# Group-wise Feature Orthogonalization and Suppression for GAN based Facial Attribute Translation 

Zhiwei Wen, Haoqian Wu, Weicheng and Linlin Shen
Computer Vision Institute, Shenzhen University

## Outline

1. Background
2. Methods
3. Experimental Results
4. Conclusions

## Background

- Attribute entanglement
- Poor generalization ability



## Motivation

- Excavate semantic attributes
- Outlier feature maps

(a) Input

(b) Face

(c) Hair

(d) Background

(e) Input

(f) Outlier FM
(g) Without FM Sup.

(h) Normal FM
(i) With FM Sup.


## Methods

1. Group-wise feature orthogonality
2. Intersection feature suppression
3. Constrained by the two methods

## Methods

## The framework of the proposed methods



## Methods

## - Feature Map Encoding and Clustering

- the runtime costs largely reduced
- excavate semantic attributes



## Methods

## Group-wise Feature Orthogonality and Suppression

(1) $\quad \mathcal{L}_{G O}=\frac{2}{m(m-1)} \Sigma_{i} \Sigma_{j} g_{i}^{T} g_{j}$ :
(2) $\quad d_{i}=\left\|f_{i}-\frac{1}{N^{(r)}} \sum_{j} f_{j}\right\|_{2} \sim \mathcal{N}\left(0, \frac{\gamma}{\sqrt{2 n} N^{(r)}}\right)$


## Methods

Network loss function

$$
\left\{\begin{array}{l}
\mathcal{L}_{\text {drop }}=E_{x, c^{\prime}}\left[\left\|G\left(x, c^{\prime}\right)-G_{\text {drop }}\left(x, c^{\prime}\right)\right\|_{1}\right] \\
\mathcal{L}_{\text {rec }}=E_{x, c, c^{\prime}}\left[\left\|x-G_{\text {drop }}\left(G\left(x, c^{\prime}\right), c\right)\right\|_{1}\right] \\
\mathcal{L}_{G}=\mathcal{L}_{O r i G}+\lambda_{\text {drop }} \mathcal{L}_{\text {drop }}+\lambda_{\text {rec }} \mathcal{L}_{r e c}+\lambda_{G O} \mathcal{L}_{G O} \\
\mathcal{L}_{D}=\mathcal{L}_{O r i D}
\end{array}\right.
$$

## Experiment

- Baselines and Dataset
- StarGAN ${ }^{[1]}$, AttGAN ${ }^{[2]}$

[1] Stargan: Unified generative adversarial networks for multi-domain image-to-image translation. In: CVPR (2018).
[2] Zhenliang He, et al.: Attgan: Facial attribute editing by only changing what you want. In: TIP (2019).


## Experiment

- Hash Encoding
- Does not cause Information degradation
- The runtime costs largely reduced

Based on StarGAN+GO+IFS for RaFD

- GO(Group-wise orthogonality), IFS(Intersection feature suppression)

| Method | Accuracy $\uparrow$ | IS $\uparrow$ | FID $\downarrow$ | RT $\downarrow$ |
| :---: | :---: | :---: | :---: | :---: |
| Hash encoding | $98.41 \%$ | $\mathbf{2 . 7 7 0}$ | $\mathbf{4 3 . 5 1}$ | $\mathbf{0 . 1 0 2}$ |
| PCA | $98.21 \%$ | 2.769 | 44.71 | 0.261 |
| Direct vectorization | $\mathbf{9 8 . 8 1 \%}$ | 2.759 | 46.92 | 1.289 |

$\uparrow$ means larger numbers are preferred, $\downarrow$ means opposite.

## Visual Results

- Two orthogonality strategies

(a) Input
(b) StarGAN
(c) Feature map-
(d) Group-wise wise orthogonality orthogonality
- Intersection feature suppression



## Visual Results

- Ablation study
- IFS (intersection feature suppression)
- GO (group-wise orthogonality )



## Visual Results

- Hair color translation



## Visual Results

- Comparison with StarGAN and AttGAN



## Quantitative Results

- CelebA and RaFD

| Meas. | Method | Black | Blond | Brown | Gender | Age |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Acc. $\uparrow$ | StarGAN | 66.77 | $\mathbf{7 8 . 9 8}$ | 55.96 | 60.06 | $\mathbf{6 3 . 4 6}$ |
|  | Ours | $\mathbf{7 8 . 0 8}$ | 71.37 | $\mathbf{6 3 . 7 6}$ | $\mathbf{6 3 . 0 6}$ | 63.36 |
|  | AttGAN | 50.55 | 31.23 | 34.33 | 63.96 | 58.16 |
|  | Ours | $\mathbf{5 5 . 1 6}$ | $\mathbf{4 2 . 1 4}$ | $\mathbf{3 6 . 0 4}$ | $\mathbf{6 5 . 9 7}$ | $\mathbf{6 9 . 3 7}$ |
| IS $\uparrow$ | StarGAN | 1.178 | 1.182 | 1.014 | 1.200 | 1.122 |
|  | Ours | $\mathbf{1 . 2 0 4}$ | $\mathbf{1 . 2 3 7}$ | $\mathbf{1 . 0 3 3}$ | $\mathbf{1 . 2 2 1}$ | $\mathbf{1 . 1 2 7}$ |
|  | AttGAN | 1.317 | 1.329 | 1.131 | 1.310 | 1.111 |
|  | Ours | $\mathbf{1 . 3 3 1}$ | $\mathbf{1 . 3 4 4}$ | $\mathbf{1 . 1 5 7}$ | $\mathbf{1 . 3 2 5}$ | $\mathbf{1 . 1 2 1}$ |
| FID $\downarrow$ | StarGAN | 65.90 | 93.06 | 71.28 | 105.06 | 85.58 |
|  | Ours | $\mathbf{5 8 . 8 6}$ | $\mathbf{7 9 . 9 2}$ | $\mathbf{6 4 . 8 6}$ | $\mathbf{1 0 1 . 7 3}$ | $\mathbf{7 6 . 6 8}$ |
|  | AttGAN | 62.29 | 84.94 | 66.41 | 101.03 | 82.56 |
|  | Ours | $\mathbf{5 6 . 6 3}$ | $\mathbf{8 2 . 5 1}$ | $\mathbf{6 0 . 9 7}$ | $\mathbf{9 8 . 7 8}$ | $\mathbf{7 8 . 0 6}$ |

