

Towards Large-Pose Face Frontalization in the Wild

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Highlights

Problem Statement:

Given a face image with arbitrary pose, generate a frontal face of the same identity.

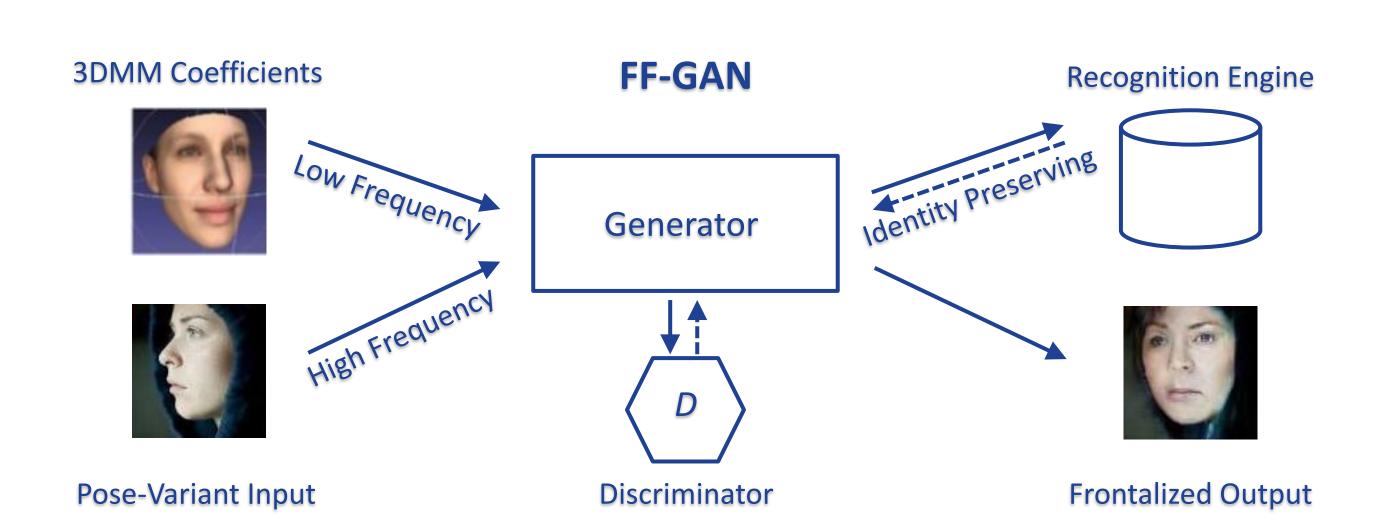
Need:

Face recognition engines favor frontal poses due to dataset biases.

Augmented reality requires photorealism from arbitrary viewpoints.

Insights and Contributions:

- ♦ Faces are constrained shapes: 3DMM priors.
- ♦ Low frequency bias in reconstruction: Adversarial framework.
- ♦ Special properties of faces: Smoothness and symmetry.
- ♦ Identity preservation: Face recognition engine.



Preliminaries

(1) 3D Morphable Model (3DMM)

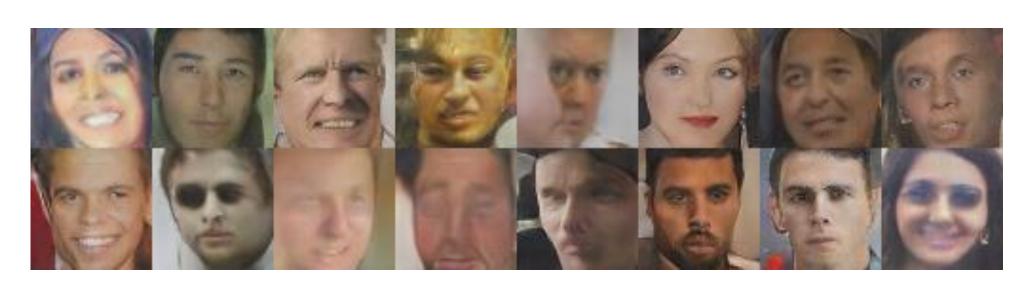
3DMM defines face shape and texture in the PCA space.

