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SATGAN: Augmenting Age Biased Dataset for Cross-Age Face Recognition

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Abstract

We propose a Stable Age Translation GAN (SATGAN) to generate fake face images at different ages to augment age biased face datasets for Cross-Age Face Recognition (CAFR) . The proposed SATGAN consists of both generator and discriminator. As a part of the generator, a novel Mask Attention Module (MAM) is introduced to make the generator focus on the face area. In addition, the generator employs a Uniform Distribution Discriminator (UDD) to supervise the learning of latent feature map and enforce the uniform distribution. Besides, the discriminator employs a Feature Separation Module (FSM) to disentangle identity information from the age information.

Motivation

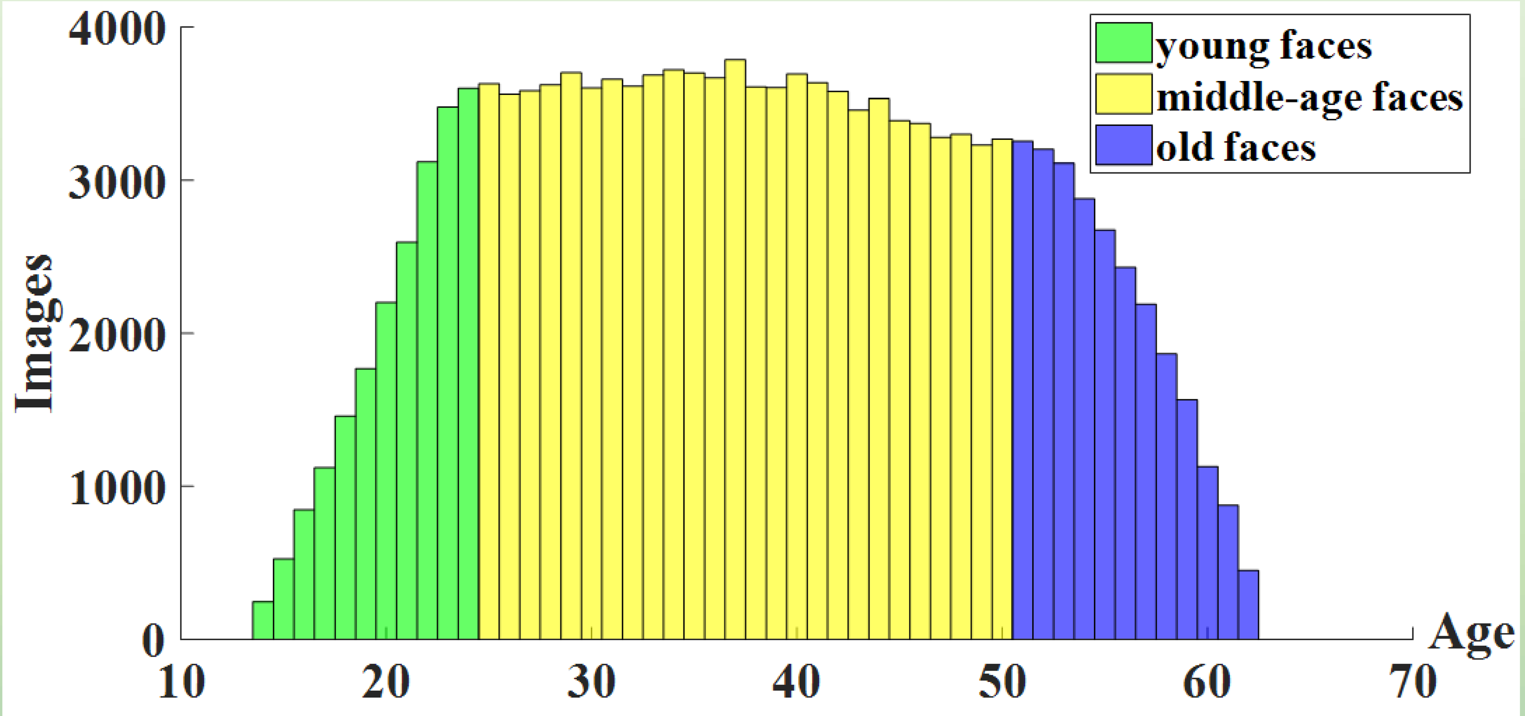

Fig: The age distribution of the CACD dataset.

- To train a CAFR model, we need large amounts of face images at different ages, but most face datasets have age bias.
- Due to the success of Generative Adversarial Networks (GANs) they have been widely applied to translate faces with different attributes like expression, hair, pose and age etc.

Dataset

Morph: 55,134 images are divided into a training set with 50020 images and a test set with 4,925 images. The images are separated into five groups with ages of 11-20, 21-30, 31-40, 41-50 and 50+.

