北京電子科技学院
Beijing Electronic Science and Technology Institute

Valse Webinar

Artistic Illumination Assessment & Manipulation for Portraits

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Published Papers

1. Xiaowu Chen, **Xin Jin**, Hongyu Wu and Qinping Zhao. Learning Templates for Artistic Portrait Lighting Analysis. IEEE Transactions on Image Processing (**TIP**)， Vol. 24, No. 2, pp. 608-618, Feb. 2015 **(Conference short version: 5)**
2. Xiaowu Chen, Hongyu Wu, **Xin Jin*** and Qinping Zhao. Face Illumination Manipulation using a Single Reference Image by Adaptive Layer Decomposition. IEEE Transactions on Image Processing (**TIP**)， Vol. 22, No. 11, pp. 4249 - 4259, Nov. 2013 **(Conference short version: 4)**
3. Xiaowu Chen, **Xin Jin***, Qinping Zhao and Hongyu Wu. Artistic Illumination Transfer for Portraits. Computer Graphics Forum (**CGF**), Vol. 31, No. 4, pp.1425-1434, 2012
4. Xiaowu Chen, Mengmeng Chen, **Xin Jin*** and Qinping Zhao. Face Illumination Transfer through Edge-preserving Filters. Computer Vision and Pattern Recognition (**CVPR**), Colorado Springs, June 20-25, pp.281-287, 2011
5. **Xin Jin**, Mingtian Zhao, Xiaowu Chen, Qinping Zhao, and Song-Chun Zhu. Learning Artistic Lighting Template from Portrait Photographs. European Conference on Computer Vision (**ECCV**), Heraklion, Crete, Greece, September 5-11, pp.101-114, 2010

A Story of Portrait Photos by me

Me

Portrait photos by me

A Story of Portrait Photos by me

Your portrait photos are quite good at
✓ composition and
✓ capturing, but with little
✗ illumination in the face.

Carefully making appropriate illumination in the face can make excellent artistic portraits

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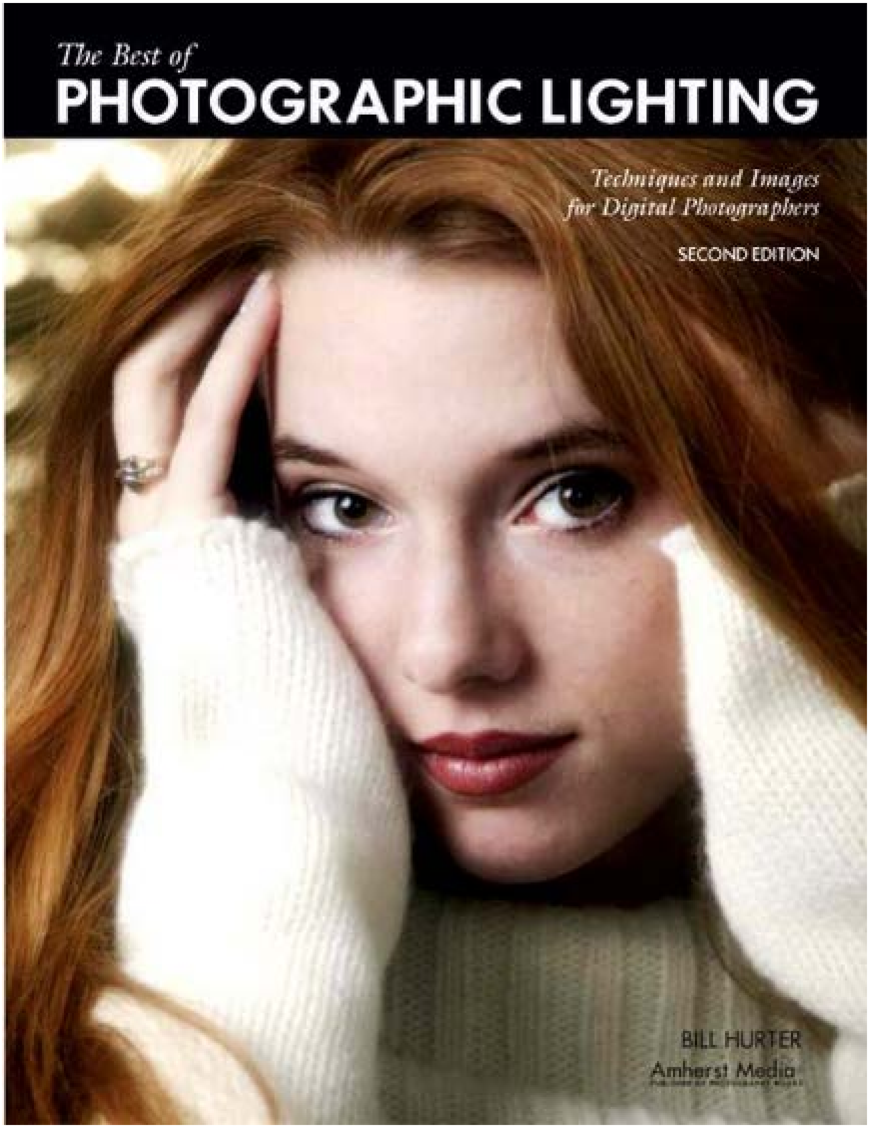
My Photography Teacher
Zijiang Zhao

A Story of Portrait Photos by me



Good lighting is the key to good portraiture. Posing, location, rapport, camera angle (the list can go on) are all important. However, that said, the lighting matters even more. We can do everything else beautifully, but if our lighting is bad, our portrait will be bad.

Bill Hurter

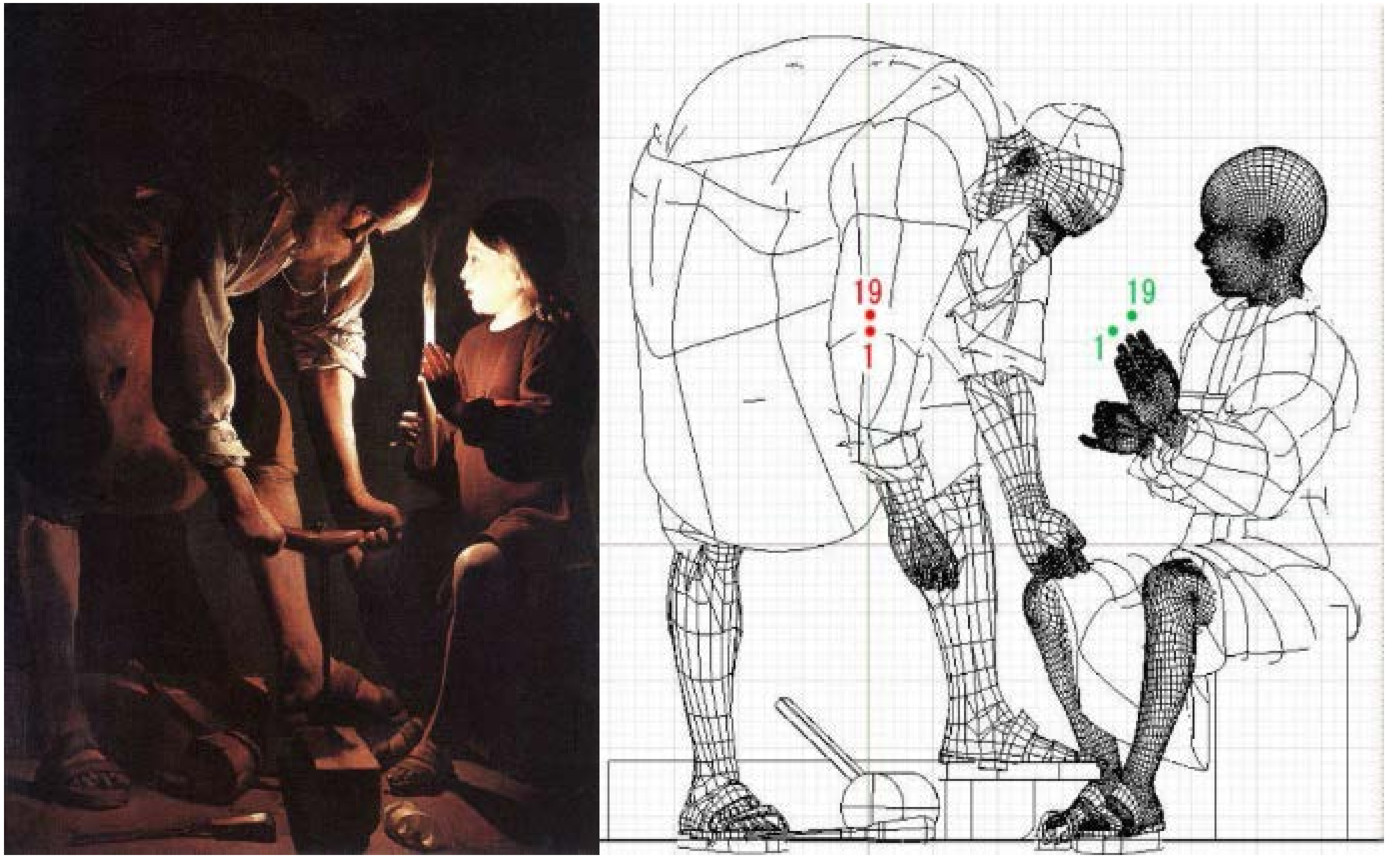
Photography is the art of
light and shadow

What is Artistic Lighting of Portraits?

Related Work

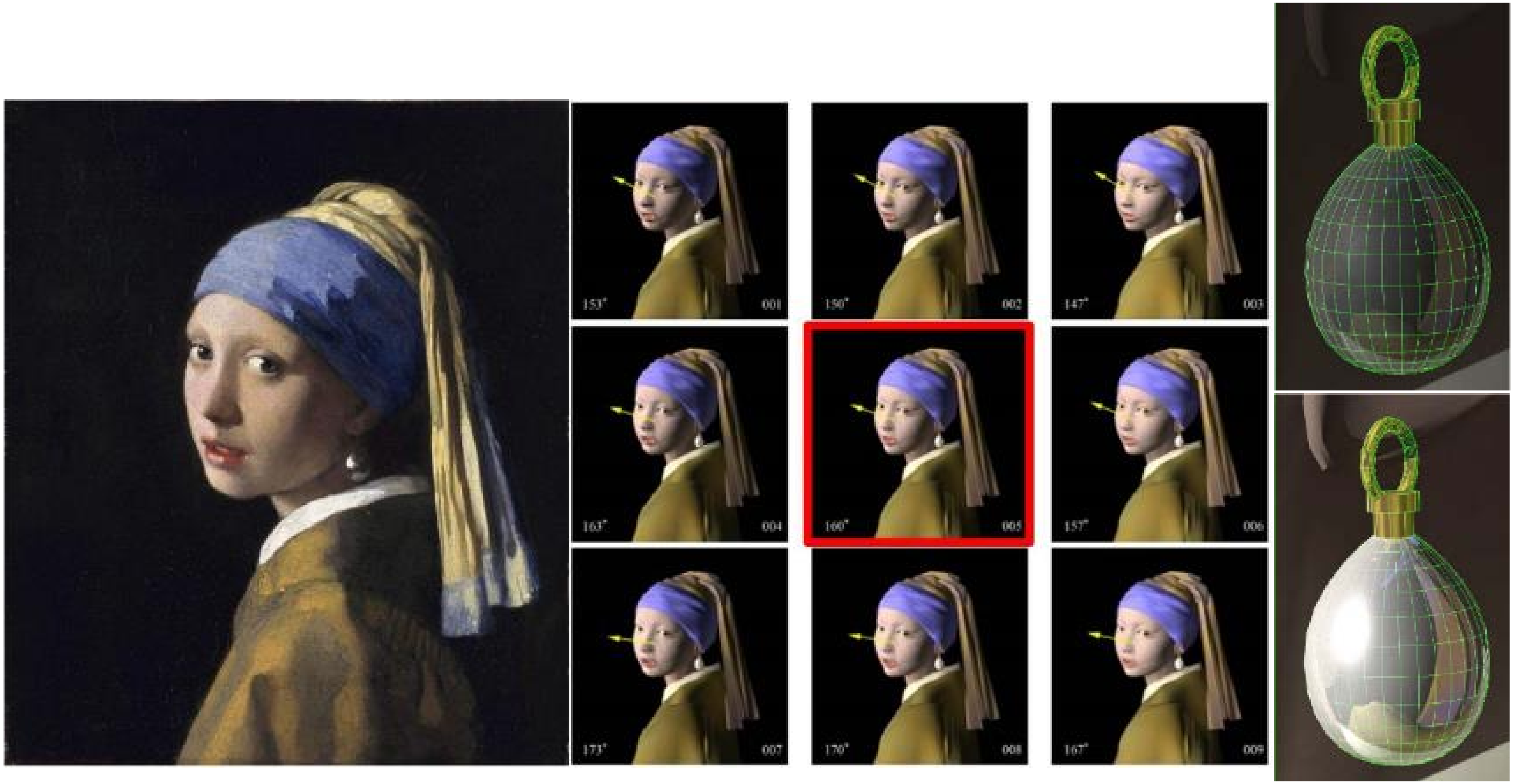
1. Artistic Image Analysis
2. Artistic Image Synthesis