Weak perspective projection: pitch, yaw, roll, scale, x-y-translations.

3DMM coefficients: shape and texture basis + projection matrix.

(2) Generative Adversarial Network (GAN)

GAN maps from a source distribution to a target distribution using a minimax optimization between a generator and a discriminator.



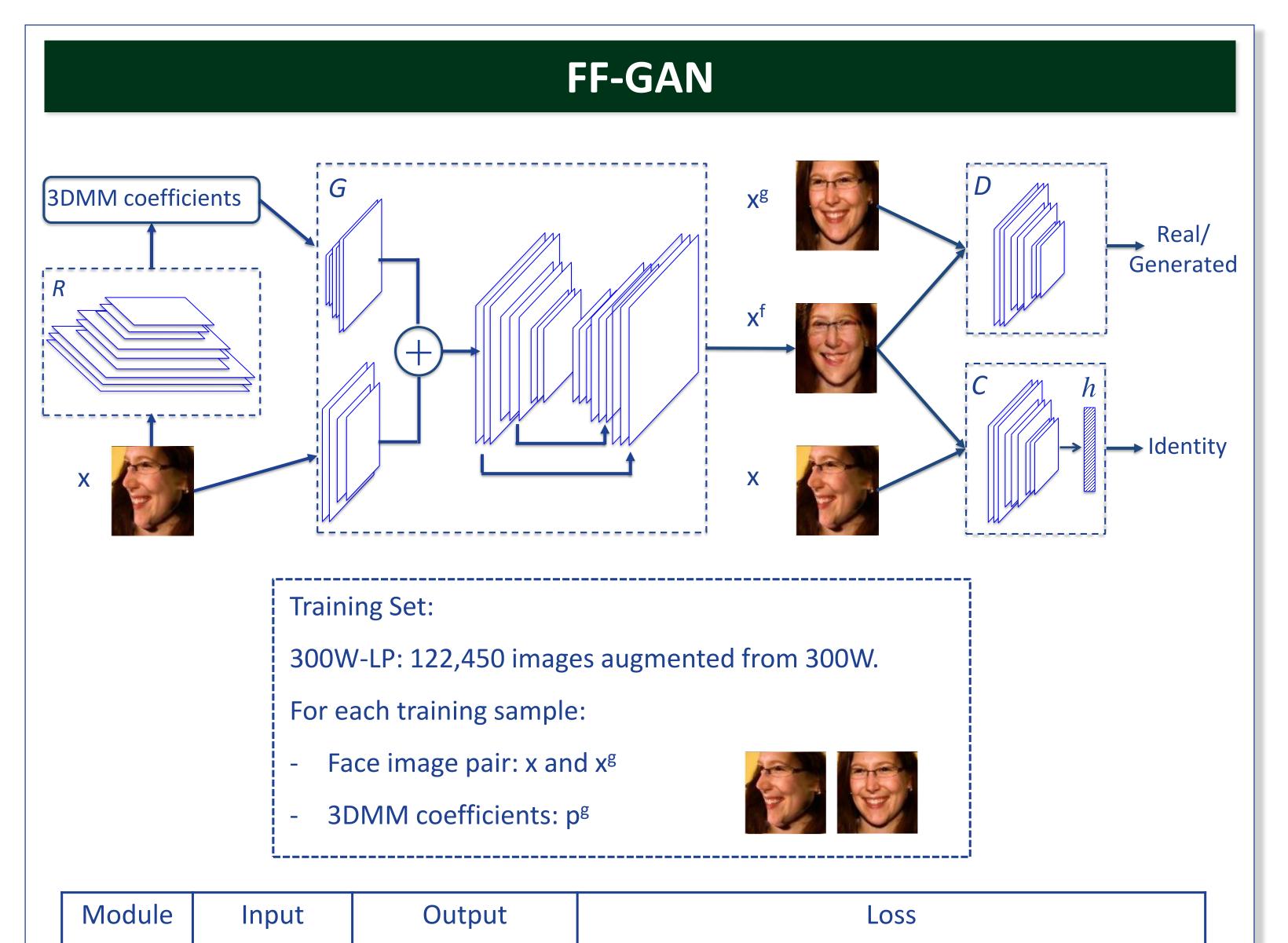
(3) Face Frontalization

Prior work [1]: use a single 3D surface as an approximation of any face shape.