Three Age Stages Dataset (TASD). 35,416 images, with both identity label and age label, are divided into three part, including young, middle-aged and elder.

Method

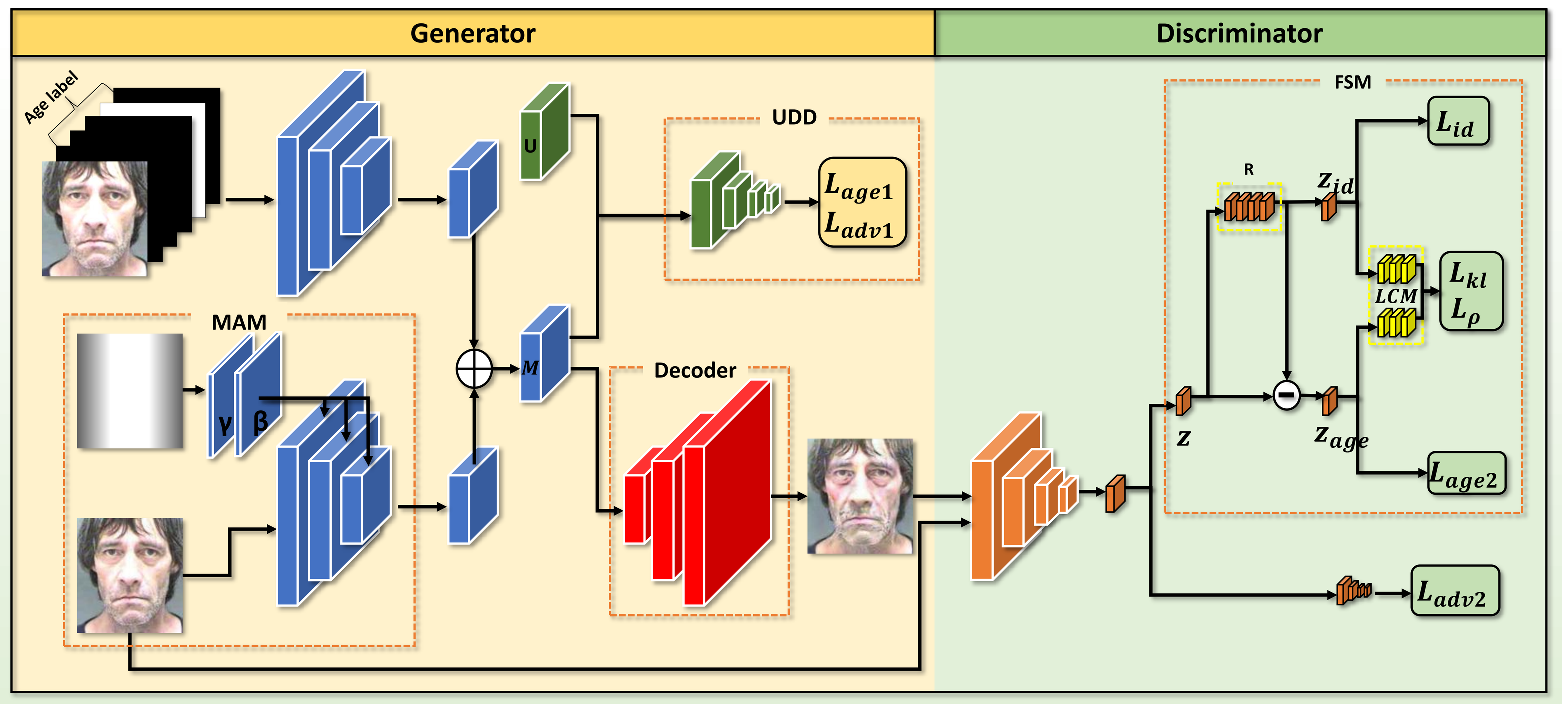

Fig: The overview of the proposed SATGAN.

Modules

MAM:

$$Pixel = \begin{cases} 100 + \left(\dfrac{255-100}{40-0}\right)x & 0 \ll x \ll 40 \\ 255 & 40 < x < 88 \\ 255 - \left(\dfrac{255-100}{40-0}\right)(x-88) & 88 \ll x \ll 128 \end{cases}$$

UDD:

$$L_{adv1} = E_M[D_1(M)] - E_U[D_1(U)]$$

$$L_{age1} = E_{M,c_{trg}}[-log D_1(c_{trg}|M)]$$

FSM:

$$L_{kl} = \frac{1}{N}\sum_i \sum_j l_{age}(j)\, log\left(\frac{l_{age}(j)}{l_{id}(j)}\right)$$

$$L_p = -\frac{1}{N}\sum_i \frac{Cov(l_{age}, l_{id})}{\sqrt{Var(l_{age})Var(l_{id})}}$$

Ablation Study

Fig: Translation result for SATGAN with/without different modules.

