



Controllable Face Privacy

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Leading The World With Asia's Best



Joe, Male,
Caucasian, Young



Existing de-
identification
methods





Joe, Male,
Caucasian, Young



Existing de-identification methods



Face
Recognition

?

Gender
Detector

?

Race
Detector

?

Age
Detector

?



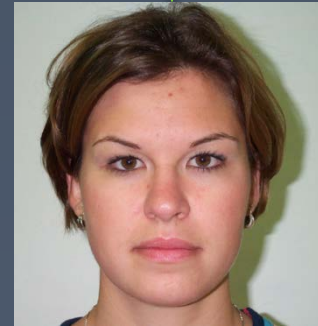
Joe, Male,
Caucasian, Young



Controllable
Privacy Protection



selective alteration



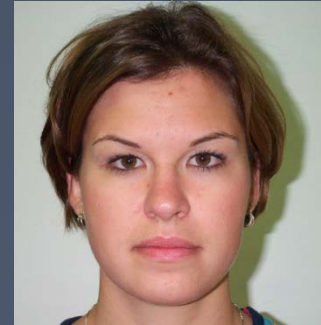


Joe, Male,
Caucasian, Young



Controllable
Privacy Protection

selective alteration



Face
Recognition

Mary

Gender
Detector

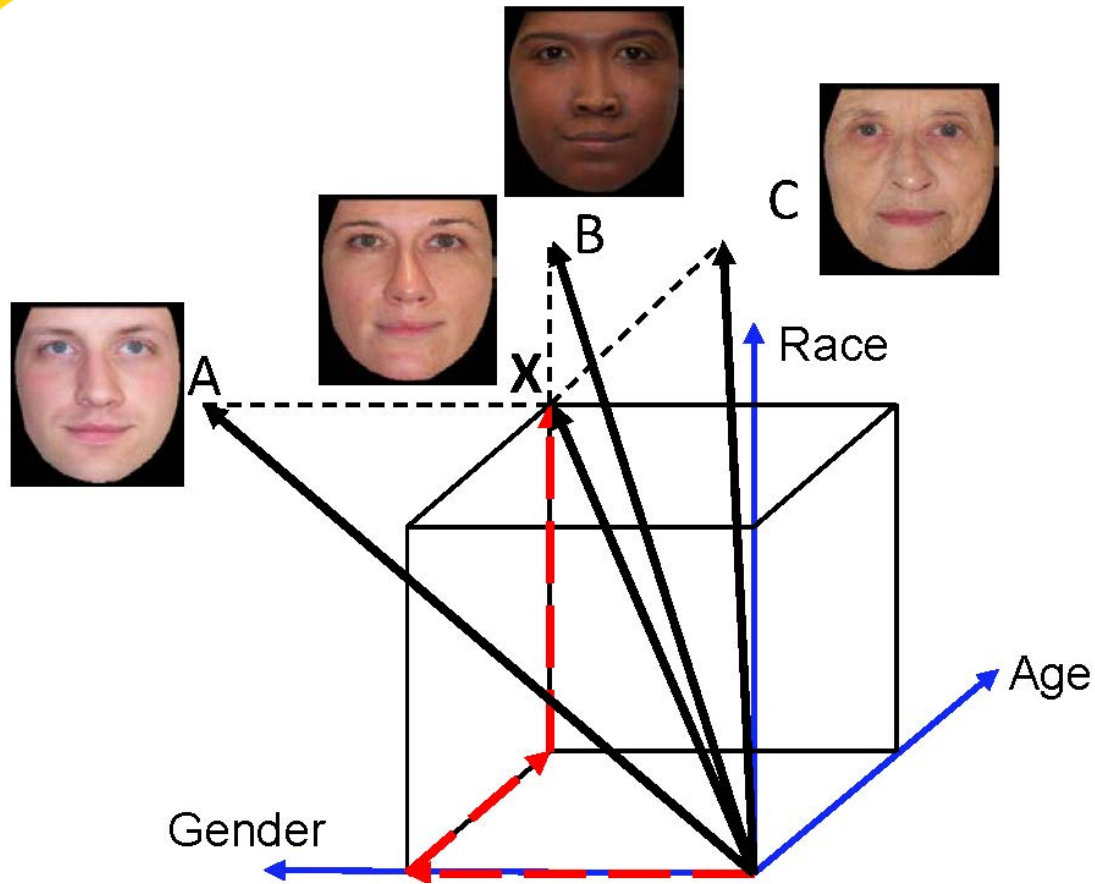
Female

Race
Detector

Caucasian

Age
Detector

Young



Orthogonal subspace decomposition

Semantic Faces

input



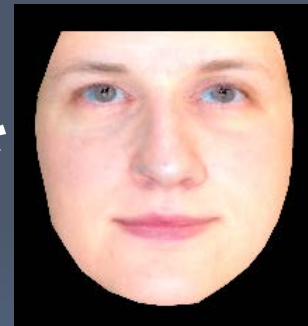
$$= g^*$$



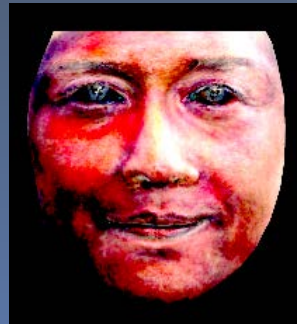
$$\oplus r_1^*$$



$$\oplus r_2^*$$



$$\oplus a_1^*$$

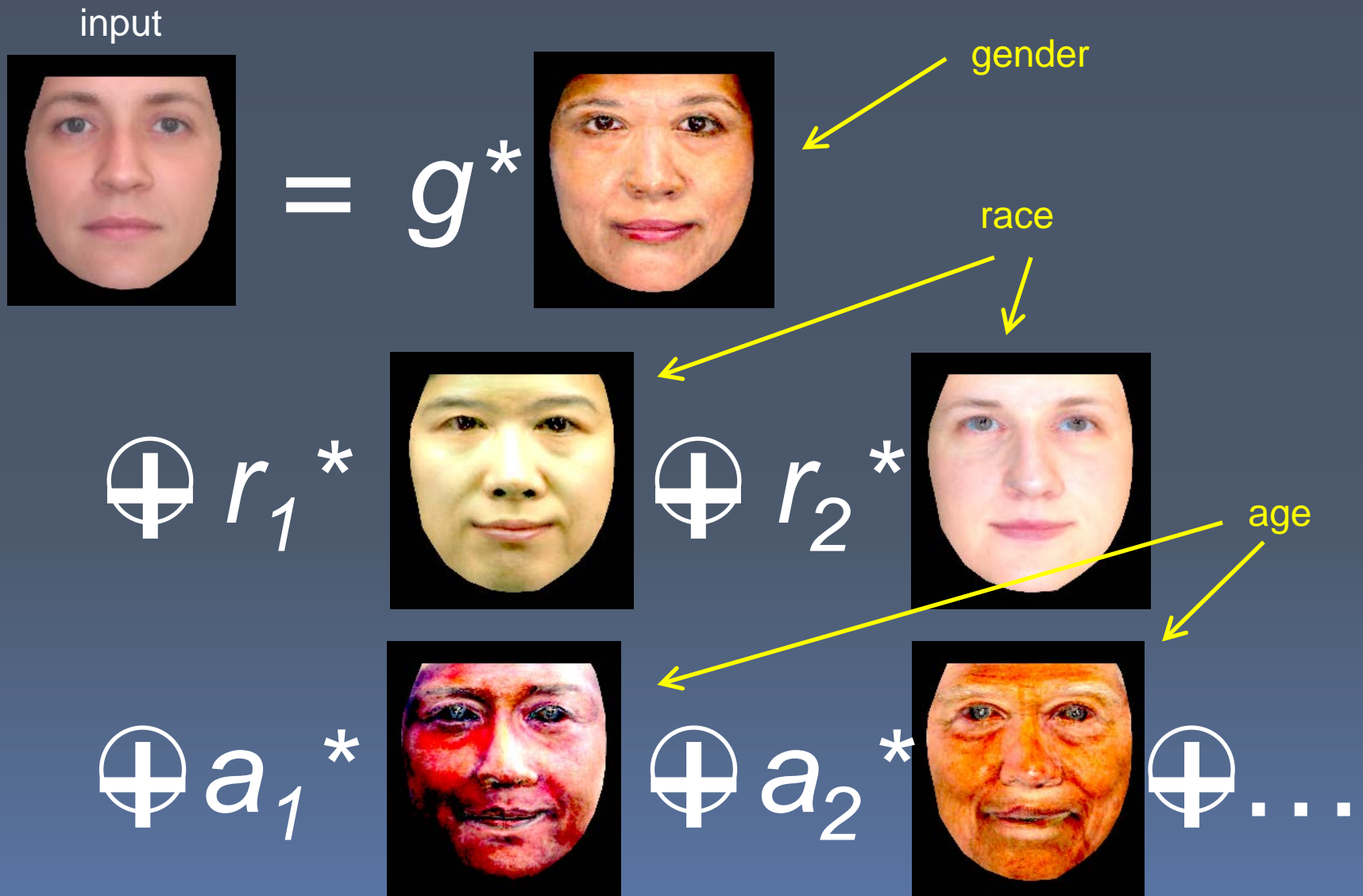


$$\oplus a_2^*$$



$$\oplus \dots$$

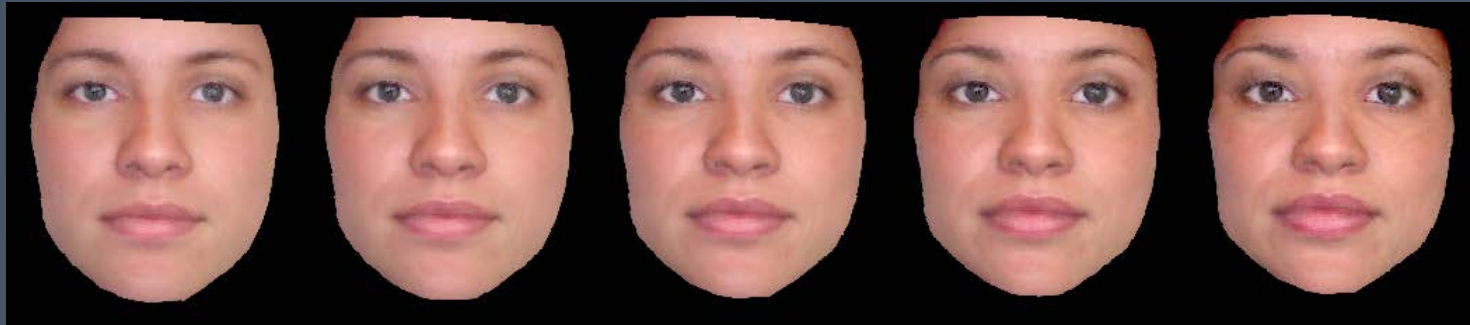