Illumination Analysis in Masterpiece Artworks



Stork D. G. and Furuichi Y. Image Analysis of Paintings by Computer Graphics Synthesis: An Investigation of the Illumination in Georges de la Tour's Christ in the Carpenter's Studio [A]. In Proceedings of the Computer Image Analysis in the Study of Art [C]. San Jose, California, USA. January 28-29, 2008: 68100J-1-12

Illumination Analysis in Masterpiece Artworks



Johnson M. K., Stork D. G., Biswas S., et al. Inferring Illumination Direction Estimated from Disparate Sources in Paintings: An Investigation into Jan Vermeer's Girl with a Pearl Earring [A]. In Proceedings of the Computer Image Analysis in the Study of Art [C]. San Jose, California, USA. January 28-29, 2008: 68100I-1-12

Illumination Analysis in Masterpiece Artworks

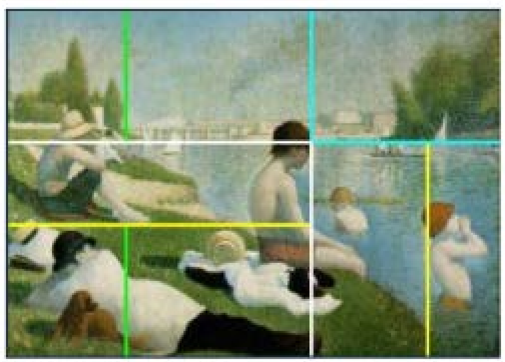


Stork D. G. Computer Analysis of Lighting Style in Fine Art: Steps towards Inter-Artist Studies [A]. In Proceedings of Computer Vision and Image Analysis of Art II [C]. January 25-26, 2011: 7869-02-1-11

Aesthetic Assessment of Artworks

4.05/5

2.43/5

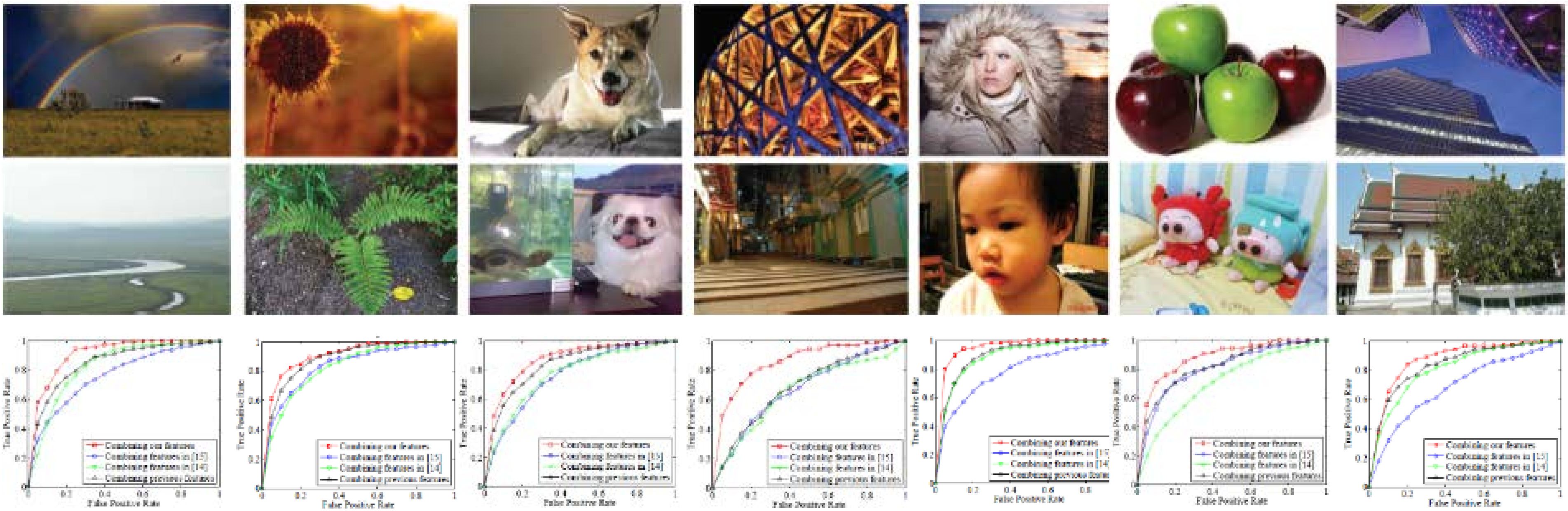


3.857/5

2.833/5

Li C. and Chen T. Aesthetic Visual Quality Assessment of Paintings [J]. IEEE Journal of Selected Topics in Signal Processing. 2009, Vol. 3, No. 2: 236-252

Aesthetic Assessment of Photos

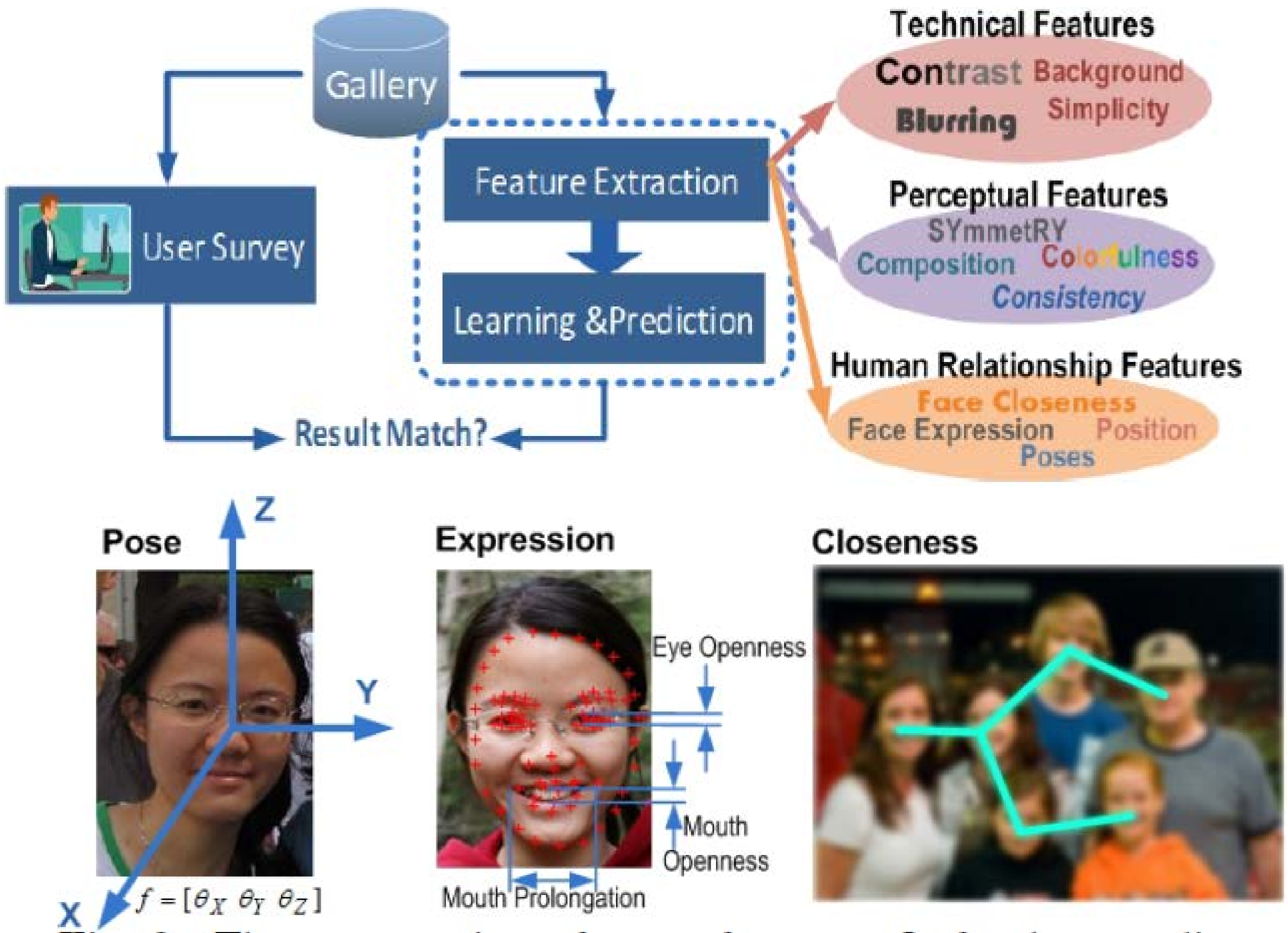


Landscape | Plant | Animal | Night | Portraits | Still | Architecture

Luo W., Wang X. and Tang X. Content-based Photo Quality Assessment [A]. In Proceedings of the 13th IEEE International Conference on Computer Vision (ICCV) [C]. Barcelona, Spain. November, 6-13, 2011: 2206-2213

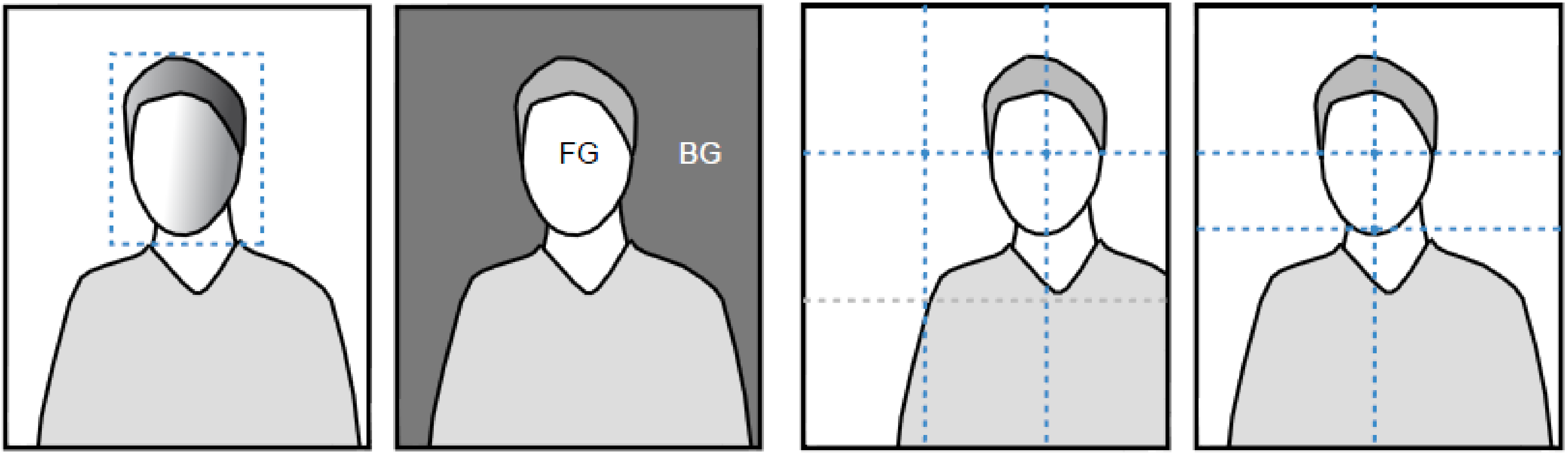
Tang X., Luo W., and Wang X. Content-Based Photo Quality Assessment [J]. IEEE Transactions on Multimedia (TMM), Vol. 15, No. 8, 2013: 1930-1943

Aesthetic Assessment of Portrait Photos



Li C., Gallagher A., Loui A. C., et al. Aesthetic Quality Assessment of Consumer Photos with Faces [A]. In Proceedings of the IEEE International Conference on Image Processing (ICIP) [C]. Hongkong, China. September 26-29, 2010: 3221-3224

Aesthetic Assessment of Portrait Photos



Khan S. S. and Vogel D. Evaluating Visual Aesthetics in Photographic Portraiture [A]. In Proceedings of the 8th Annual Symposium on Computational Aesthetics in Graphics, Visualization, and Imaging [C]. Annecy, France. June 4-6, 2012: 55-62

3 Questions

- **Q1: Can computers assess portrait lighting automatically?**
- **Q2: Can we transfer good illumination to a normal lighting face ?**
- **Q3: How about artistic illumination from Masterpieces?**