Results of Age Translation on Morph

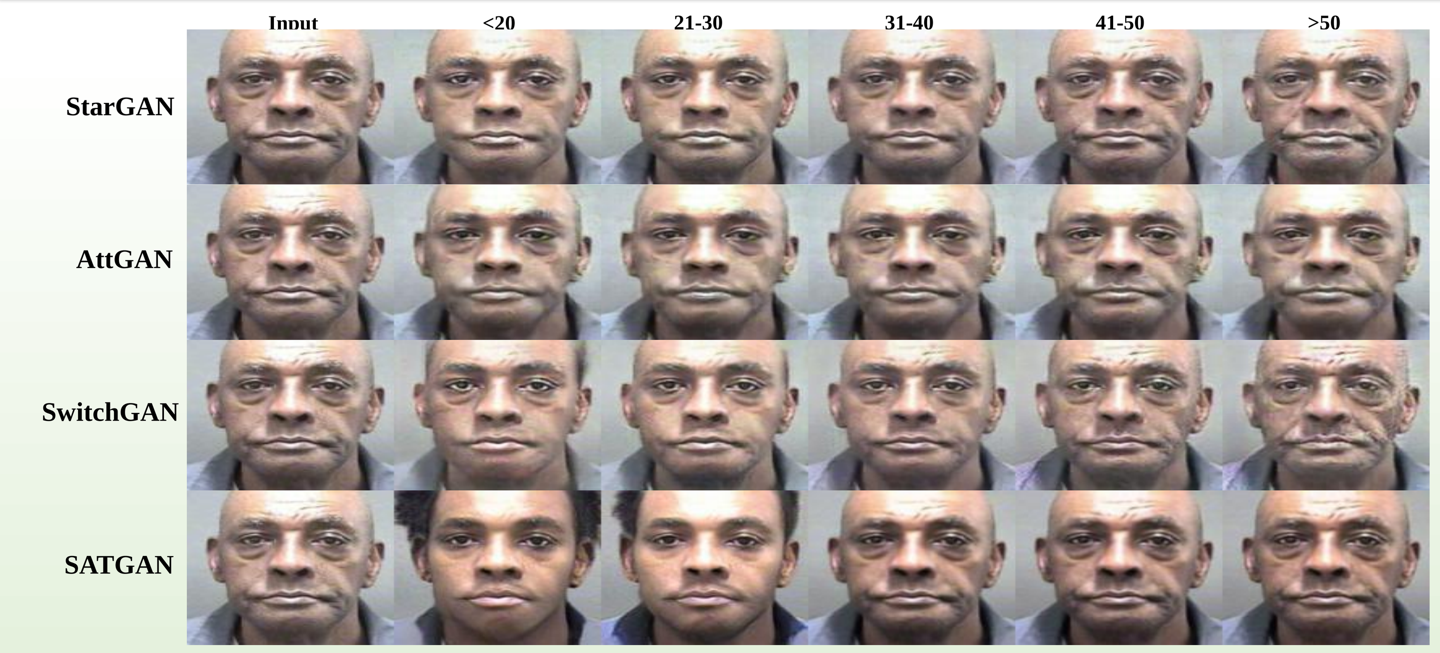

Fig: Results of age progression and regression .

Method	Accuracy(%)	FID score
StarGAN	59.70	13.83
AttGAN	57.21	10.34
SwitchGAN	85.38	6.87
SATGAN	**90.53**	**6.22**

Tab: Results of the GAN based models.