Semantic Faces



Increasing
Femininity



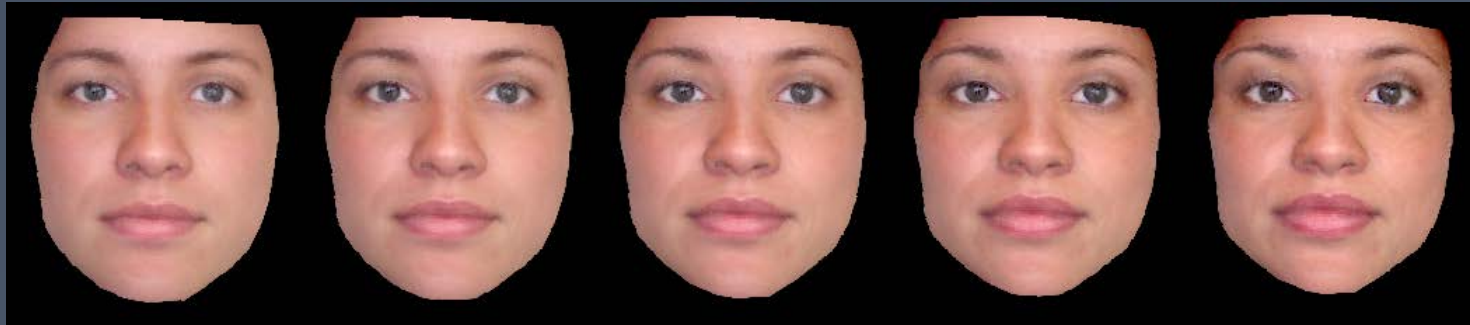
Increasing
Femininity



Intensifying
"African"-ness



Increasing
Femininity



Intensifying
"African"-ness



Growing
older



How to learn Semantic Faces?

[Sim et al., ICCV 2009]

Multimodal Discriminant Analysis



Key Idea



repeated Fisher Linear Discriminant
analysis

N=18 Labeled Training images

Gender: Male, Female

Race: Caucasian, African, Oriental

Age: Young, Middle-aged, Old



Data matrix



...

Encoding



$Z =$



...



