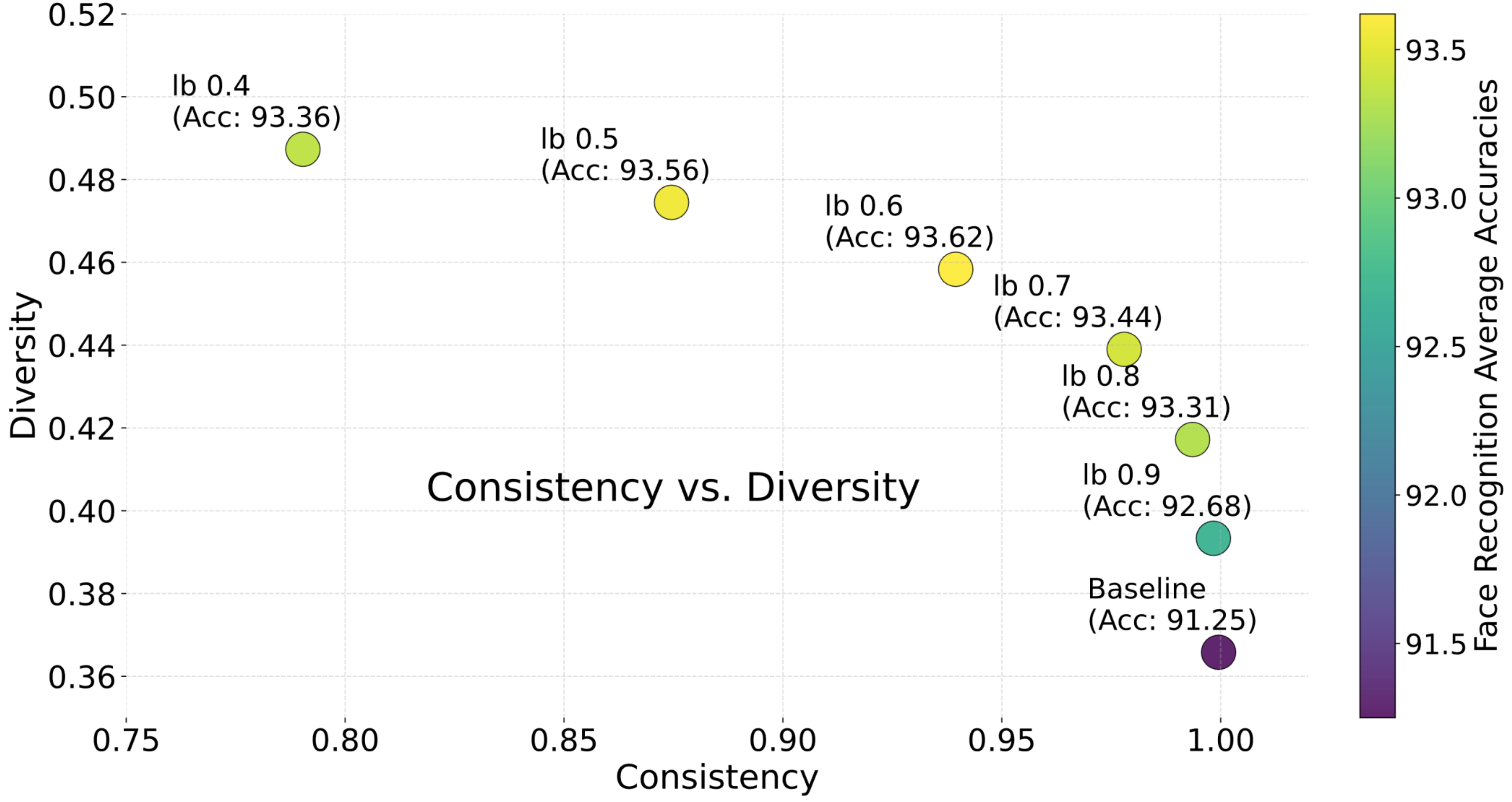

IDPERTURB vs. SOTA

Method	Data Generation	DGMs Train Dataset	#imgs (IDs × imgs/ID)	LFW	AgeDB	CFP-FP	CA-LFW	CP-LFW	Avg	IJB-C	
										10^{-5}	10^{-4}
C-WF [5, 49]	Authentic	-	0.49M(∼10.5k × 47)	99.55	94.55	95.31	93.78	89.95	94.63	93.96	96.05
DigiFace [1] WACV'22		-	0.5M(10k × 50)	95.40	76.97	87.40	78.62	78.87	83.45	-	-
DigiFace [1]* WACV'22	Digital Rendering	-	0.5M(10k × 50)	91.15	74.00	82.93	75.30	73.40	79.36	30.01	44.78
DigiFace [1] WACV'22		-	1.2M(10k × 72 + 100k × 5)	96.17	81.10	89.81	82.55	82.23	86.37	-	-
IDnet [27] CVPRW'23		C-WF	0.53M(10.5k × 50)	92.58	73.53	75.40	79.90	74.25	79.13	38.85	53.25
SFace [4] IJCB'22		C-WF	0.63M(10.5k × 60)	91.87	71.68	73.86	77.93	73.20	77.71	12.70	19.87
SFace2+ [9] TBIOM'24		C-WF	0.63M(10.5k × 60)	95.60	77.37	77.11	83.40	74.60	81.62	0.85	5.36
SynFace [37] ICCV'21	GAN-Based	FFHQ	0.5M(10k × 50)	88.98	-	-	-	-	-	-	-
SynFace (w/IM) [37] ICCV'21		FFHQ	0.5M(10k × 50)	91.93	61.63	75.03	74.73	70.43	74.75	-	-
USynthFace [6] FG'23		FFHQ	0.4M(400k × 1)	92.23	71.62	78.56	77.05	72.03	78.30	-	-
ExFaceGAN(Con) [7] IJCB'23		FFHQ	0.5M(10k × 50)	93.50	78.92	73.84	82.98	71.60	80.17	12.92	43.28
ID^3 [48] NeurIPS'24		FFHQ	0.5M(10k × 50)	97.28	83.78	85.00	89.30	77.13	86.50	-	-
IDiff-Face [5] ICCV'23		FFHQ	0.5M(10k × 50)	98.00	86.43	**85.47**	90.65	80.45	88.20	20.60	62.60
NegFaceDiff [10] ICCV-W'25		FFHQ	0.5M(10k × 50)	97.60	86.53	85.33	90.28	80.73	88.10	**58.09**	73.93
IDPERTURB (Ours)		FFHQ	0.5M(10k × 50)	**98.55**	**88.85**	84.27	**91.42**	**80.85**	**88.79**	37.88	**74.49**
Arc2Face [35] ECCV'24		WF4M + FFHQ + CelebA	0.5M(10k × 50)	98.81	90.18	91.87	92.63	85.16	91.73	-	-
