SynFace: Face Recognition with Synthetic Data

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Introduction

- **Problems:**
  - **Privacy Issue:** Struggling with the consent of all involved person/identities.
  - **Long-tailed Distribution:** Collected data samples are extremely imbalanced.
  - **Attribute Annotation:** Lacking detailed facial attribute annotations (e.g., pose and expression).
- **Observations:** Face synthesis based on GANs and 3DMM has made an extraordinary progress, making it possible to:
  - generate large-scale high-fidelity face images of non-existing identities without data privacy issues.
  - explore the impacts of different dataset properties and facial attributes on face recognition accuracy.
- **Solution:** Exploring the potentials of synthetic face images for face recognition.

Figure 1: Real (top) and synthetic (bottom) face images.

Analysis

- **Observation:** A performance gap between SynFace and RealFace.

Method	Training Dataset	LFW	Syn-LFW
RealFace	CASIA-WebFace	99.18	98.85
SynFace	Syn_10K_50	88.98	99.98

Table 1: Cross-domain evaluation of SynFace and RealFace.

- **Analysis:** As shown in Table 1 and Figure 3, the domain gap with a special focus on poor intra-class variations of synthetic data contributes to the performance gap.

Method

- **Identity Mixup (IM):** A mixture of identities in the coefficient space, i.e., interpolating two different identities as a new intermediate one to enlarge the intra-class variations.

$$\alpha = \varphi \cdot \alpha_1 + (1-\varphi)\cdot \alpha_2,$$
$$\eta = \varphi \cdot \eta_1 + (1-\varphi)\cdot \eta_2,$$

- **Domain Mixup (DM):** A mixture of large-scale synthetic face images and a small number of labeled real-world face images is proposed to alleviate the domain gap.

$$X = \psi \cdot X_S + (1-\psi)\cdot X_R,$$
$$Y = \psi \cdot Y_S + (1-\psi)\cdot Y_R,$$

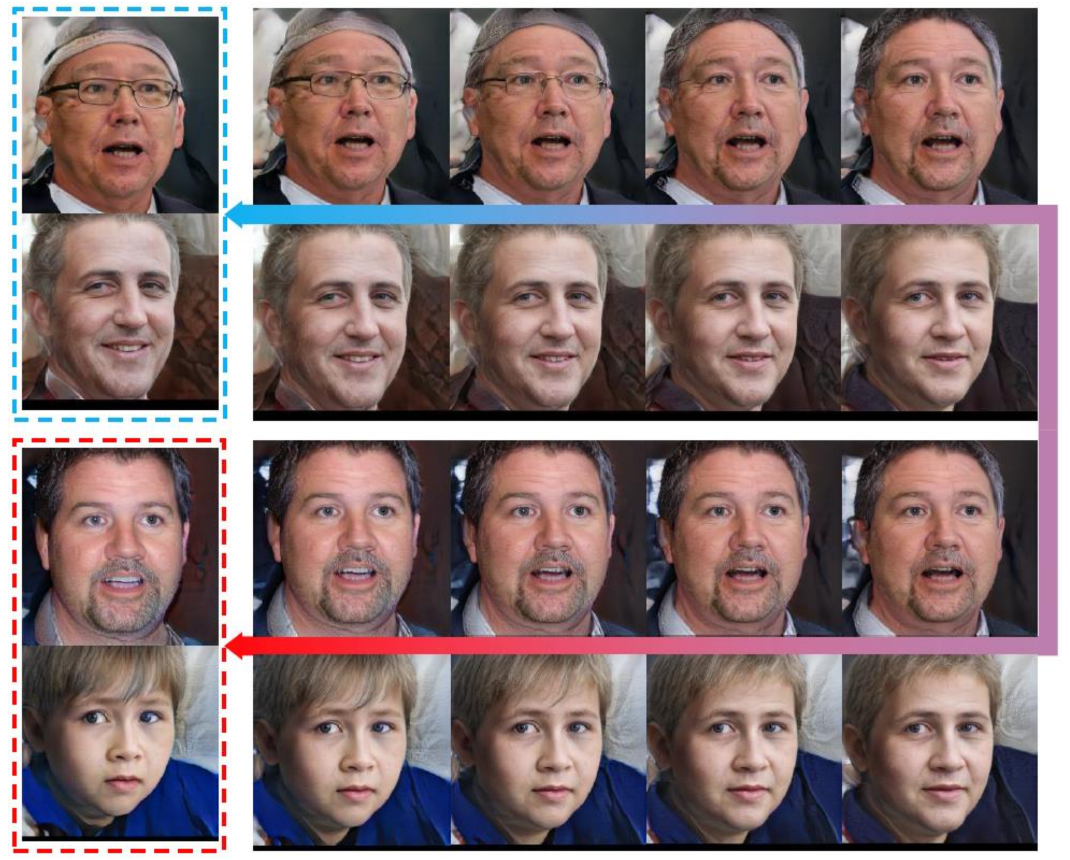


Figure 2: One identity gradually and smoothly varies to another identity with IM.