1. Center to mean

$$\mathbf{X} = \mathbf{Z} - \mathbf{M}$$

2. Whiten

$$\tilde{\mathbf{X}} = \mathbf{P}^{\top} \mathbf{X}$$

where $\mathbf{X}\mathbf{X}^{\top} = \mathbf{U}\mathbf{D}\mathbf{U}^{\top}$
 $\mathbf{P} = \mathbf{U}\mathbf{D}^{-1/2}$

3. For each mode $i = \{\text{gender, race, age}\}$, compute between-class and within-class scatter matrices on : $\tilde{\mathbf{X}}$

$$\mathbf{S}_b^i, \mathbf{S}_w^i$$

4. Maximize Fisher Criterion

$$\mathbf{J}_F(\mathbf{V}^i) = \frac{(\mathbf{V}^i)^\top \mathbf{S}_b^i (\mathbf{V}^i)}{(\mathbf{V}^i)^\top \mathbf{S}_w^i (\mathbf{V}^i)}$$

5. Form matrix

$$\mathbf{V} = [\mathbf{V}^{gender} \ \mathbf{V}^{race} \ \mathbf{V}^{age} \ \mathbf{V}^0]$$

5. Form matrix

$$\mathbf{V} = [\mathbf{V}^{gender} \mathbf{V}^{race} \mathbf{V}^{age} \mathbf{V}^0]$$

Residual Space

- \mathbf{V} is an $(N-1) \times (N-1)$ orthogonal matrix, whose columns are the bases for the gender (1-dim), race (2-dim) and age (2-dim) subspaces.
- These subspaces capture the variations of gender, race and age, respectively.
- Residual space is 12-dim, and captures facial identity.

6. Decomposition

$$\mathbf{y} = \mathbf{V}^\top \mathbf{P}^\top \mathbf{x}$$

$$\mathbf{y}^\top = [g \quad r_1 \quad r_2 \quad a_1 \quad a_2 \quad \mathbf{s}^\top]$$

gender

race

age

residual

Semantic Faces

input



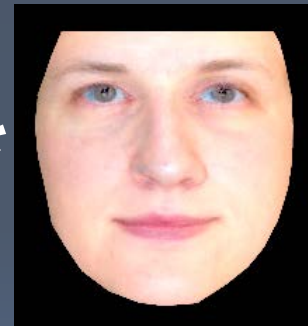
$$= g^*$$



$$\oplus r_1^*$$



$$\oplus r_2^*$$



$$\oplus a_1^*$$



$$\oplus a_2^*$$



$$\oplus \dots$$

7. Synthesis

$$\mathbf{x}' = \mathbf{P}_r \mathbf{y}' = \mathbf{Q} \mathbf{y}'$$

This equation allows the synthesis of new faces.