Artistic Portraits vs. Daily Portraits

Art

Daily

Illumination in Portraits

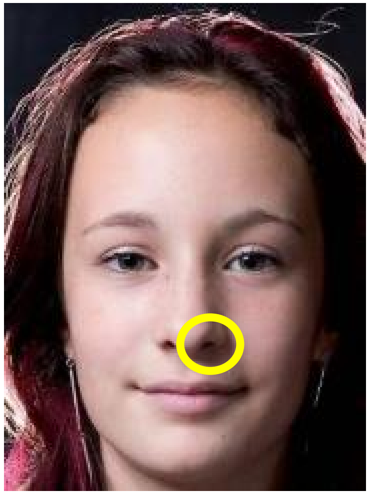
Good → **Bad**

Typical artistic lighting styles

Rembrandt

Paramount

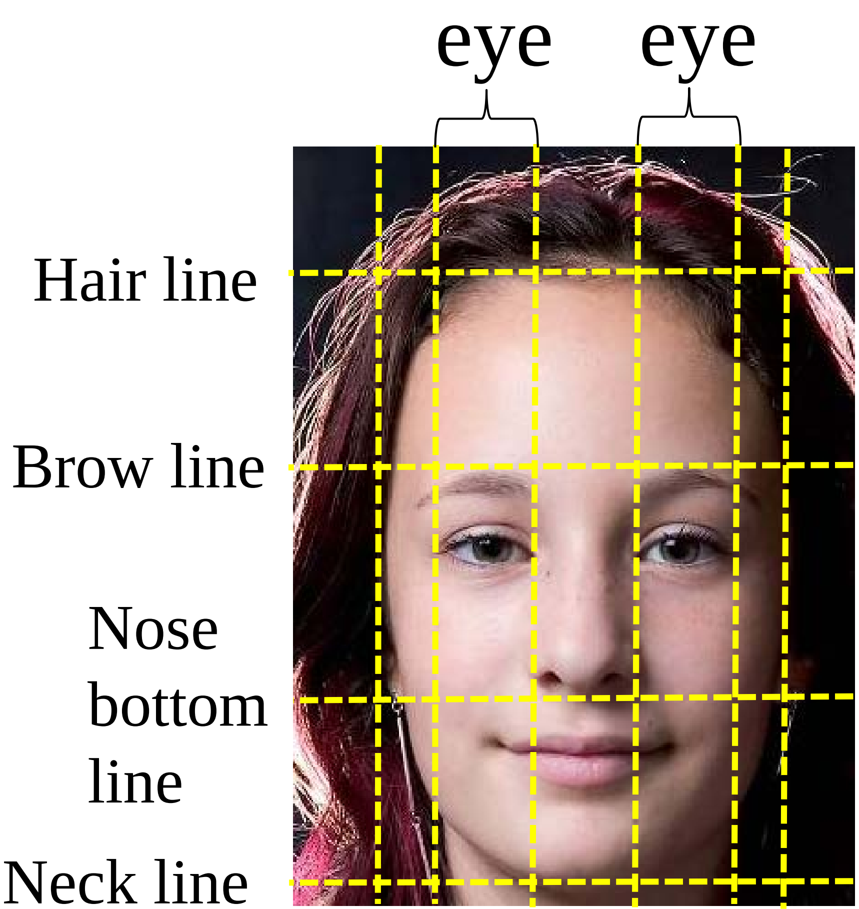
Loop



Split

How professional photographers assess portrait lighting?

(失传的人像拍摄绝技)三庭五眼拍人像 熊正寅



“3-5 Principle”

从眉线到发际线，上庭这一部分用光很清楚，额丘、额沟、眉弓、眉毛4个地方表现得非常清楚，立体效果很强。

从眉线到鼻底线的中庭部分，最主要是表现眼睛，它代表一个人的精神面貌，这张照片的眼睛很传神，很真实，眼睛视线和视觉方向使人感到画面以外还有画面。较好地把人物心态反映出来。

脸颊这块肌肉的隆起是由光和影造成的，假如没有这块光斑，“球体”就瘪下去了；因为有了这个光斑，这块肌肉突出起来了，所以看上去才丰满。

鼻唇沟的阴影曲线挺好，使脸部显得很真实，富有立体感。

鼻子的高度在人的面部起伏最大，需要充分地表现出来，鼻子头是球形，阳面用凸型的一个光斑把它表现出来，鼻尖有一点光亮，这个光点相当重要，可以使鼻子的立体感体现出来，如果没有它，这部分就缩下去了。

下庭最复杂的是嘴，嘴形表现较好，与脸部其他四观（眉、眼、鼻、耳）搭配合理，反映出被摄者良好的状态。她的牙齿整齐，嘴形很漂亮显得整个人物非常健康，有朝气。

Local Lighting Contrast

三庭五眼

From Artists to Computers

Local
Lighting
Contrast
Features

Where?

How?

What?


从眉线到发际线，上庭这一部分用光很清楚，额丘、额沟、眉弓、眉毛4个地方表现得非常清楚，立体效果很强。

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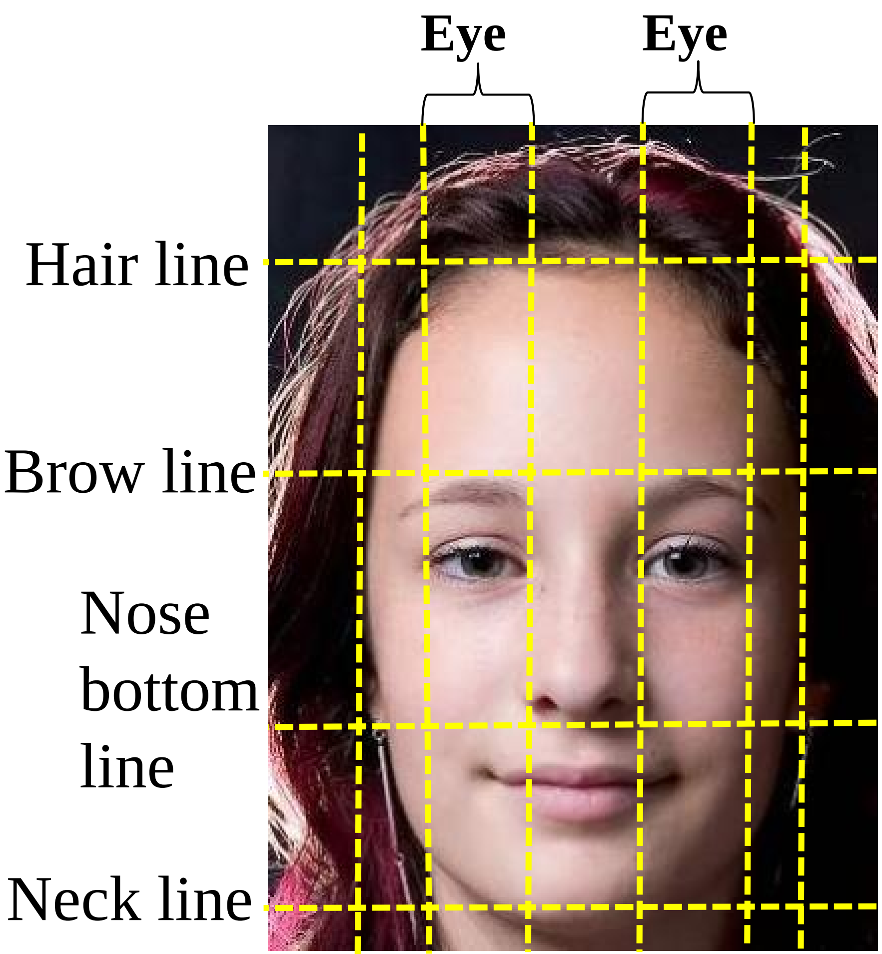
Computer

Artists

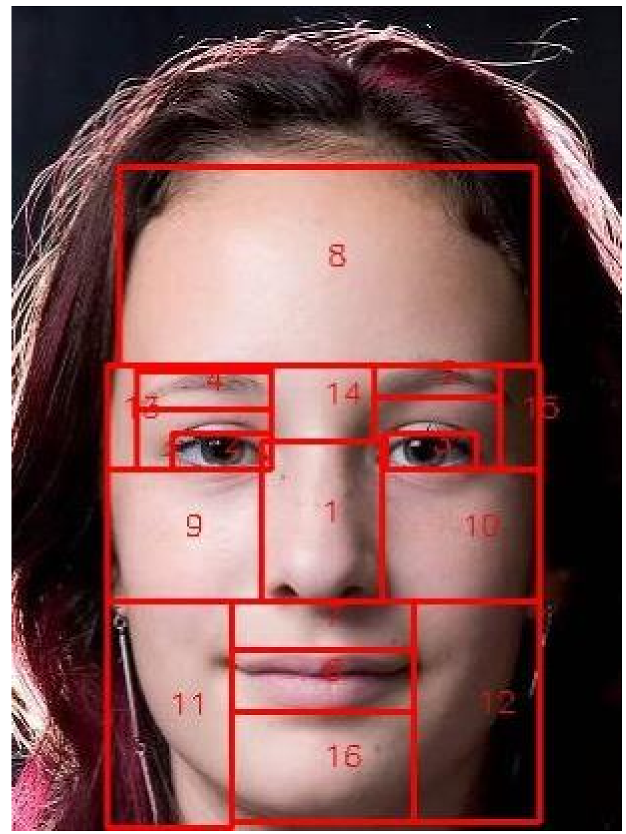
Local Lighting Contrast Features

- **Local Regions**



Where?

