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

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Introduction

Generative Adversarial Network (GAN) has been widely used for object attribute editing. However, the semantic correlation, resulted from the feature map interaction in the generative network of GAN, may impair the generalization ability of the generative network.

In this work, semantic disentanglement is introduced in GAN to reduce the attribute correlation. Meanwhile, the feature maps in the intersection regions are further suppressed to reduce the attribute-wise interaction.

Contribution

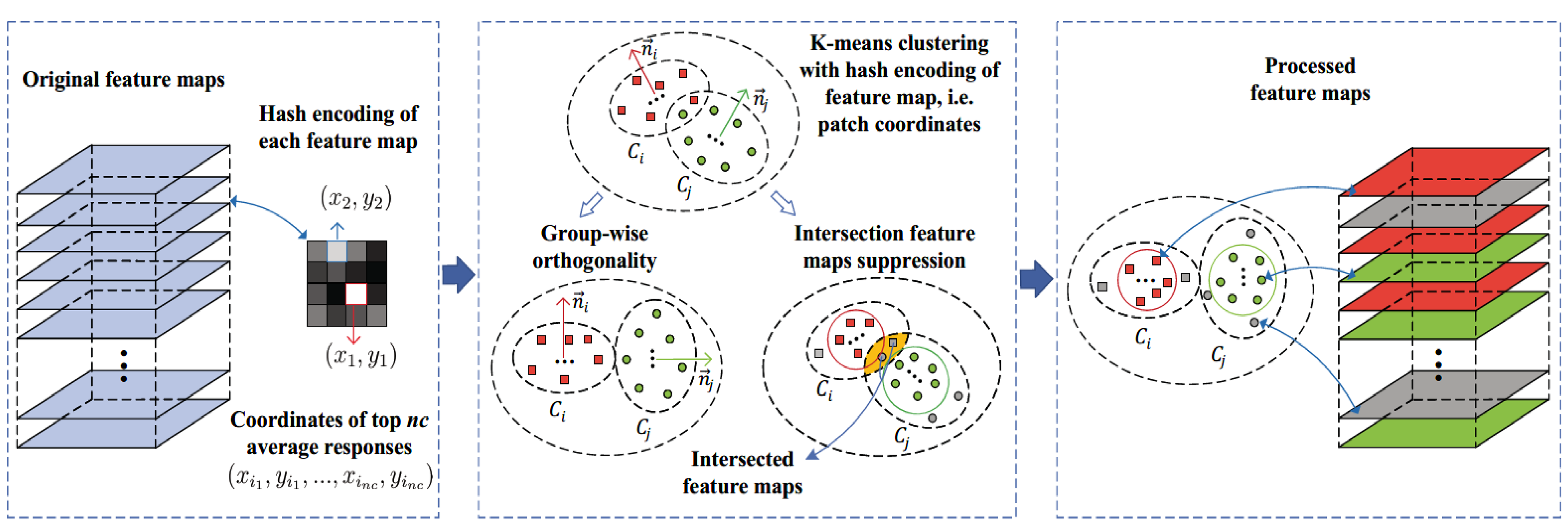
Hash Encoding: Feature map clustering is proposed to excavate semantic attributes and reduce their correlation based on an effective encoding of the feature maps.

Semantic Disentanglement: Group-wise orthogonality and intersection feature suppression are proposed to reduce attribute interaction.

Generalization Performances: Better generalization performances on visual and quantitative results are achieved by the proposed GAN.

Proposed Method

- **The framework of the proposed GAN**

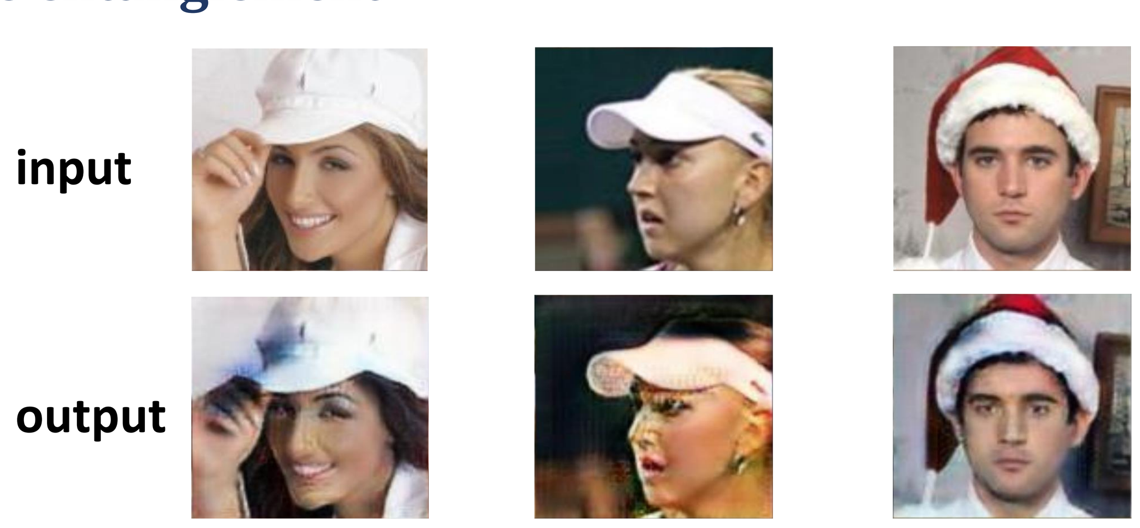


(a) (b) (c) (d)