$$\mathbf{P}_r = \mathbf{U} \mathbf{D}^{1/2}$$

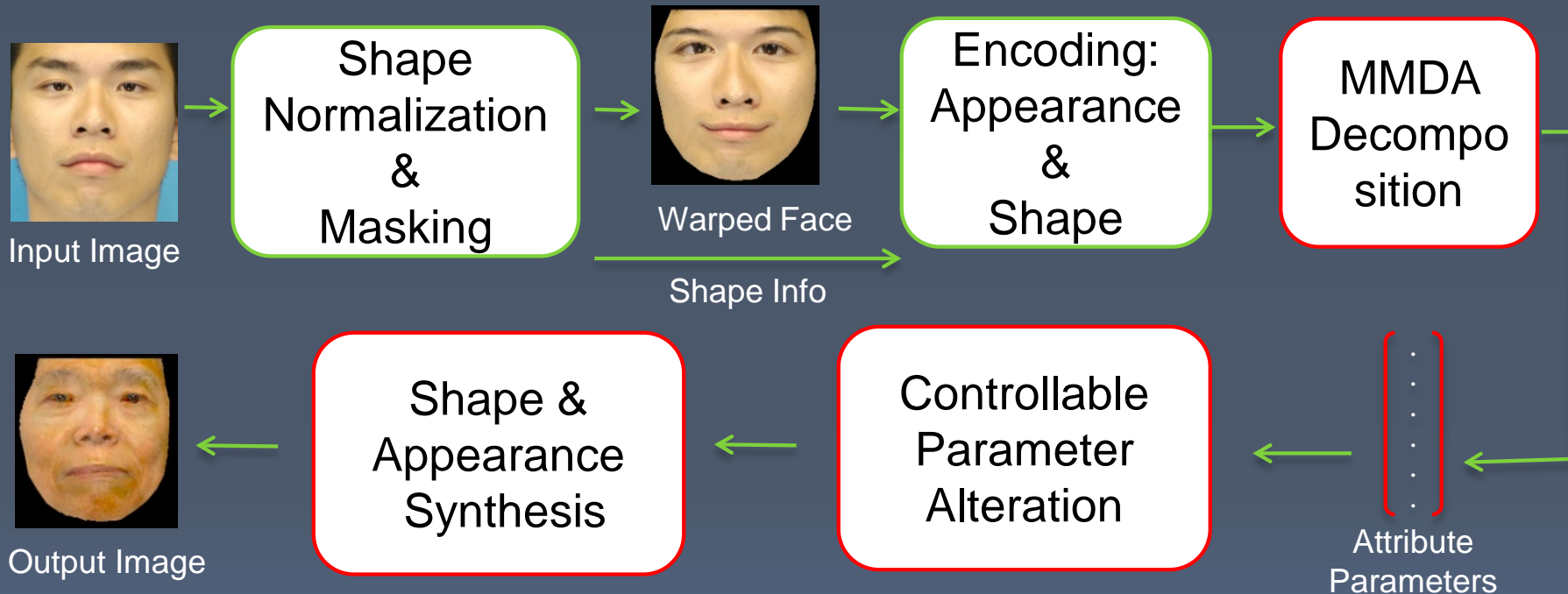
Undoes the whitening operation

Visualizing Q

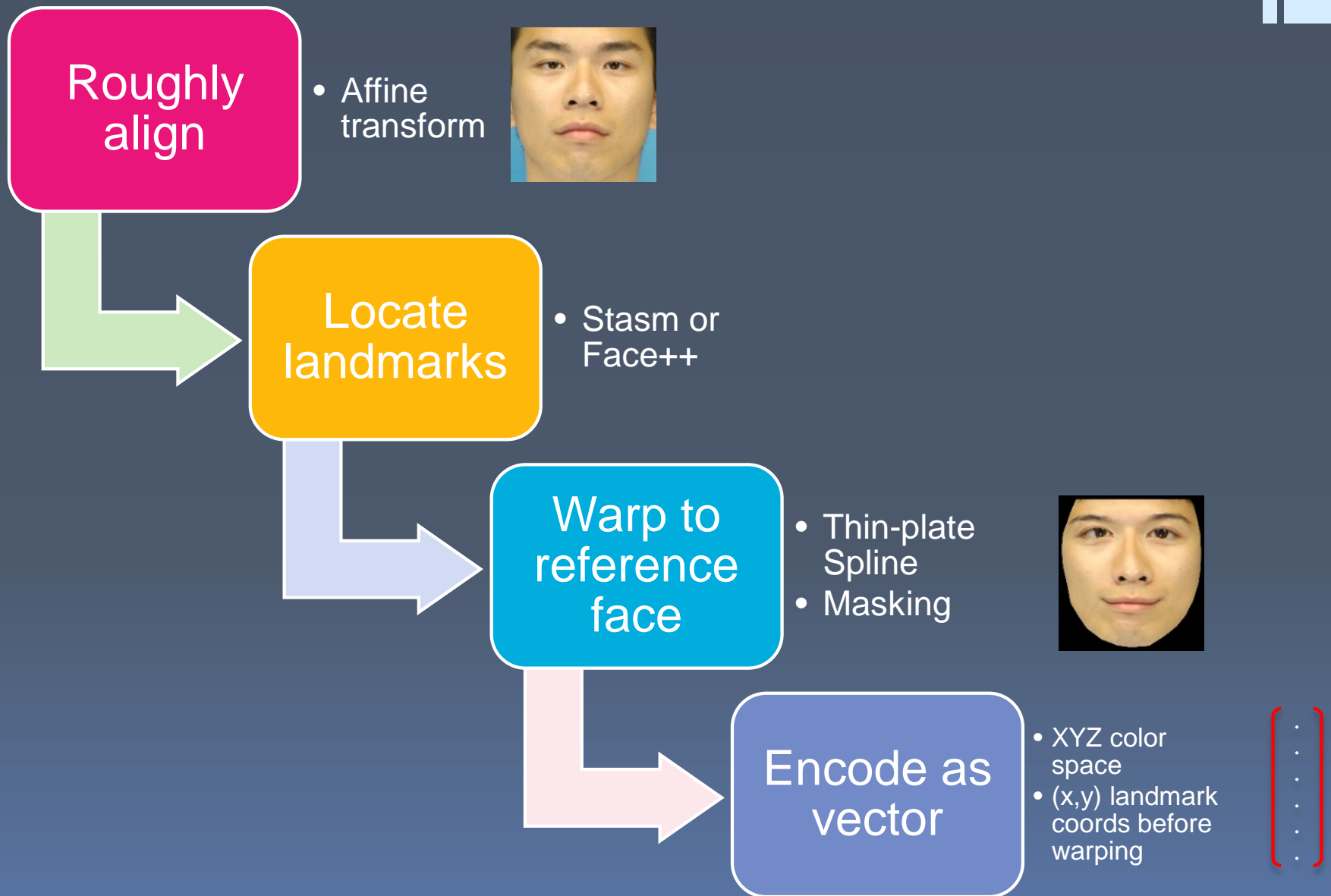


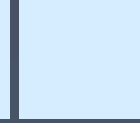
Taking appropriate linear combinations of these Semantic Faces will alter gender, race, age, and identity.