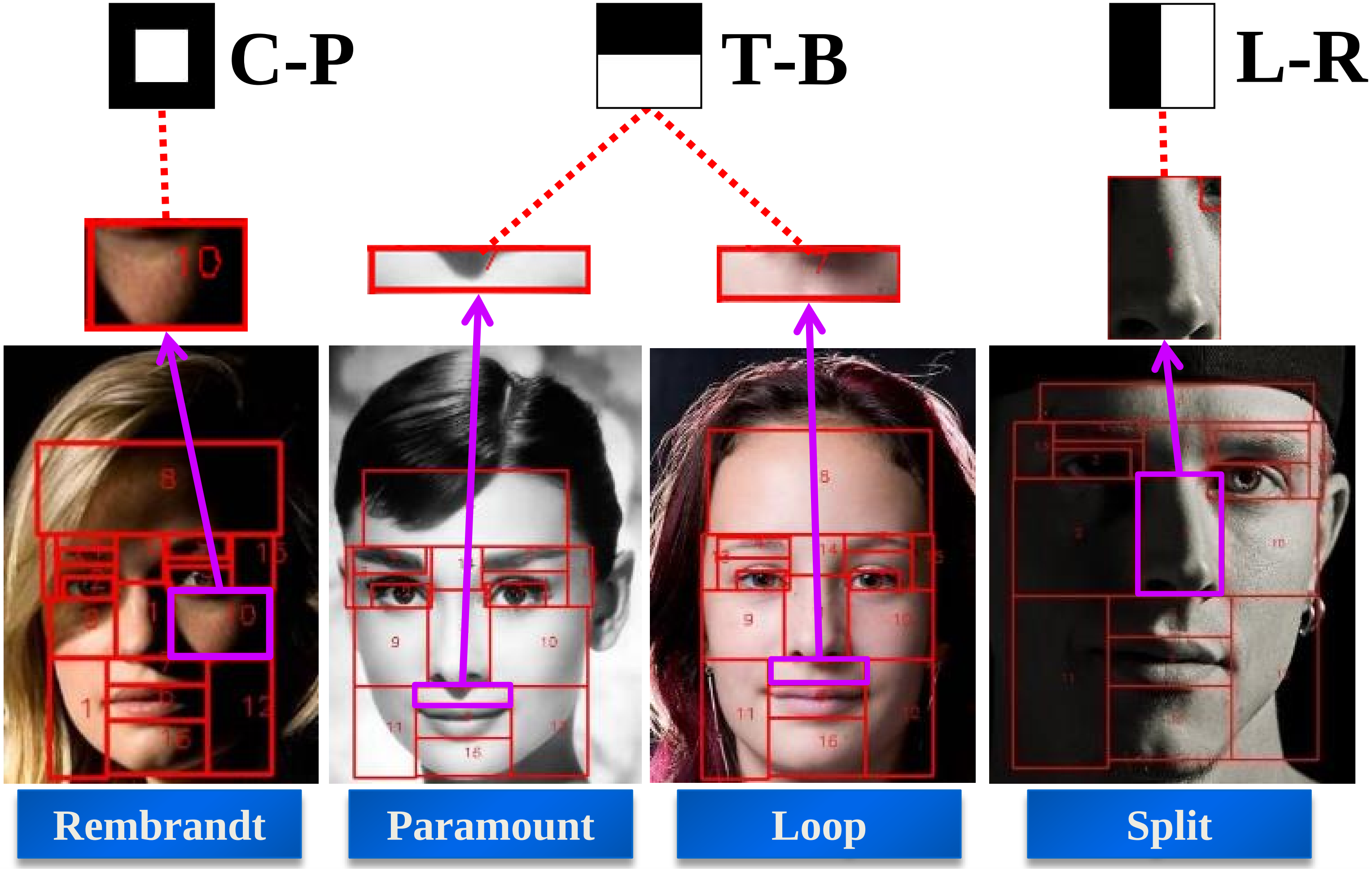
16 local regions



Local Lighting Contrast Features

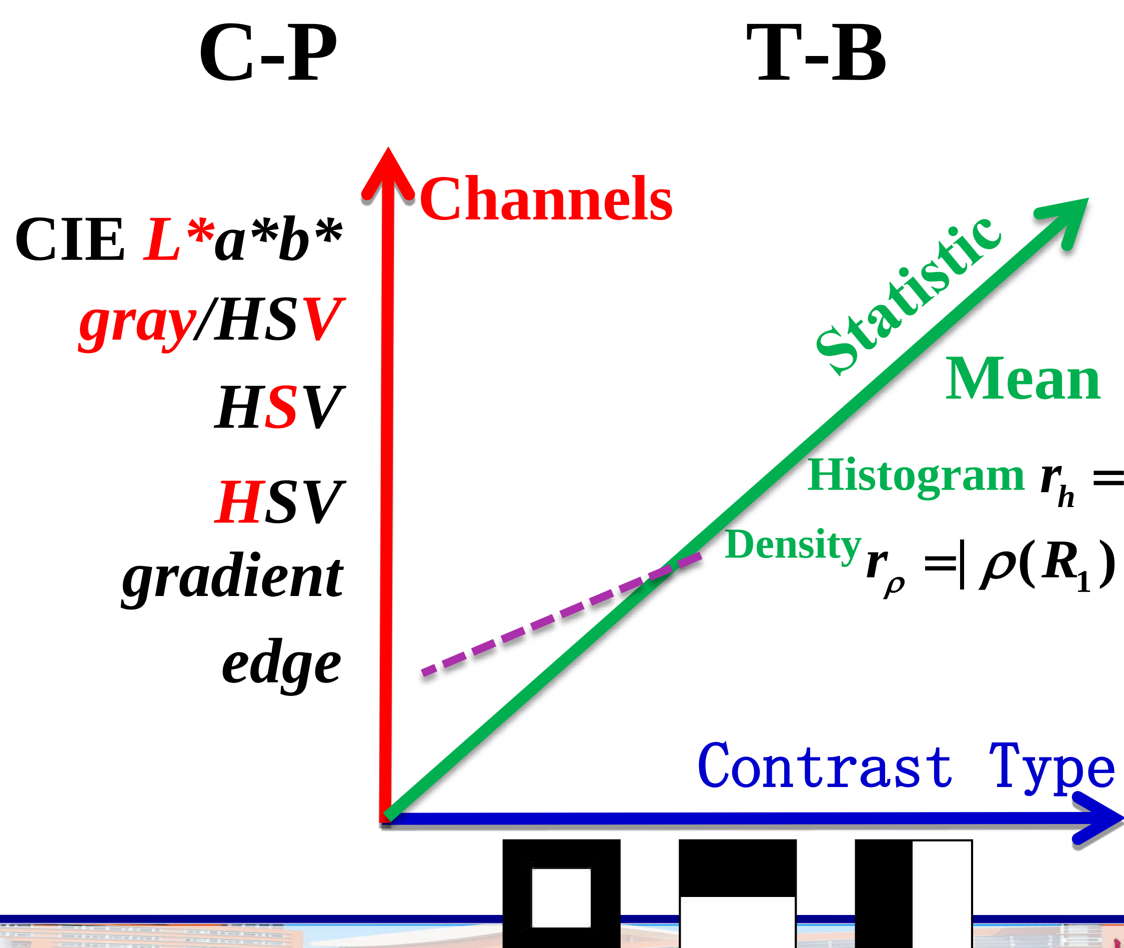
- 3 Basic Contrast Types

How?



Local Lighting Contrast Features

Contrast Features F



R_0 ■ R_1 □

$r_\mu = |\mu(R_1) - \mu(R_0)|$

$r_h = \mathrm{JS}(h(R_1) \| h(R_0))$

$r_\rho = |\rho(R_1) - \rho(R_0)|$

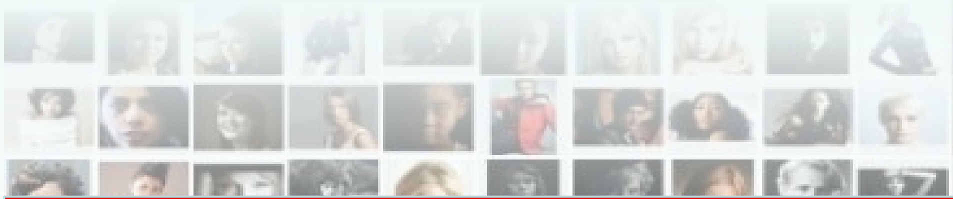
Learning Artistic Lighting Template

- **Candidate Features** $F_C:\{F_1 \ldots\ldots F_L\}$

3 Basic Contrast Types（3×8×16=384）			
Contrast Type	Statistic	channel	Region
L-R T-P C-P	Mean	Gray	1-16
	Mean	L	
	Hist.	Gradient	
	Hist.	Gray	
	Hist.	S	
	Hist.	L	
	Density	Edge	
	Mean	H	

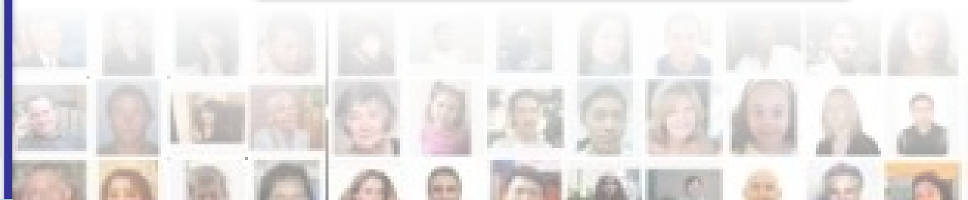
Learning Artistic Lighting Template

Art



- ✓ Masterpieces
- ✓ Professional Website
- ✓ Scan of Portrait Book

Daily



- ✓ BBS
- ✓ Social Network
- ✓ Search Engine

Learning Artistic Lighting Template

Feature Selection

$$F_C : \{F_1 \;\ldots\ldots\; F_L\}$$

$$p(\mathrm{I}) = q(\mathrm{I}) \prod_{k=1}^{K} \left[\frac{1}{z_k} \exp\{\lambda_k r_k(\mathrm{I})\} \right]$$

P N Features

Information Projection

$$gain(F) \approx \mathrm{KL}(h_A(r_k(I)) \| h_D(r_k(I)))$$

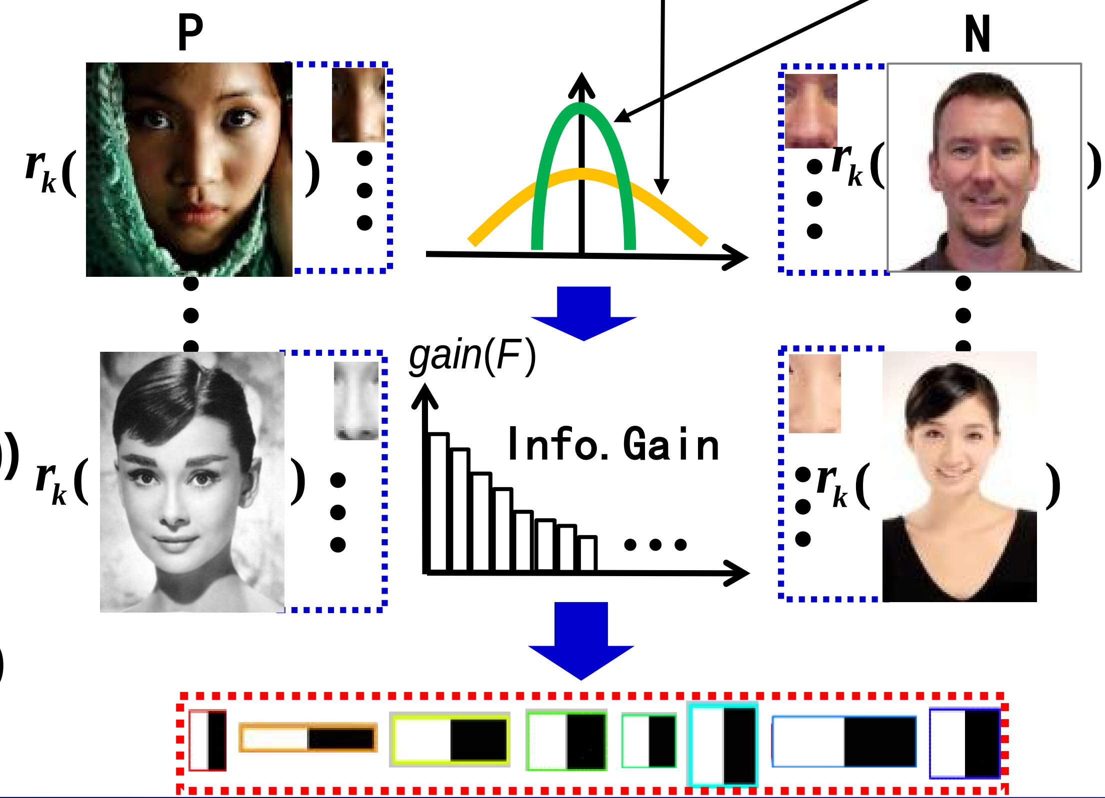
Stepwise Feature Selection

$$p_0 = q \dashrightarrow p$$

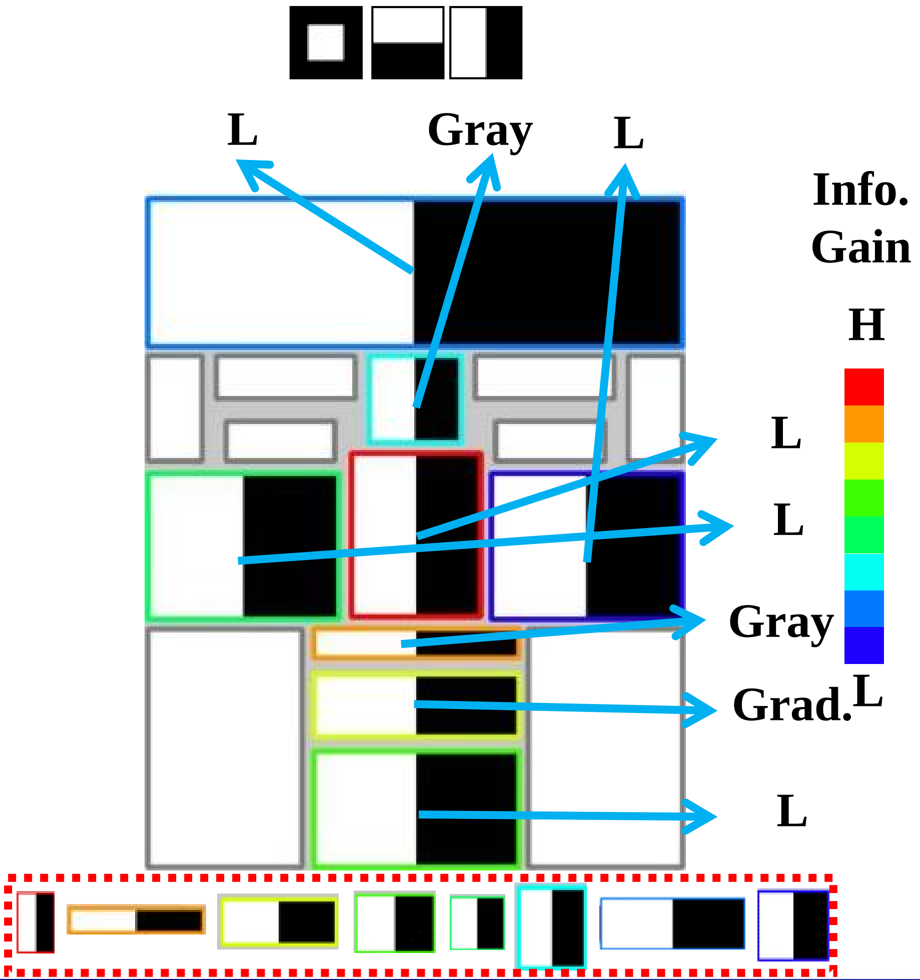
$$F_j = \arg\max_{F_k} \mathrm{KL}(p_j(r_k(\mathrm{I})) \| p_{j-1}(r_k(\mathrm{I})))$$

$$\approx \arg\max_{F_k} \mathrm{KL}(p_j(r_k(\mathrm{I})) \| q(r_k(\mathrm{I})))$$