$\uparrow$ means larger numbers are preferred, $\downarrow$ means opposite.

| Method | Accuracy $\uparrow$ | IS $\uparrow$ | FID $\downarrow$ |
| :---: | :---: | :---: | :---: |
| StarGAN | $97.62 \%$ | 2.516 | 46.59 |
| Star $G A N+I F S$ | $97.02 \%$ | 2.673 | 46.53 |
| StarGAN+GO | $97.62 \%$ | 2.617 | 44.56 |
| Star $G A N+I F S+G O$ | $\mathbf{9 8 . 4 1 \%}$ | $\mathbf{2 . 7 7 0}$ | $\mathbf{4 3 . 5 1}$ |
| AttGAN | $65.48 \%$ | 2.785 | 60.39 |
| AttGAN+IFS | $69.84 \%$ | 2.803 | 51.02 |
| AttGAN+GO | $70.63 \%$ | 2.827 | $\mathbf{5 0 . 0 1}$ |
| AttGAN $+I F S+G O$ | $\mathbf{7 3 . 0 2 \%}$ | $\mathbf{2 . 9 1 8}$ | 53.24 |

$\uparrow$ means larger numbers are preferred, $\downarrow$ means opposite.

## Generalization Performances

- Visual and quantitative results

CelebA and RaFD are used for training and testing

Input

Blond
Hair


Brown Hair


Gender
Age

| Metric | Method | Black | Blond | Brown | Gender | Age |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Acc. $\uparrow$ | StarGAN | 53.75 | $\mathbf{6 2 . 5 0}$ | 57.29 | 70.63 | 66.67 |
|  | Ours | $\mathbf{8 0 . 4 2}$ | 50.63 | $\mathbf{6 0 . 6 3}$ | $\mathbf{7 4 . 7 9}$ | $\mathbf{7 7 . 5 0}$ |
|  | AttGAN | 56.46 | $\mathbf{1 5 . 8 3}$ | 43.33 | 41.04 | 50.42 |
|  | Ours | $\mathbf{5 9 . 1 7}$ | 11.46 | $\mathbf{4 9 . 5 8}$ | $\mathbf{4 4 . 3 8}$ | $\mathbf{7 4 . 3 8}$ |
| IS $\uparrow$ | StarGAN | 1.192 | 1.083 | 1.003 | 1.126 | 1.067 |
|  | Ours | $\mathbf{1 . 2 1 1}$ | $\mathbf{1 . 0 8 7}$ | $\mathbf{1 . 0 2 4}$ | $\mathbf{1 . 1 7 6}$ | $\mathbf{1 . 0 7 8}$ |
|  | AttGAN | 1.238 | 1.050 | 1.180 | 1.028 | 1.069 |
|  | Ours | $\mathbf{1 . 2 7 6}$ | $\mathbf{1 . 0 5 2}$ | $\mathbf{1 . 1 8 3}$ | $\mathbf{1 . 0 5 0}$ | $\mathbf{1 . 0 8 2}$ |
| FID $\downarrow$ | StarGAN | 138.74 | 169.35 | 150.26 | 176.01 | 188.59 |
|  | Ours | $\mathbf{1 3 6 6 . 8 5}$ | $\mathbf{1 6 3 . 4 9}$ | $\mathbf{1 4 2 . 7 8}$ | $\mathbf{1 6 1 . 1 0}$ | $\mathbf{1 7 2 . 4 6}$ |
|  | AttGAN | $\mathbf{1 3 8 . 9 7}$ | 191.56 | $\mathbf{1 5 2 . 3 4}$ | 184.23 | 171.03 |
|  | Ours | 139.43 | $\mathbf{1 8 4 . 7 3}$ | 154.79 | $\mathbf{1 7 0 . 2 3}$ | $\mathbf{1 5 6 . 6 9}$ |

$\uparrow$ means larger numbers are preferred, $\downarrow$ means opposite.

## Conclusions

1. group-wise orthogonalization and intersection feature suppression.
2. semantic attribute disentanglement improve network generalization ability.
3. synthesize much more genuine images and significantly less abnormality.
