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## Supplementary materials for: Towards Open-Set Identity Preserving Face Synthesis

Anonymous CVPR submission

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### 1. Analysis of $\lambda$

The hyper parameter  $\lambda$  in Equation (2) in the paper influence the capability of maintaining the attributes. In this section, we conduct an experiment to investigate the sensitivity of parameter  $\lambda$ .

In the experiment, we use the same framework structure and training strategy, and vary  $\lambda$  from 0.01 to 1 to learn different models. We compare the face synthesis results of these models in Figure 1. It shows that  $\lambda$  influence the capability of the framework for maintaining attributes. When  $\lambda = 0.01$ , the generated images lose the attributes details, especially the emotion. When  $\lambda = 1$ , the generated images have many artifacts. On the other hand, the generated images using  $\lambda = 0.1$  are realistic and maintain the attributes. Therefore, a small value of  $\lambda$  cause the generated images losing the given attributes, a big value of  $\lambda$  cause the generated images have many artifacts. Therefore, we choose  $\lambda = 0.1$  to maintain the attributes and realism of the generated images in our experiment.

### 2. Face Synthesis using Random Noise as Attributes

In our framework, the attributes distribution is regularize to a prior distribution  $P(z) \sim N(0, 1)$  by the loss function  $\mathcal{L}_{KL}$ . So we can sample the attribute vector  $z_A$  from the prior distribution as the attributes to generate face images.

With the random noise as the attributes, Figure 2 shows the face synthesize results on the identities appeared in training dataset. Our framework demonstrate good performance for synthesizing diverse, realistic and identity-preserving face images.

Another important feature of our method is that it can synthesize unseen faces from the training set. Figure 3 shows the zero-shot identities face synthesis results. With the random noise as the attributes, our framework can also generate high quality face images which keep the identity of the given faces.

### 3. More Face Morphing Results

In this section, we conduct face morphing on more complicate attributes. Please refer to the video for the detail.

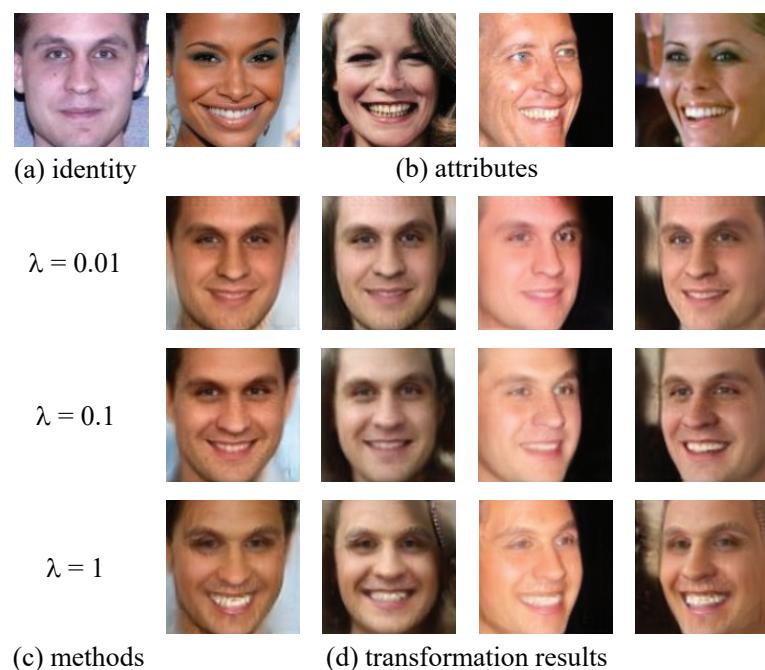
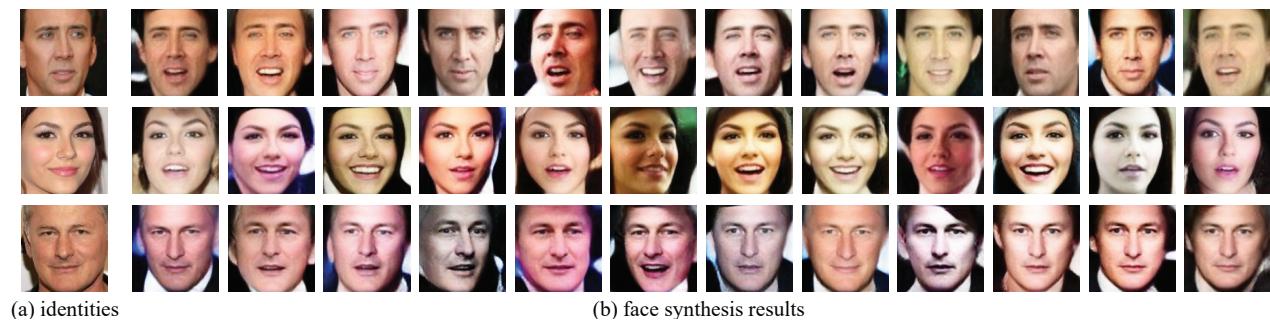
Figure 1. Model comparison: face synthesis results using the framework training with different  $\lambda$ .

Figure 2. Face synthesis results using the identities appeared in training dataset and random noise as attributes.

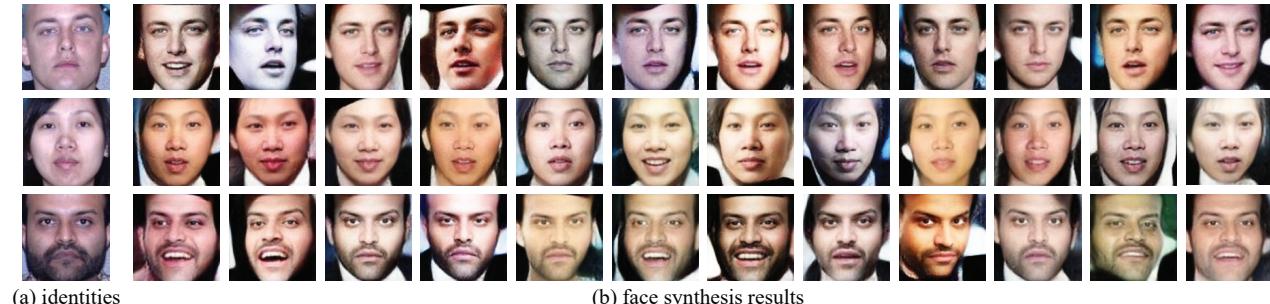


Figure 3. Face synthesis results using zero-shot identities and random noise as attributes.