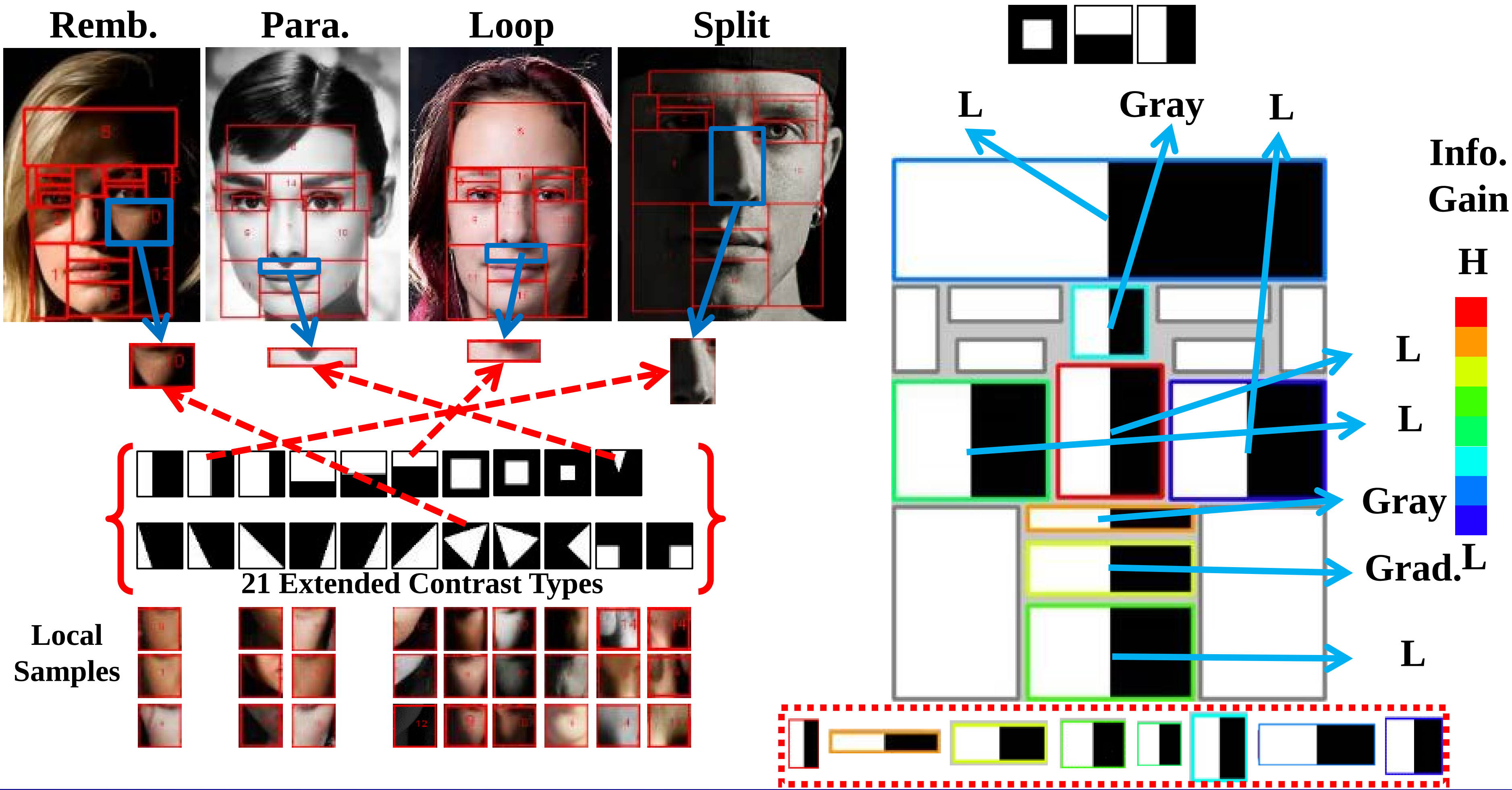
$$\approx \arg\max_{F_k} \mathrm{KL}(h_A(r_k(\mathrm{I})) \| h_D(r_k(\mathrm{I})))$$



Learned Artistic Lighting Template



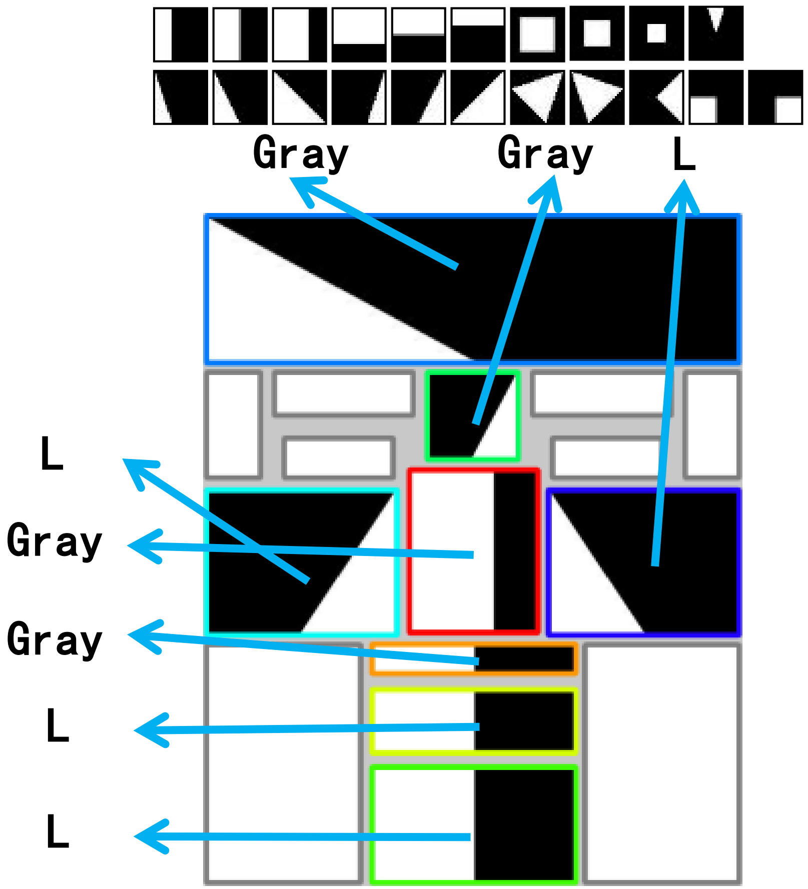
Learning Artistic Lighting Template

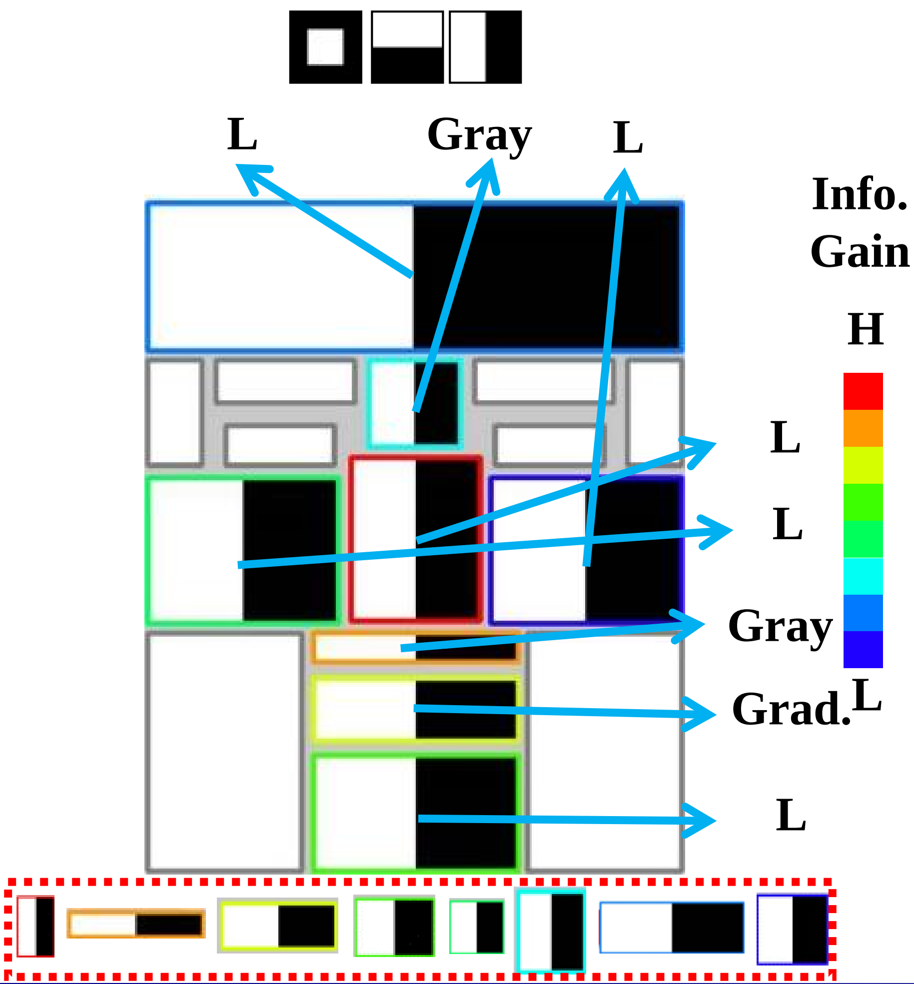


Learning Artistic Lighting Template

21 Extended Contrast Types（21×8×16=2688）			
Contrast Type	**Statistic**	**channel**	**Region**
L-R T-P C-P	Mean	Gray	1-16
	Mean	L	
	Hist.	Gradient	
	Hist.	Gray	
	Hist.	S	
	Hist.	L	
	Density	Edge	
	Mean	H	

Learned Artistic Lighting Template



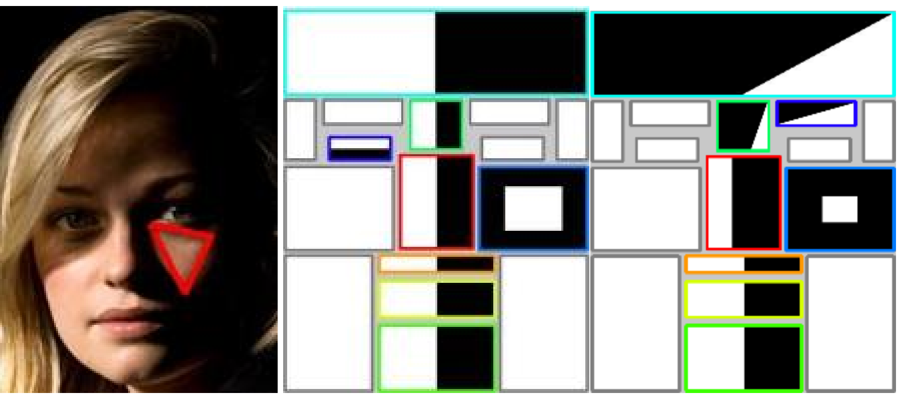


Learning Artistic Lighting Template

Positive	Negative	Lighting Template
Art (350)	Daily (500)	Common Template
Remb. (45)	Others (805)	Remb. Template
Para. (30)	Others (820)	Para. Template
Loop (54)	Others (796)	Loop Template
Split (34)	Others (816)	Split Template