Results of CAFR on CALFW

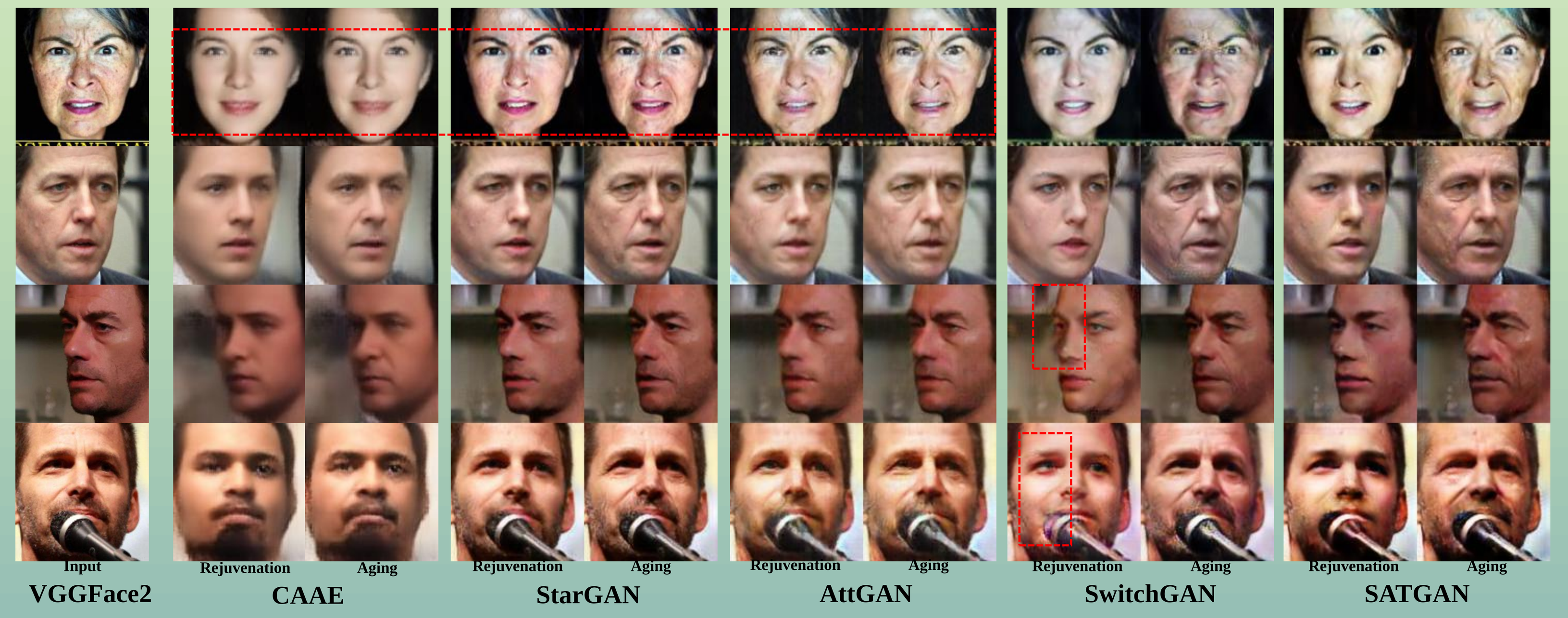

Fig: Visual comparison of different models on VGGFace2

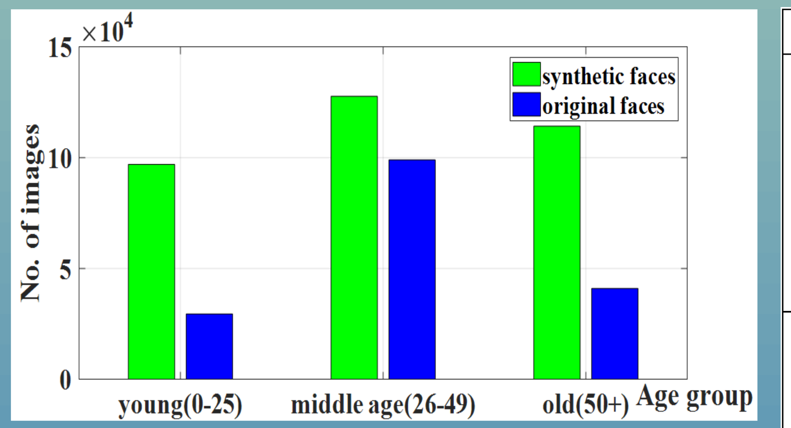

Fig: The age distribution.

Method	CALFW	AgeDB-30
SphereFace [4]	90.30	97.56
VGGFace2 [24]	90.57	-
ConsineFace [5]	-	97.91
ArcFace [6]	95.87	98.08
PyTorch Implementation of ArcFace		
Original MS1M	95.78	98.10
Augmented MS1M	**95.92**	**98.43**

Tab: Comparison with SOTA.

Size	Subset	Model	Result
Small	Original	-	68.15
	Augmented	CAAE	63.40
		StarGAN	67.85
		AttGAN	68.12
		SwitchGAN	68.38
		SATGAN	**70.20**
Medium	Original	-	77.22
	Augmented	CAAE	68.45
		StarGAN	77.38
		AttGAN	78.13
		SwitchGAN	78.03
		SATGAN	**79.08**
Large	Original	-	81.82
	Augmented	CAAE	75.08
		StarGAN	82.27
		AttGAN	82.15
		SwitchGAN	82.75
		SATGAN	**83.40**

Tab: ACC(%) on CALFW.