Algorithm overview



Face normalization & encoding





Results

Altering 2 attributes

Original

1.0

2.0

Gender + Age



Race + Gender



Race + Age



Altering 3 attributes

Original

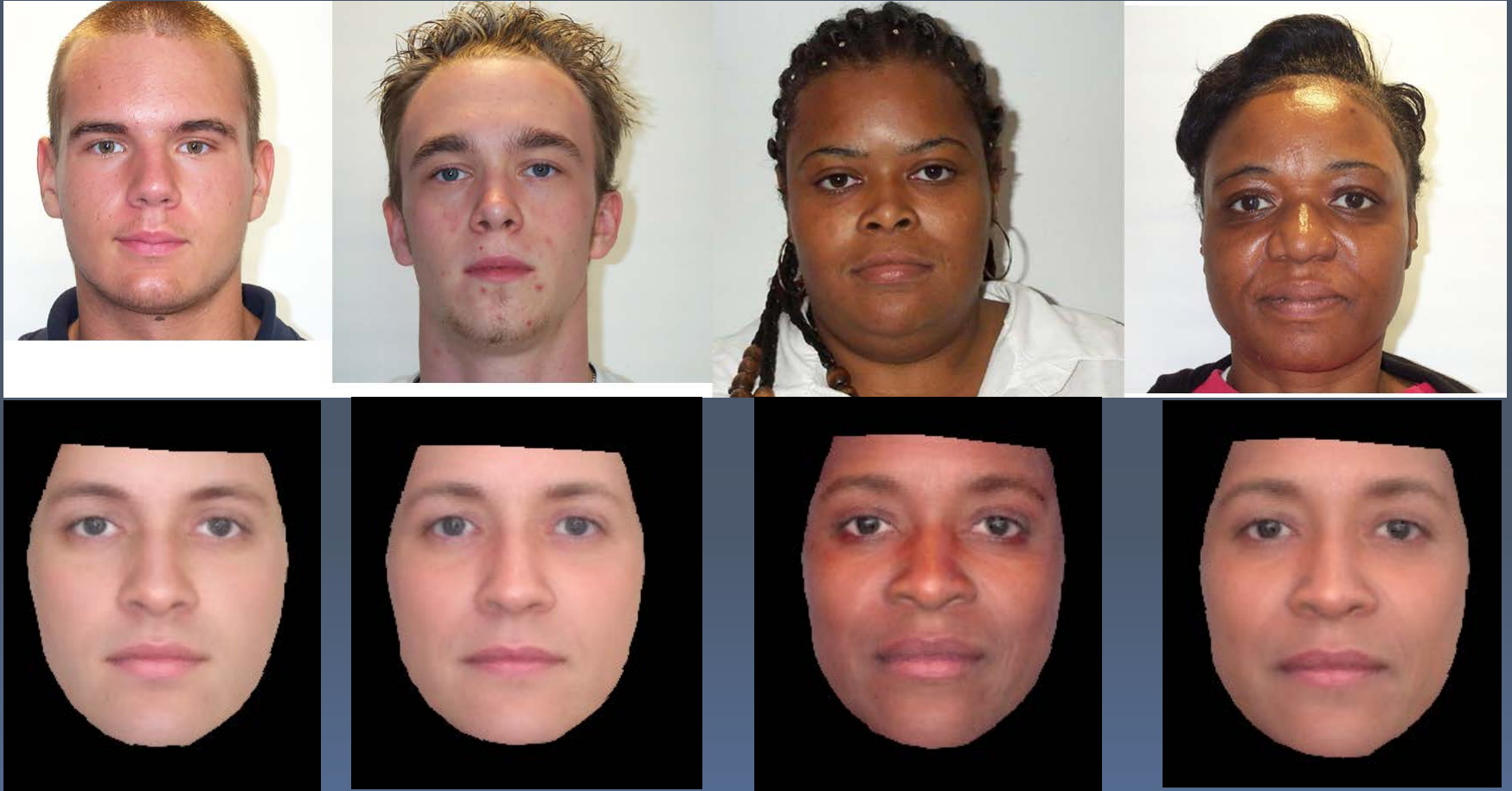
1.0

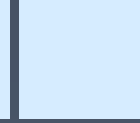
2.0



Gender + Race + Age

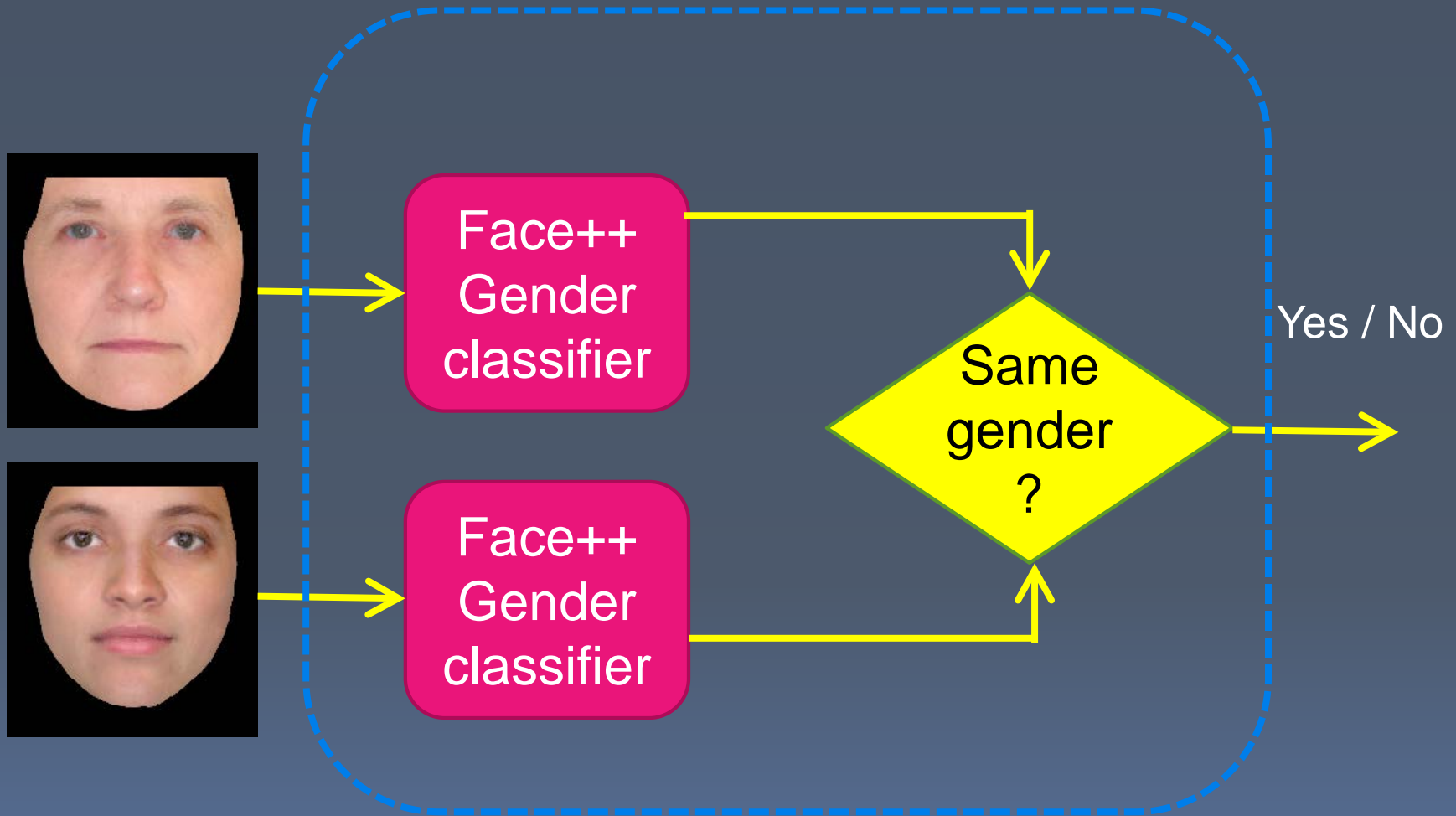
Altering Identity irreversibly





But can we fool vision algorithms?