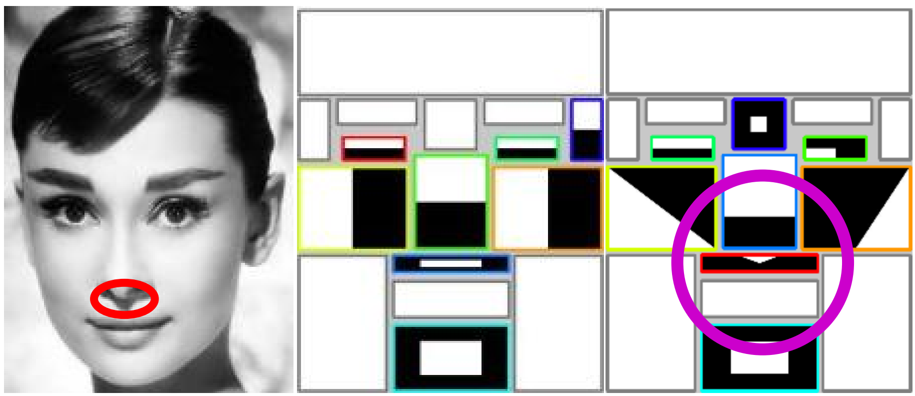
Learned Artistic Lighting Template

3 Basic 21 Extended



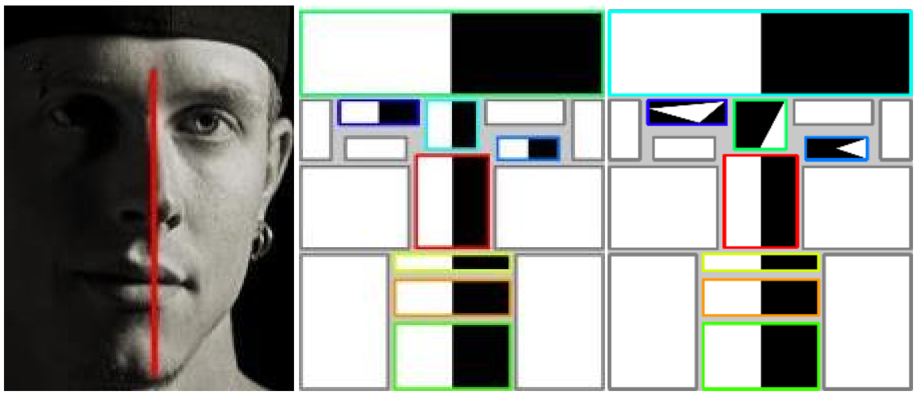
Rembrandt

3 Basic 21 Extended



Paramount

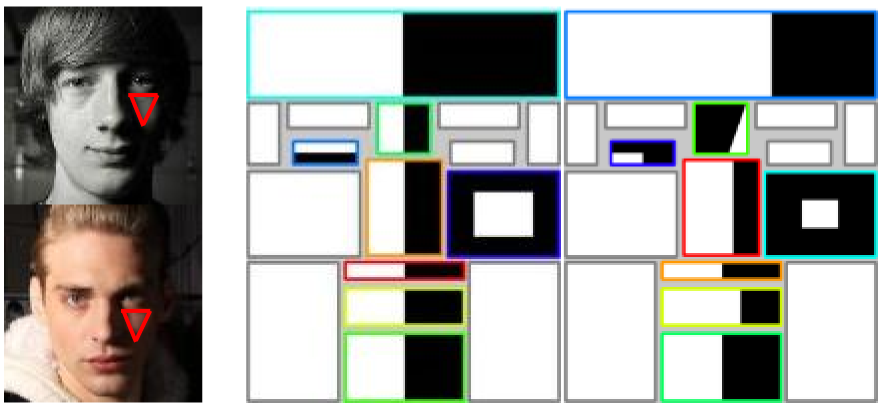
Loop



Split

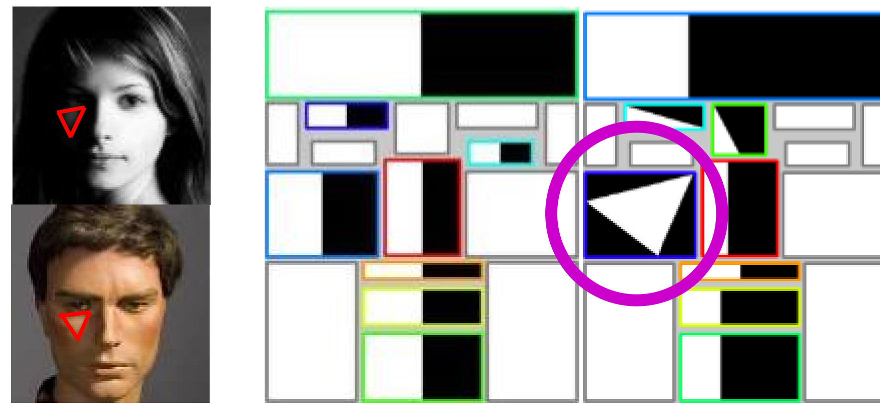
Learned Artistic Lighting Template

3 Basic 21 Extended

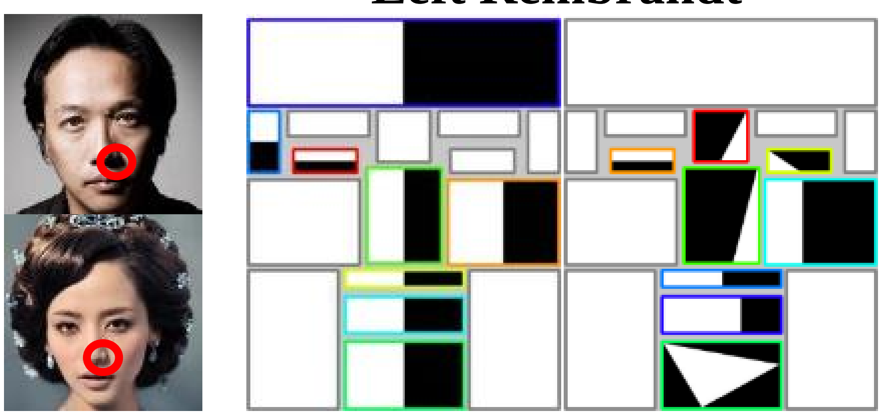


Left Rembrandt

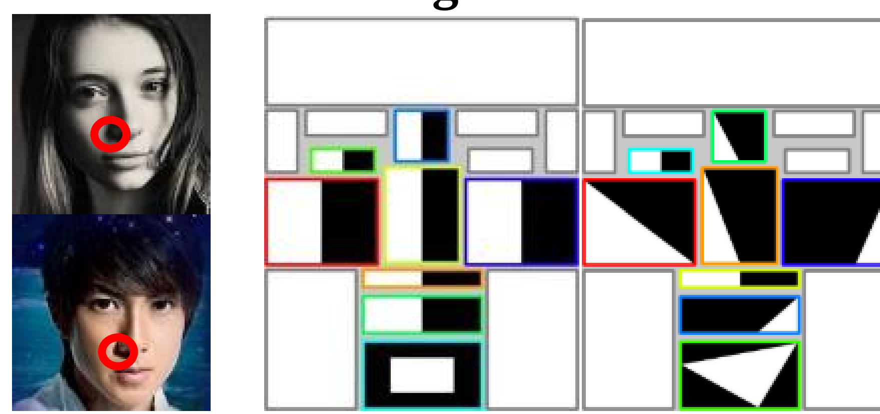
3 Basic 21 Extended



Right Rembrandt

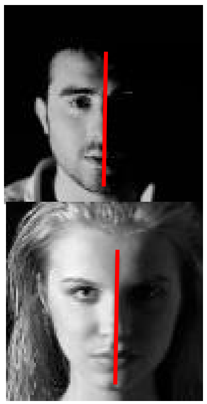


Left Loop

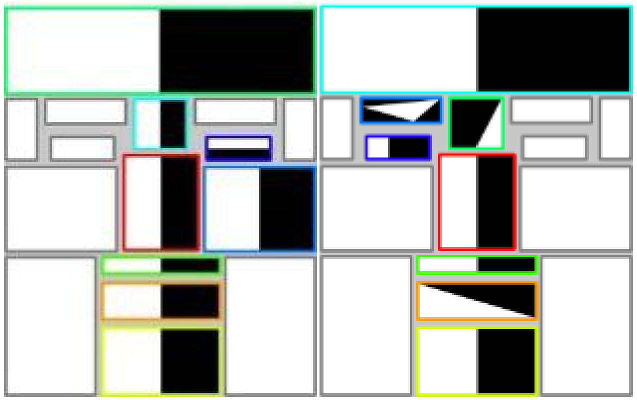


Right Loop

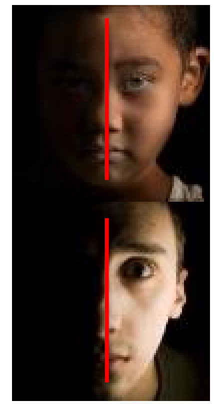