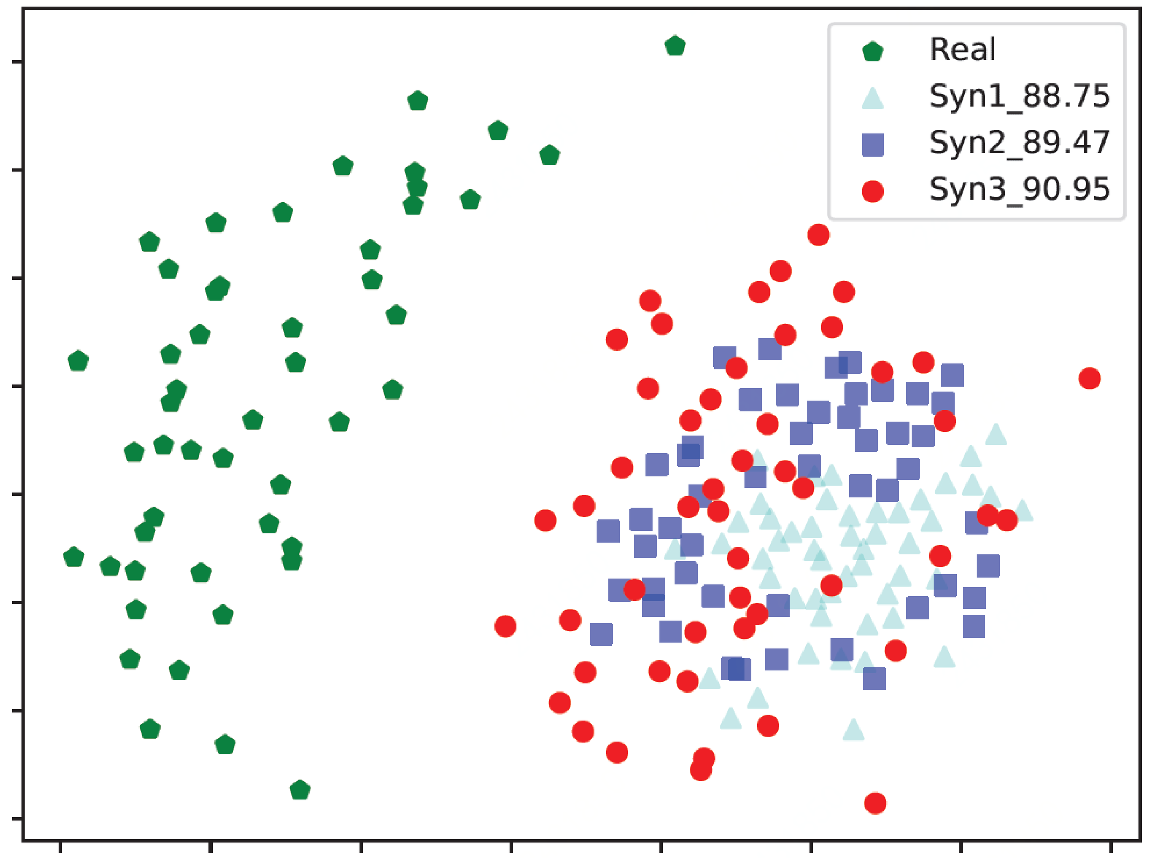
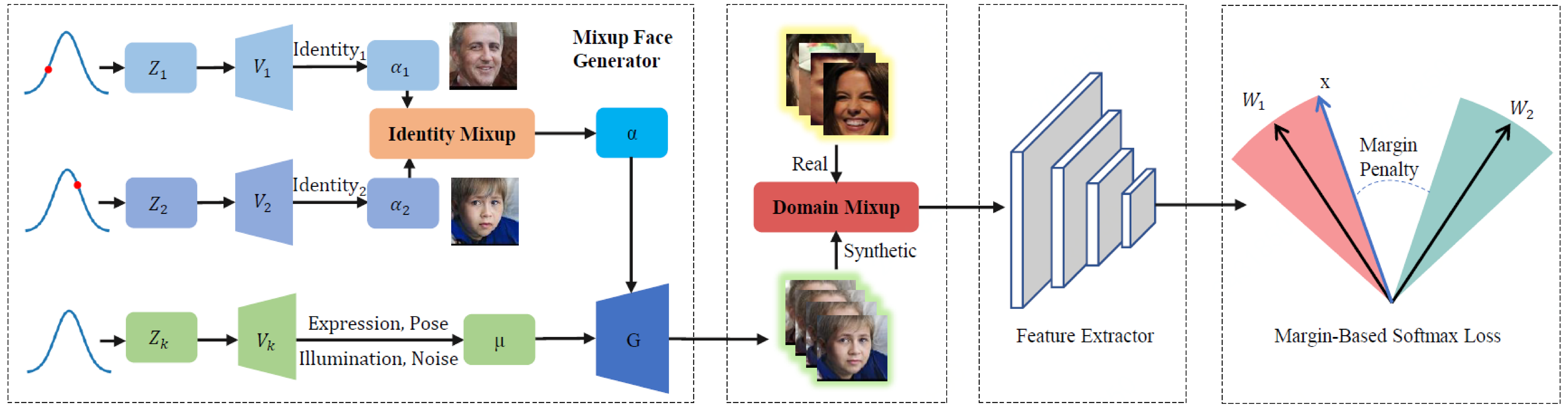


Figure 3: Visualizations of feature distributions from real and three different synthetic datasets.