Change Detector



Gender Change Detector

Experiments: Single-attribute change

“Changed rates” of 3 Change Detectors

	Intensity σ	0.5	1.0	1.5	2.0	2.5
Gender Change	Gender CD	0.50	0.63	0.75	0.88	1.00
	Race CD	0.31	0.31	0.31	0.31	0.31
	Age CD	0.56	0.19	0.38	0.38	0.19
Race Change	Gender CD	0.38	0.31	0.44	0.38	0.31
	Race CD	0.57	0.64	0.70	0.76	0.89
	Age CD	0.19	0.19	0.47	0.66	0.28
Age Change	Gender CD	0.31	0.38	0.31	0.38	0.19
	Race CD	0.25	0.25	0.12	0.12	0.25
	Age CD	0.66	0.84	1.00	1.00	1.00

Altered attributes are detected as changed, while unaltered attributes are unchanged

Experiments: Multi-attribute change

“Changed rates” of 3 Change Detectors

Intensity σ	Gender+Race			Gender+Age			Race+Age			All 3 attributes		
	Gender	Race	Age	Gender	Race	Age	Gender	Race	Age	Gender	Race	Age
1.0	0.45	0.52	0.23	0.55	0.26	0.71	0.39	0.54	0.77	0.36	0.47	0.72
2.0	0.60	0.60	0.68	0.53	0.25	0.82	0.33	0.72	0.88	0.50	0.71	0.82

Higher intensity needed to fool detectors.

Age attribute affected.

Experiments: Identity change

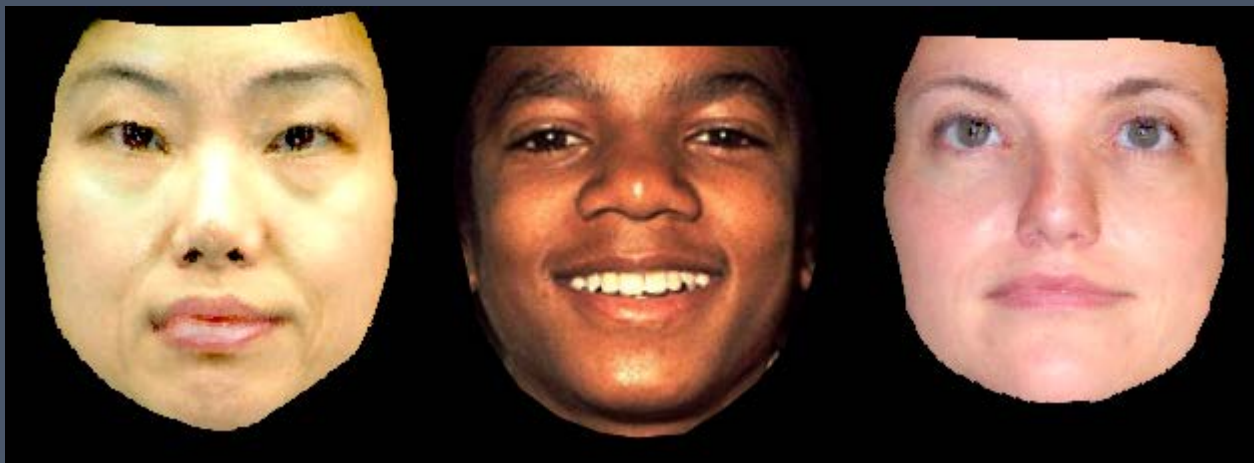
Confidence values returned by Face++

Intensity σ	0.5	1.0	1.5	2.0
Average Confidence	0.9137	0.943	0.951	0.966

Fun results



Fun results



Conclusion

Controllable Face Privacy

- Nuanced alteration of facial attributes

Orthogonal subspace decomposition

- Separate the parameters that control gender, race and age variations

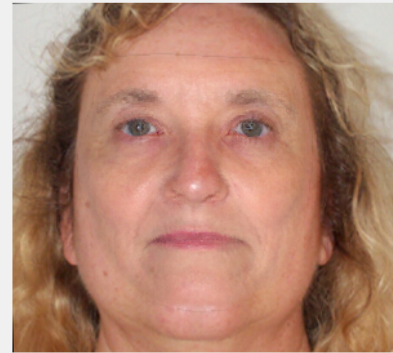
Privacy guarantees

- K-anonymity, L-diversity, t-closeness may be incorporated

Experimental validation

- Extensive experiments with commercial detector confirm the effectiveness of our method

The End: but come see our demo!



Original Face

Landmark

Altered Face

Input Mode

- Photo
- Camera

Detector

- Stasm
- Face++

Age

- Young
- Middle Age
- Old
- Default

Intensity: 1.0

Race

- Caucasian
- African
- Oriental
- Default

Intensity: 1.0

Gender


- Male
- Female
- Default

Intensity: 1.0

Alter Attribute

Alter Identity: -0.784

Additional slides


$$\beta = \frac{\alpha - f_p}{t_p - f_p}$$

α : observed “changed rate”

β : actual “changed rate”

f_p : false positive rate

t_p : true positive rate