Learned Artistic Lighting Template



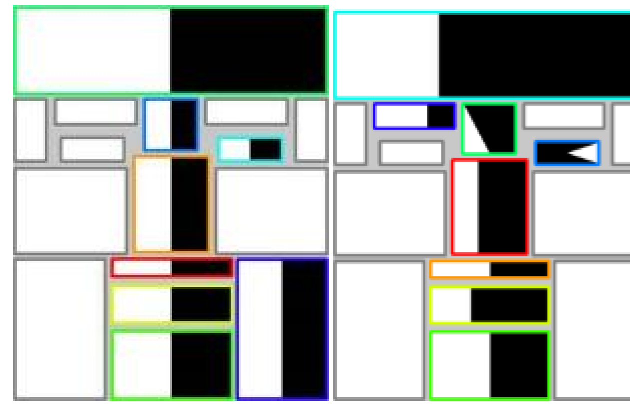
3 Basic 21 Extended



Left Split



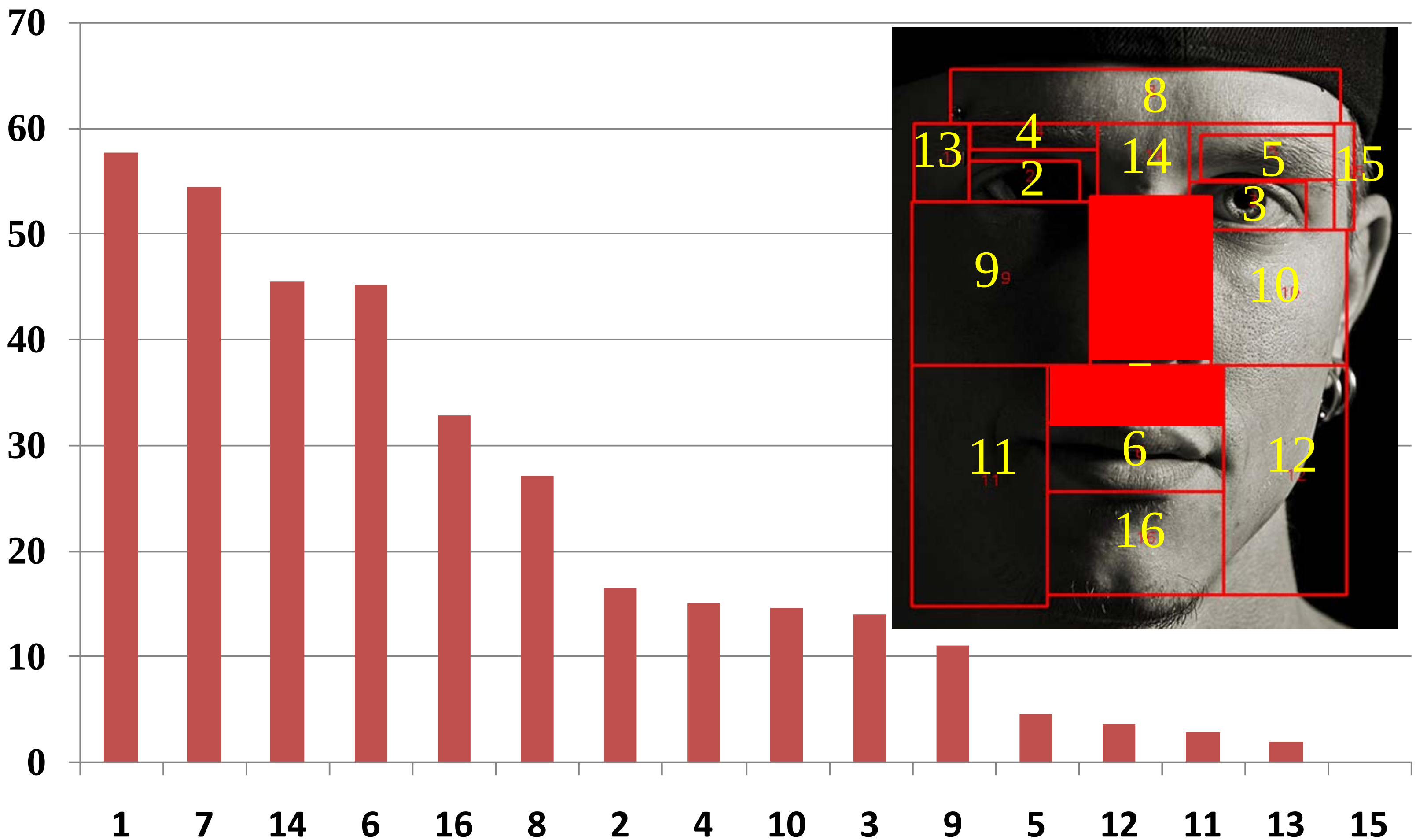
3 Basic 21 Extended



Right Split

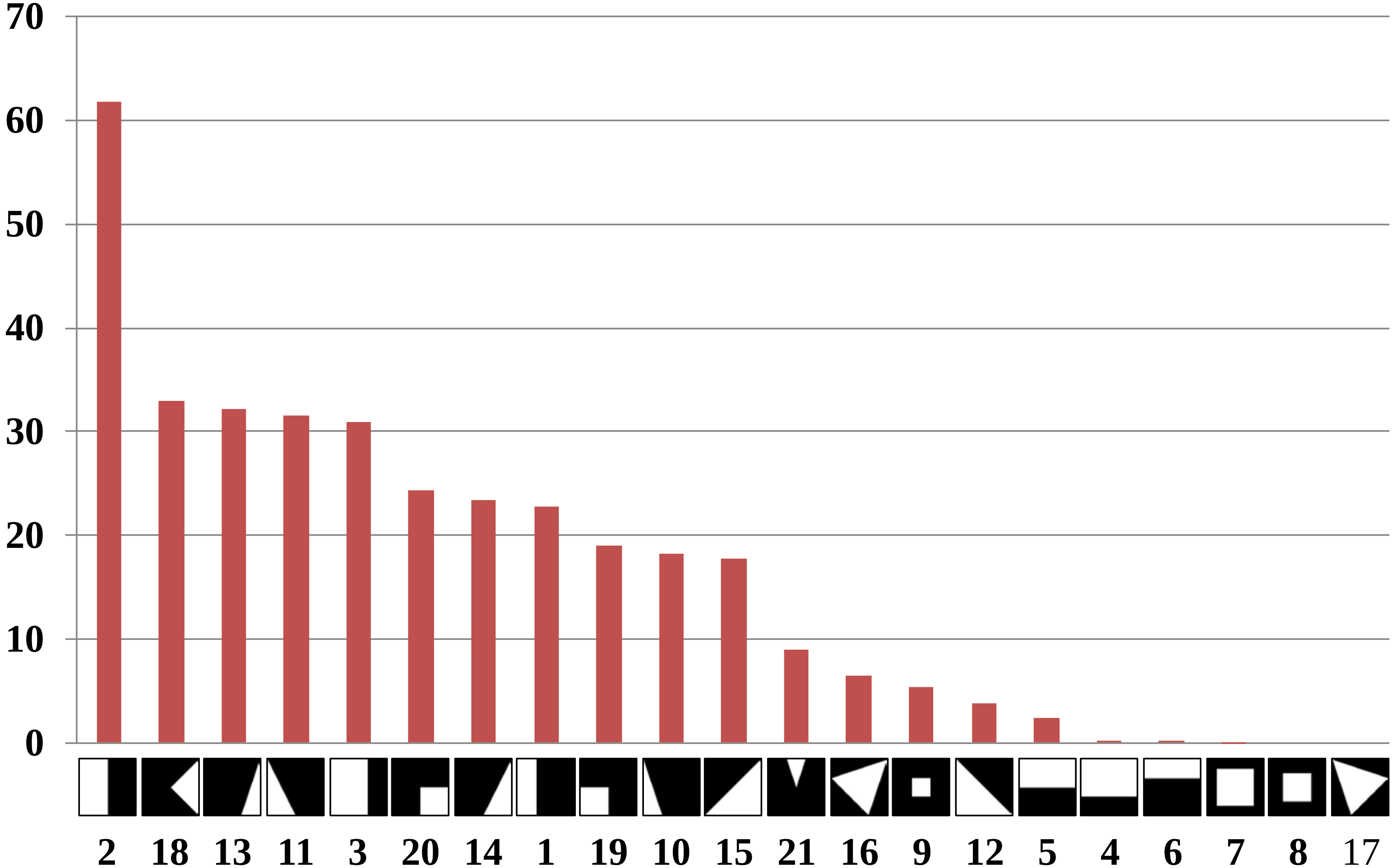
Learned Artistic Lighting Template

- **Accumulated Info. Gain: Local Region**



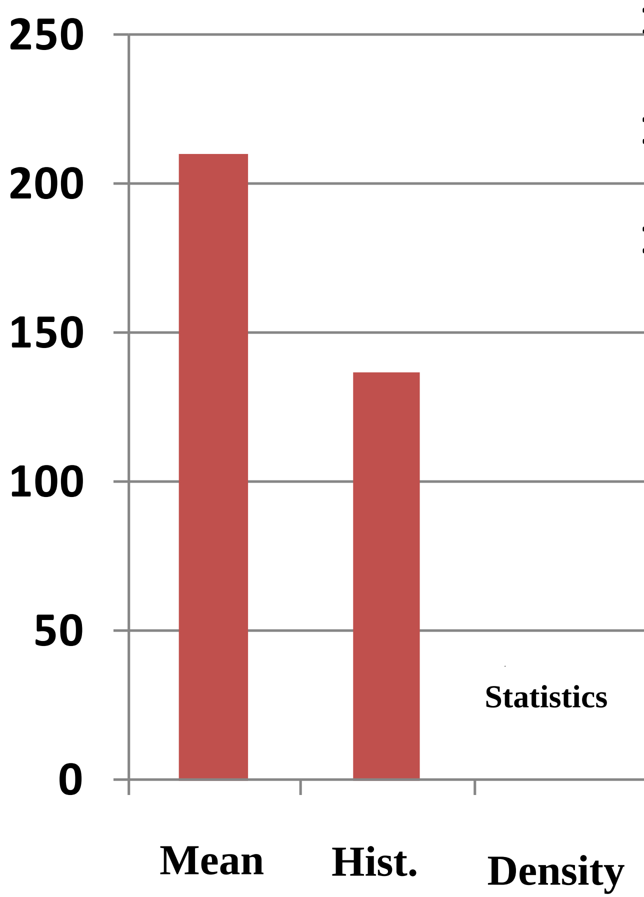
Learned Artistic Lighting Template

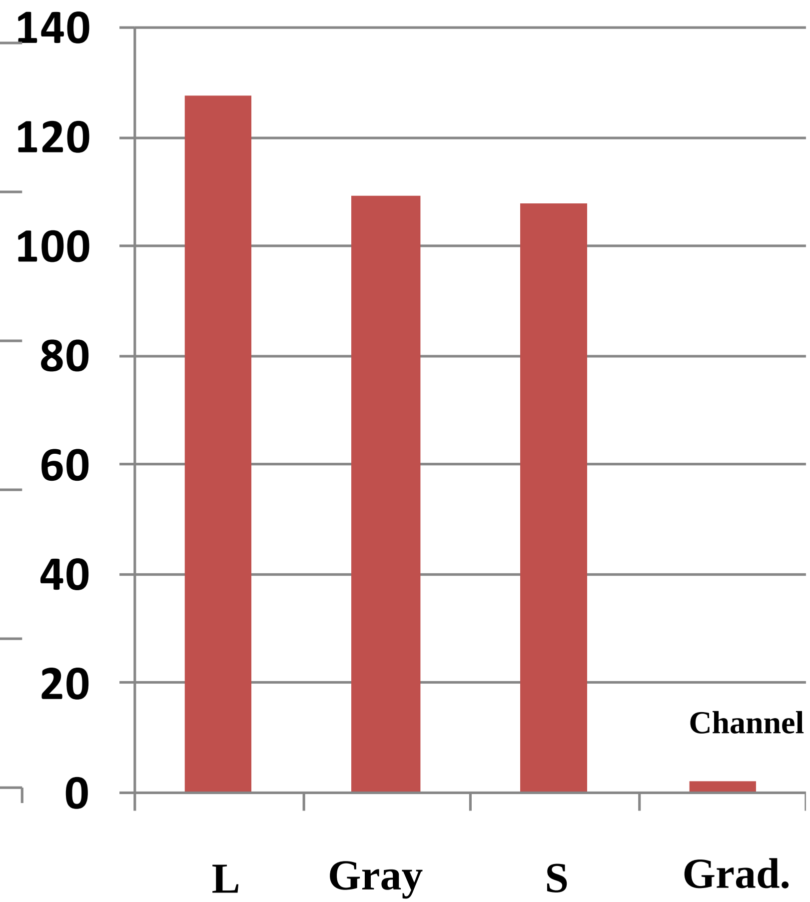
- **Accumulated Info. Gain: Contrast Type**



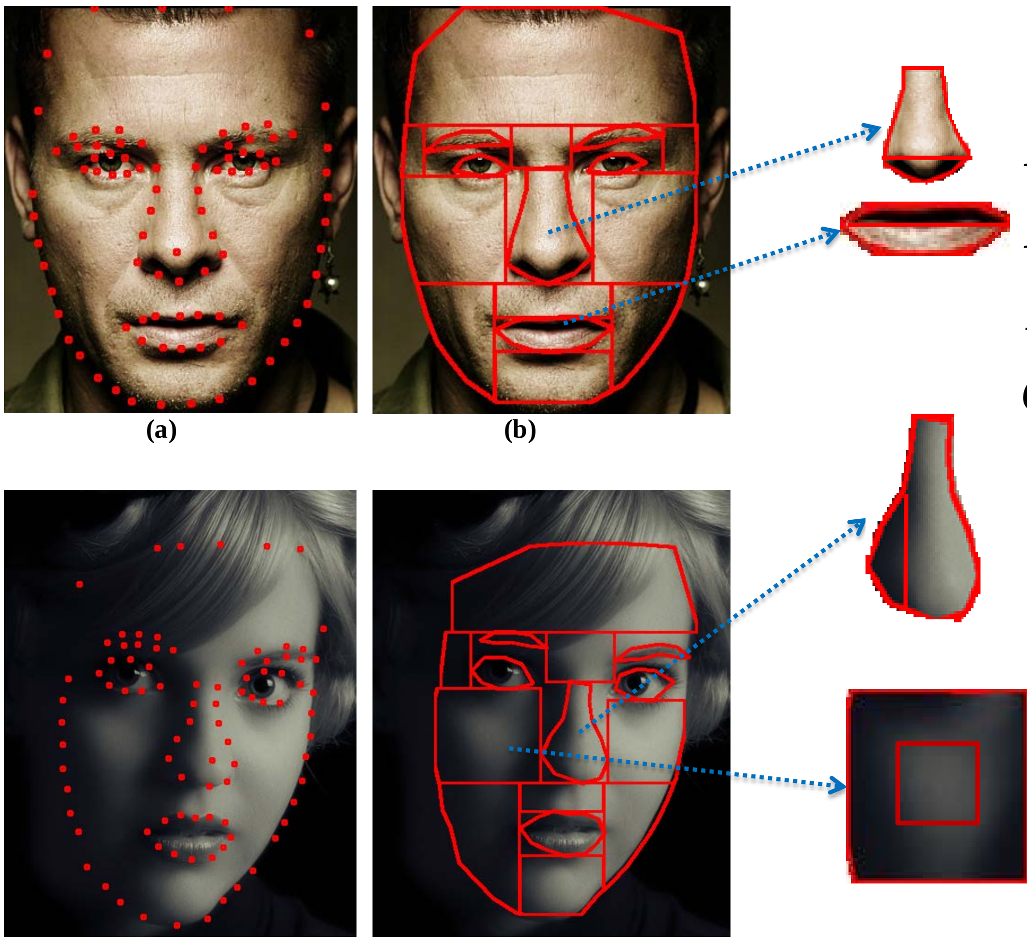
Learned Artistic Lighting Template

- **Accumulated Info. Gain: Statistics & Channel**





Face Illumination Descriptor



(a) (b)

(c) (d) (e)