HyperFace [33] ICLR'25		WF4M + FFHQ + CelebA	0.5M(10k × 50)	98.50	86.53	88.83	89.40	84.23	89.29	-	-
Vec2Face [47] ICLR'25		WF4M	0.5M(10k × 50)	98.87	93.12	88.97	93.57	85.47	92.00	-	-
DCFace [26] CVPR'23		FFHQ + C-WF	0.5M(10k × 50)	98.55	89.70	85.33	91.60	82.62	89.56	60.80	74.63
ID^3 [48] NeurIPS'24	Diffusion Model	C-WF	0.5M(10k × 50)	97.68	91.00	86.84	90.73	82.77	89.80	-	-
CemiFace [43] NeurIPS'24		C-WF	0.5M(10k × 50)	99.03	91.33	91.06	92.42	87.65	92.30	-	-
NegFaceDiff [10] ICCV-W'25		C-WF	0.5M(10k × 50)	98.98	90.02	91.67	91.65	88.82	92.23	77.38	86.11
UIFace [28] ICLR'25		C-WF	0.5M(10k × 50)	99.27	90.95	**94.29**	92.25	**89.58**	93.27	81.78*	88.70*
IDPERTURB (Ours)		C-WF	0.5M(10k × 50)	**99.40**	**93.20**	93.61	**93.50**	88.37	**93.62**	**82.28**	**89.49**
DCFace [26] CVPR'23		FFHQ + C-WF	1.2M(20k × 50 + 40k × 5)	98.58	90.97	88.61	92.82	85.07	91.21	-	-
CemiFace [43] NeurIPS'24		C-WF	1.0M(20k × 50)	99.18	91.97	92.75	93.01	88.42	93.07	-	-
Arc2Face [35] ECCV'24		WF4M + FFHQ + CelebA	1.2M(20k × 50 + 40k × 5)	98.92	92.45	94.58	93.33	86.45	93.14	-	-
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UIFace [28] ICLR'25		C-WF	1.0M(20k × 50)	99.22	92.45	**95.03**	93.18	**90.42**	94.06	-	-
IDPERTURB (Ours)		C-WF	1.0M(20k × 50)	**99.48**	**94.03**	95.01	**93.85**	90.01	**94.48**	**85.57**	**91.19**

Take home message

IDPERTURB is a geometry-driven sampling method for identity-conditioned diffusion models.

It enhances intra-class diversity through angular perturbation of identity embeddings.

It requires no retraining, no architectural changes, and no extra attribute labels.

It improves face recognition generalization and achieves state-of-the-art synthetic-data results.

https://github.com/fdbtrs/IDperturb