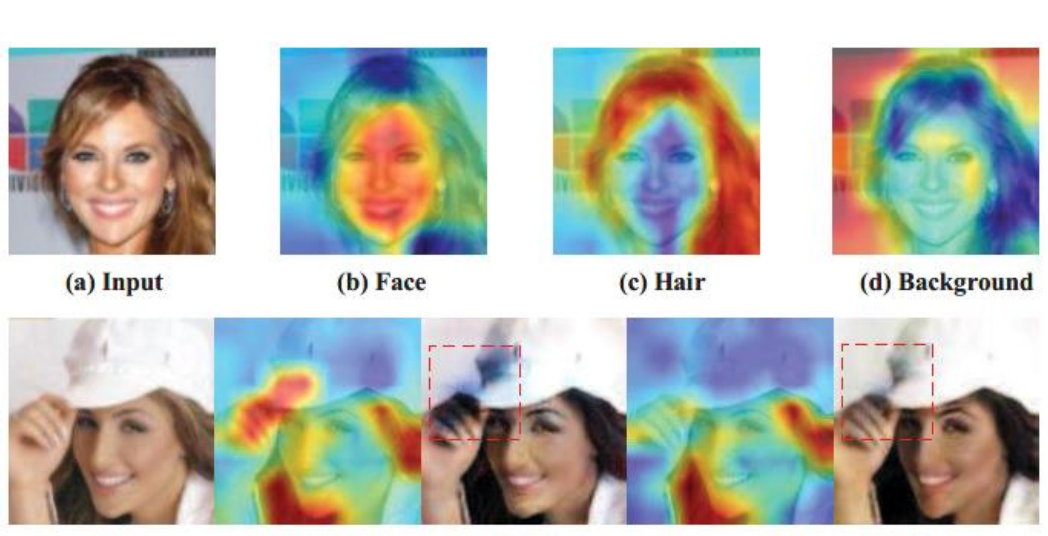
- **Network loss function**

$$
\begin{cases}
\mathcal{L}_{drop} = E_{x,c'}[||G(x,c') - G_{drop}(x,c')||_1], \\
\mathcal{L}_{rec} = E_{x,c,c'}[||x - G_{drop}(G(x,c'),c)||_1], \\
\mathcal{L}_G = \mathcal{L}_{OriG} + \lambda_{drop}\mathcal{L}_{drop} + \lambda_{rec}\mathcal{L}_{rec} + \lambda_{GO}\mathcal{L}_{GO}, \\
\mathcal{L}_D = \mathcal{L}_{OriD}.
\end{cases}
$$

- **Attribute entanglement**



- **Excavate semantic attributes**



Experiment

- **Hash Encoding**

Method	Accuracy ↑	IS ↑	FID ↓	RT ↓
Hash encoding	98.41%	**2.770**	**43.51**	**0.102**
PCA	98.21%	2.769	44.71	0.261
Direct vectorization	**98.81%**	2.759	46.92	1.289

↑ means larger numbers are preferred, ↓ means opposite.

- **CelebA and RaFD**

Meas.	Method	Black	Blond	Brown	Gender	Age
Acc. ↑	*StarGAN*	66.77	**78.98**	55.96	60.06	**63.46**
	Ours	**78.08**	71.37	**63.76**	**63.06**	63.36
	AttGAN	50.55	31.23	34.33	63.96	58.16
	Ours	**55.16**	**42.14**	**36.04**	**65.97**	**69.37**
IS ↑	*StarGAN*	1.178	1.182	1.014	1.200	1.122
	Ours	**1.204**	**1.237**	**1.033**	**1.221**	**1.127**
	AttGAN	1.317	1.329	1.131	1.310	1.111
	Ours	**1.331**	**1.344**	**1.157**	**1.325**	**1.121**
FID ↓	*StarGAN*	65.90	93.06	71.28	105.06	85.58
	Ours	**58.86**	**79.92**	**64.86**	**101.73**	**76.68**
	AttGAN	62.29	84.94	66.41	101.03	82.56
	Ours	**56.63**	**82.51**	**60.97**	**98.78**	**78.06**

↑ means larger numbers are preferred, ↓ means opposite.

Method	Accuracy ↑	IS ↑	FID ↓
StarGAN	97.62%	2.516	46.59
StarGAN+IFS	97.02%	2.673	46.53
StarGAN+GO	97.62%	2.617	44.56
StarGAN+IFS+GO	**98.41%**	**2.770**	**43.51**
AttGAN	65.48%	2.785	60.39
AttGAN+IFS	69.84%	2.803	51.02
AttGAN+GO	70.63%	2.827	**50.01**
AttGAN+IFS+GO	**73.02%**	**2.918**	53.24

↑ means larger numbers are preferred, ↓ means opposite.

- **Generalization Performances**

Metric	Method	Black	Blond	Brown	Gender	Age
Acc. ↑	*StarGAN*	53.75	**62.50**	57.29	70.63	66.67
	Ours	**80.42**	50.63	**60.63**	**74.79**	**77.50**
	AttGAN	56.46	**15.83**	43.33	41.04	50.42
	Ours	**59.17**	11.46	**49.58**	**44.38**	**74.38**
IS ↑	*StarGAN*	1.192	1.083	1.003	1.126	1.067
	Ours	**1.211**	**1.087**	**1.024**	**1.176**	**1.078**
	AttGAN	1.238	1.050	1.180	1.028	1.069
	Ours	**1.276**	**1.052**	**1.183**	**1.050**	**1.082**
FID ↓	*StarGAN*	138.74	169.35	150.26	176.01	188.59
	Ours	**136.85**	**163.49**	**142.78**	**161.10**	**172.46**
	AttGAN	**138.97**	191.56	**152.34**	184.23	171.03
	Ours	139.43	**184.73**	154.79	**170.23**	**156.69**

↑ means larger numbers are preferred, ↓ means opposite.

Visual Results