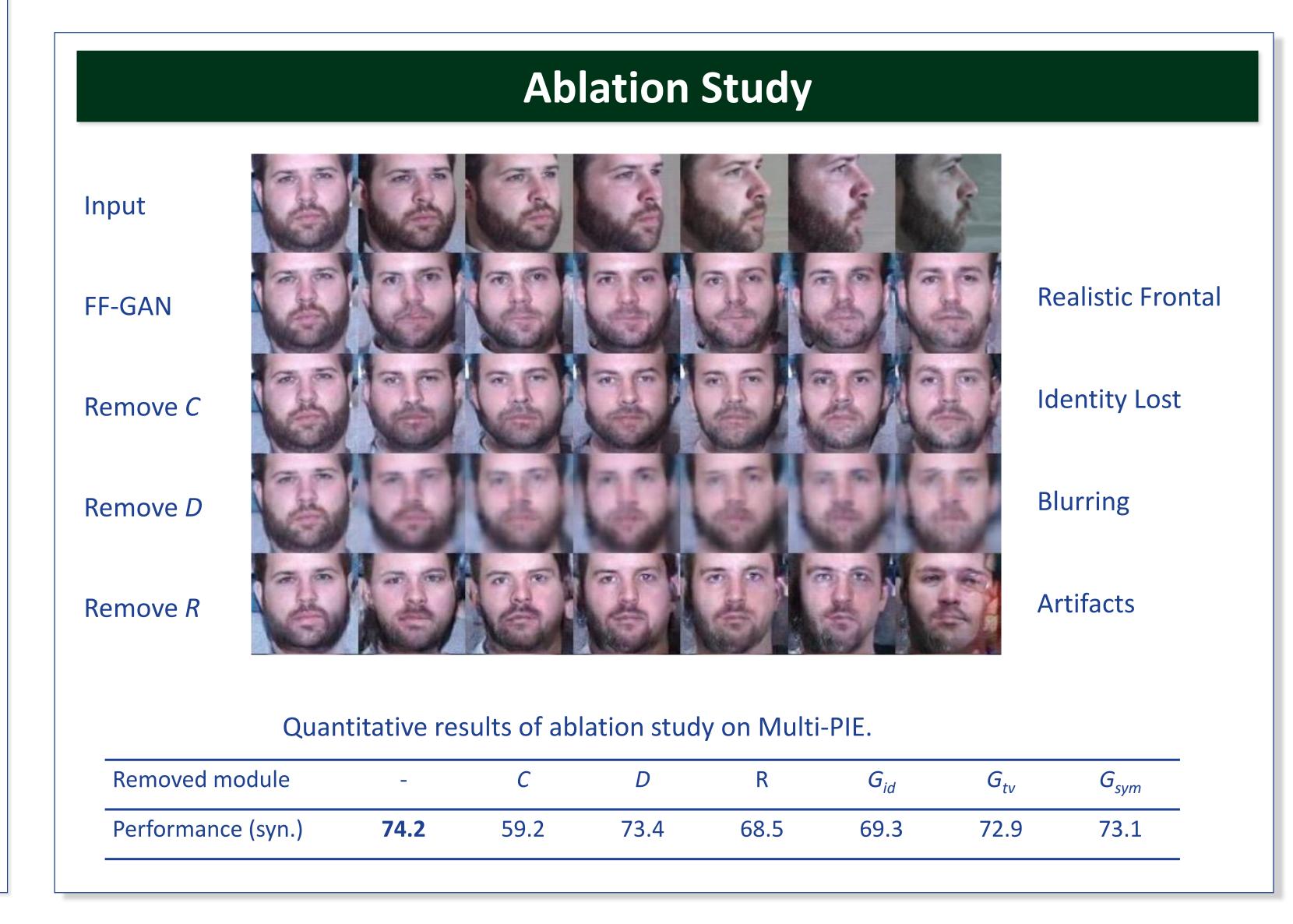
Prior work [2]: 3DMM-based pose and expression normalization.