- **Overall Framework:** Identity mixup is first embedded into the face generator, which then generates face images with different identities and intermediate states. Next, the synthetic face images are cooperating with a few real face images via domain mixup. Finally, a backbone network is used for feature extraction and margin-based loss function are employed for embedding learning.



Experiments

- **Effectiveness of Identity Mixup (IM):**

Method	ID	Samples	LFW	LFW(w/ IM)
(a) 1K_50	1K	50	83.85	**87.53**
(b) 2K_50	2K	50	86.18	**89.28**
(c) 5K_50	5K	50	88.75	**90.95**
(d) 10K_2	10K	2	78.85	**80.30**
(e) 10K_5	10K	5	88.22	**88.32**
(f) 10K_10	10K	10	89.48	**90.28**
(g) 10K_20	10K	20	89.90	**90.87**
(h) 10K_30	10K	30	89.73	**91.17**
(i) 10K_50	10K	50	88.98	**91.97**

Table 2: The influences of different depth and width w/wo identity mixup (IM).

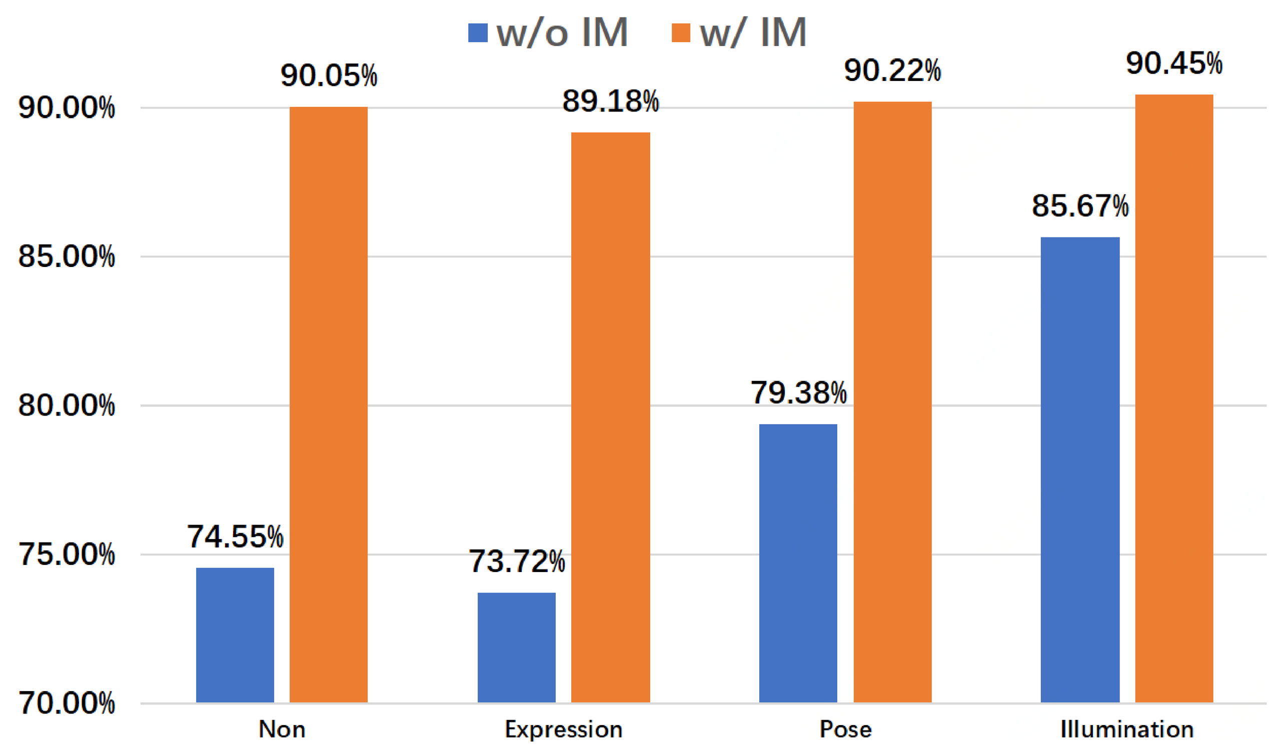


Figure 4: The influences of different facial attributes w/wo identity mixup (IM).

- **Effectiveness of Domain Mixup (DM):**

Method	R_ID	Samples per R_ID	Accuracy
Syn_10K_50	0	0	91.97
Real_1K_10	1K	10	87.50
Mix_1K_10	1K	10	**92.28**
Real_1K_20	1K	20	92.53
Mix_1K_20	1K	20	**95.05**
Real_2K_10	2K	10	91.22
Mix_2K_10	2K	10	**95.78**

Table 3: Results of synthetic, real and mixed datasets w/wo domain mixup (DM).