Drawbacks: small pose, artifacts.





Х			
	р	weighted L2 between p and p ^g	
x and p	X ^f	L1 reconstruction, smoothness, symmetric; fool D to classify x^f as real; fool C to classify x^f as the same identity	
x ^g or x ^f	real / generated	cross-entropy classification loss	
x or x ^f	identity	cross-entropy classification loss	
_	x ^g or x ^f	xg or xf real / generated	

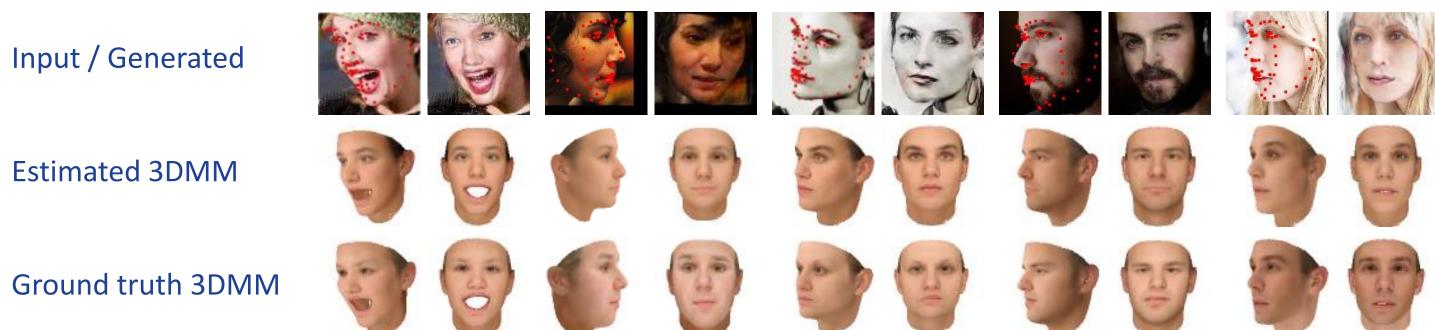


Experimental Results

(1) 3D Face Reconstruction

Input / Generated

Estimated 3DMM



(1) Face Recognition

Face verification results on LFW, compared to face frontalization methods.

	ACC (%)	AUC (%)					
Ferrari et al.	-	94.29					
Hassner et al. [1]	93.62 ± 1.17	98.36 ± 0.06					
HPEN [2]	96.25 ± 0.76	99.39 \pm 0.02					
FF-GAN (syn.)	96.42 ± 0.89	99.45 ± 0.03					

Face recognition results on IJB-A.

	Verification		Identification	
	FAR=.01	FAR=.001	Rank-1	Rank-5
Wang et al.	72.9 \pm 3.5	51.0 ± 6.1	82.2 ± 2.3	93.1 ± 1.4
DCNN	78.7 ± 4.3	-	85.2 ± 1.8	93.7 ± 1.0
DR-GAN	77.4 \pm 2.7	53.9 ± 4.3	85.5 ± 1.5	94.7 \pm 1.1
FF-GAN (fuse)	85.2 ± 1.0	66.3 ± 3.3	90.2 ± 0.6	95.4 ± 0.5

(1) Face Frontalization

Multi-PIE:





AFLW2000:





References:

[1] T. Hassner, S. Harel, E. Paz, and R. Enbar. "Effective face frontalization in unconstrained images". In CVPR, 2015.

[2] X. Zhu, Z. Lei, J. Yan, D. Yi, and S. Li. "High-Fidelity Pose and Expression Normalization for Face Recognition in the Wild". In CVPR, 2015.