FID

Face Illumination Descriptor

$$FID(P)=\{r^{\mu}_{mask}(F_i) | F_i \in F_D\}$$

$$F_i:\{R_i, T_i, C_i, S_i\},\ F_D:\{F_i | i=1,2,...,256\}$$

$$R_i \in \{R_1,...,R_{16}\},\ T_i \in \{T_1,...,T_{16}\}$$

$$C_i = L,\ S_i = \mu$$

16 Local Regions 16个 Contrast Types

L Channel Mean Statistics

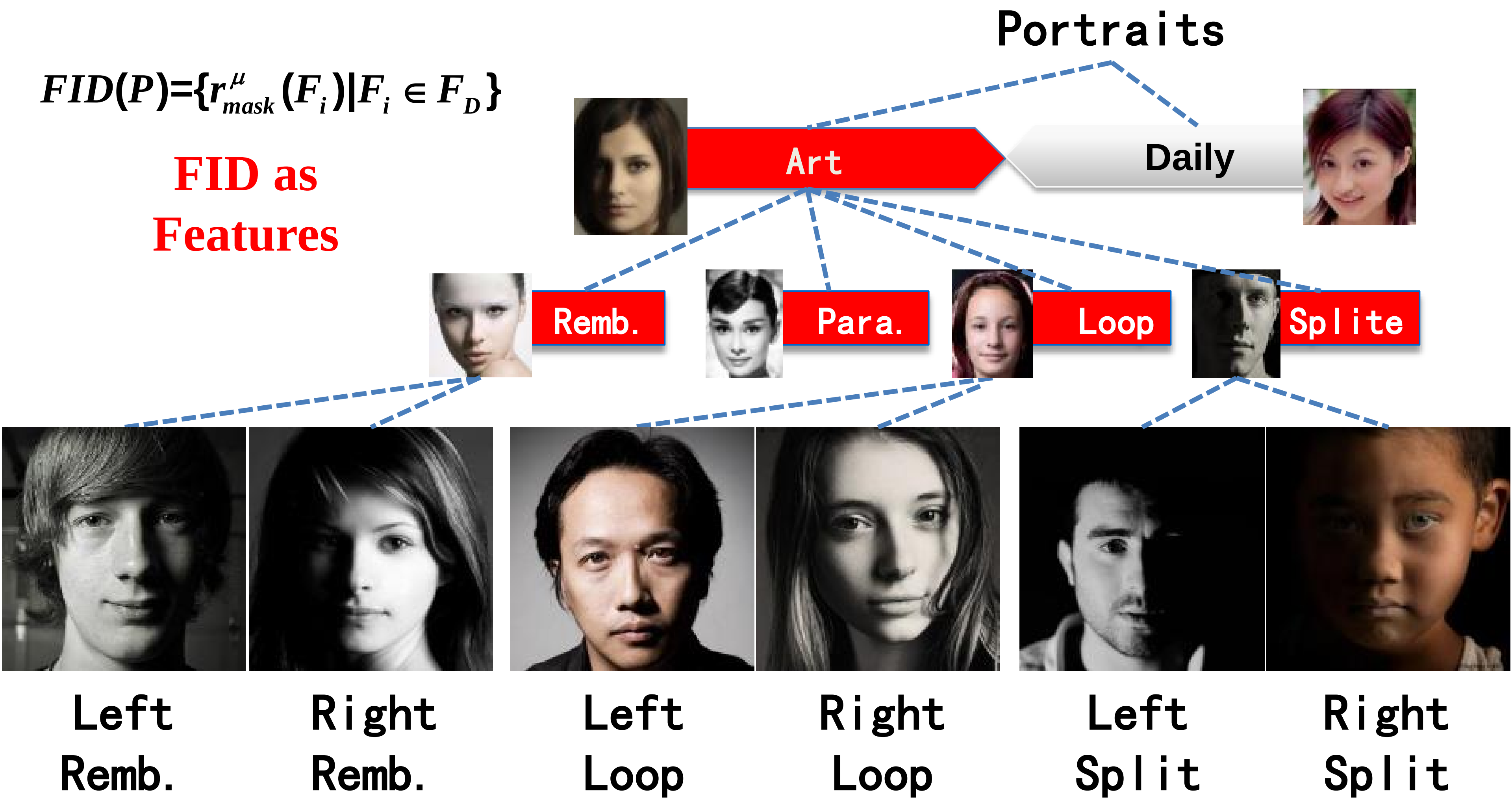
$$D(P_1,P_2) = ED(FID(P_1), FID(P_2))$$

$$= \sqrt{\sum_{i=1}^{256} (r^{\mu_1}_{mask}(F_i) - r^{\mu_2}_{mask}(F_i))^2}$$

Weakly Supervised Clustering

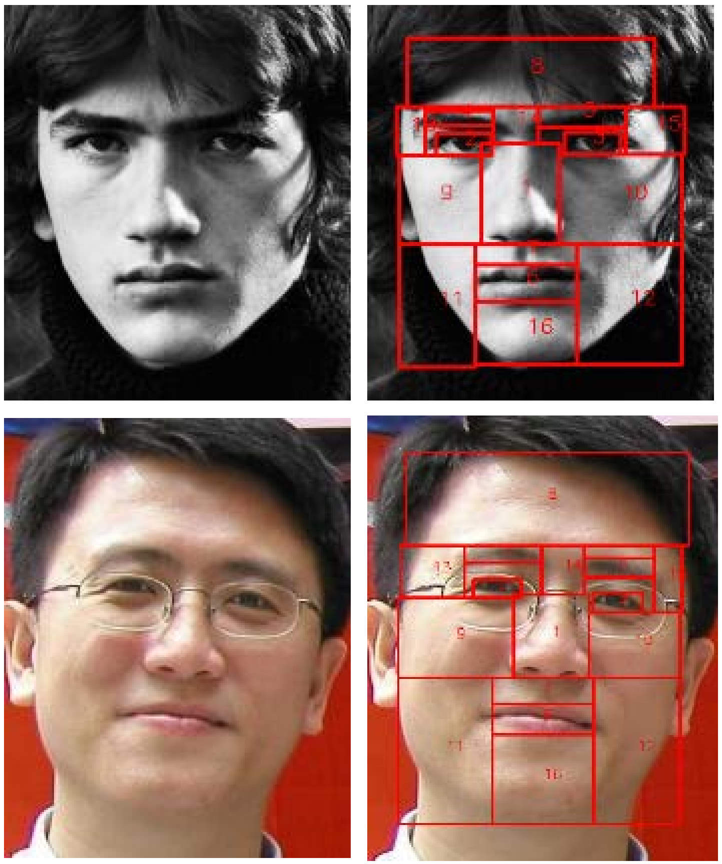
$$FID(P)=\{r_{mask}^{\mu}(F_i)|F_i \in F_D\}$$

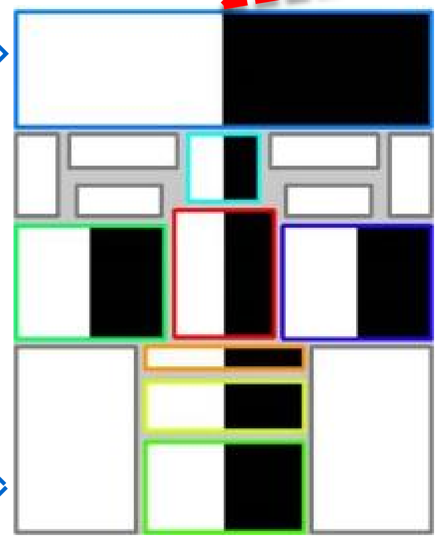
FID as Features



Classification of Portrait Illumination

$$MatchingScore(P,T_A) = \log\frac{p(P)}{q(P)} = \sum_{k=1}^{K}\left(\lambda_k r_k(P) - \log z_k\right)$$





Common Template

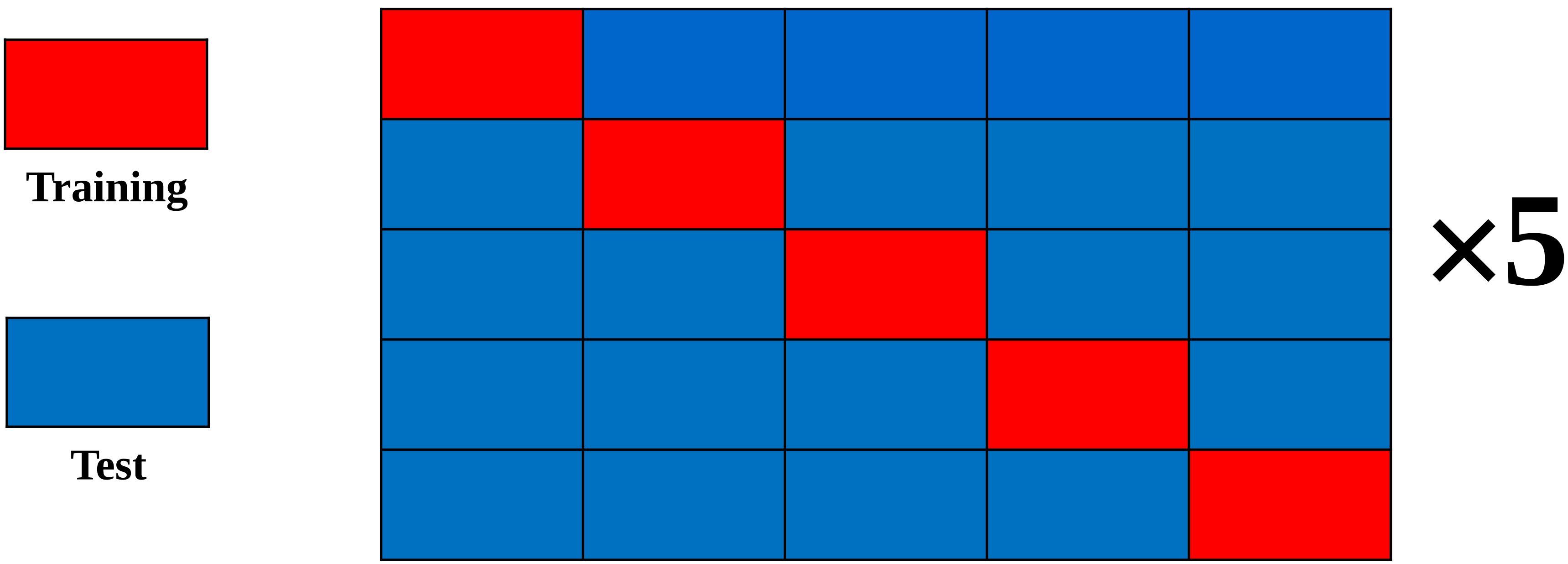
Matching Score -63.1821 → Artistic Illum.

Thresh. -76.6577

Matching Score -82.5216 → Daily Illum.

Classification of Portrait Illumination

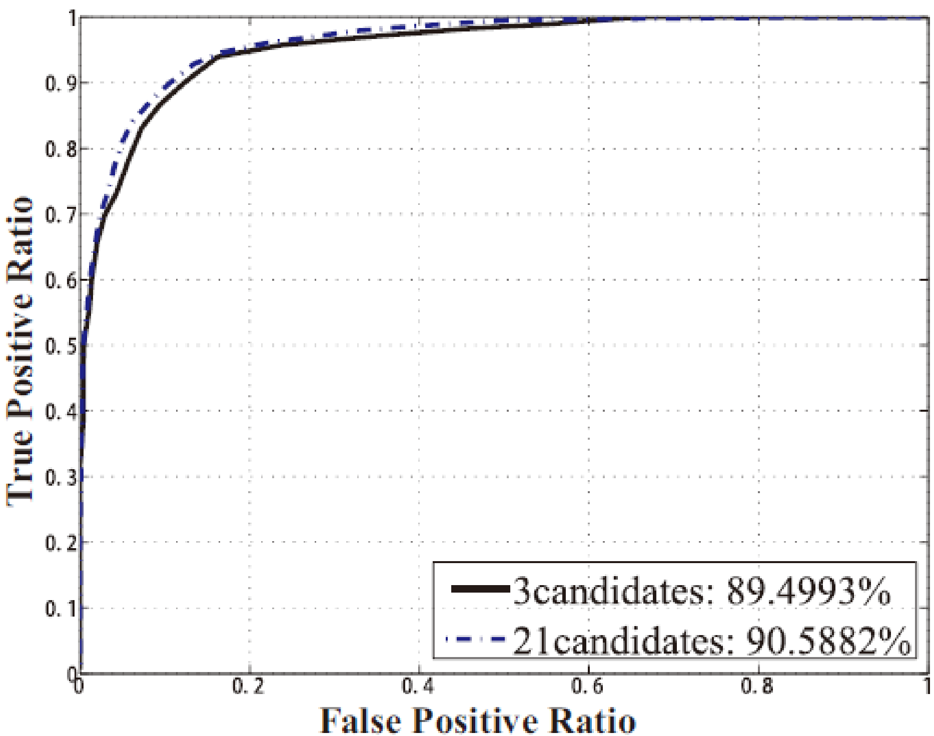
5 times 5 folds Cross Validation

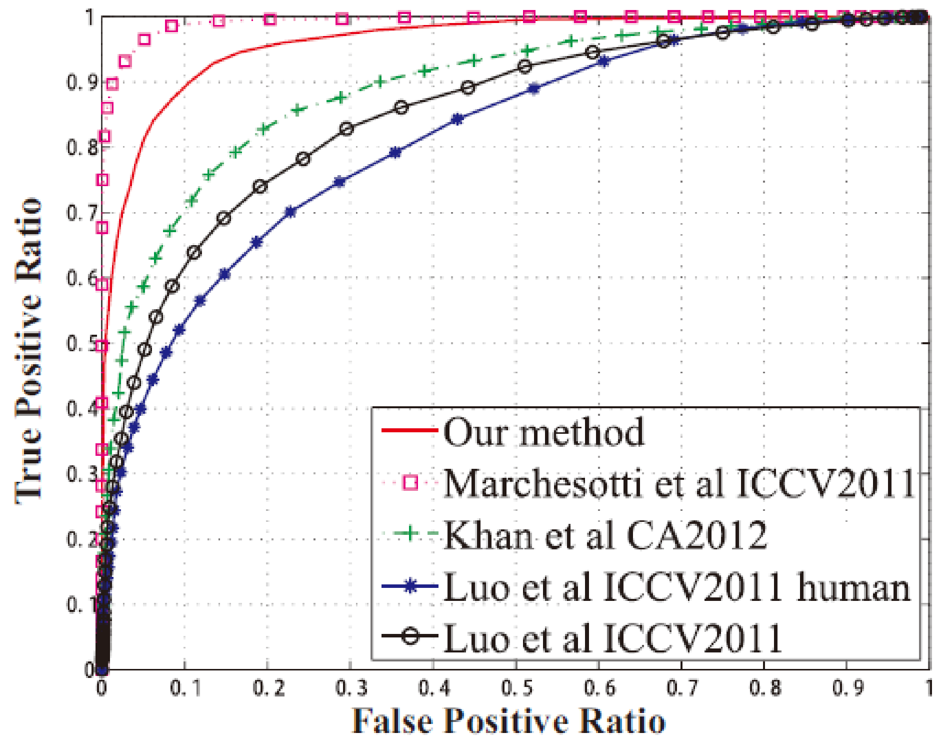


Classification of Portrait Illumination

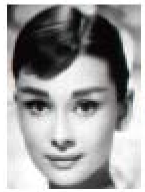
Classification of Portrait Illumination

Artistic vs. Daily

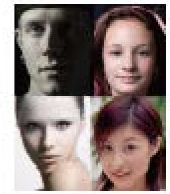


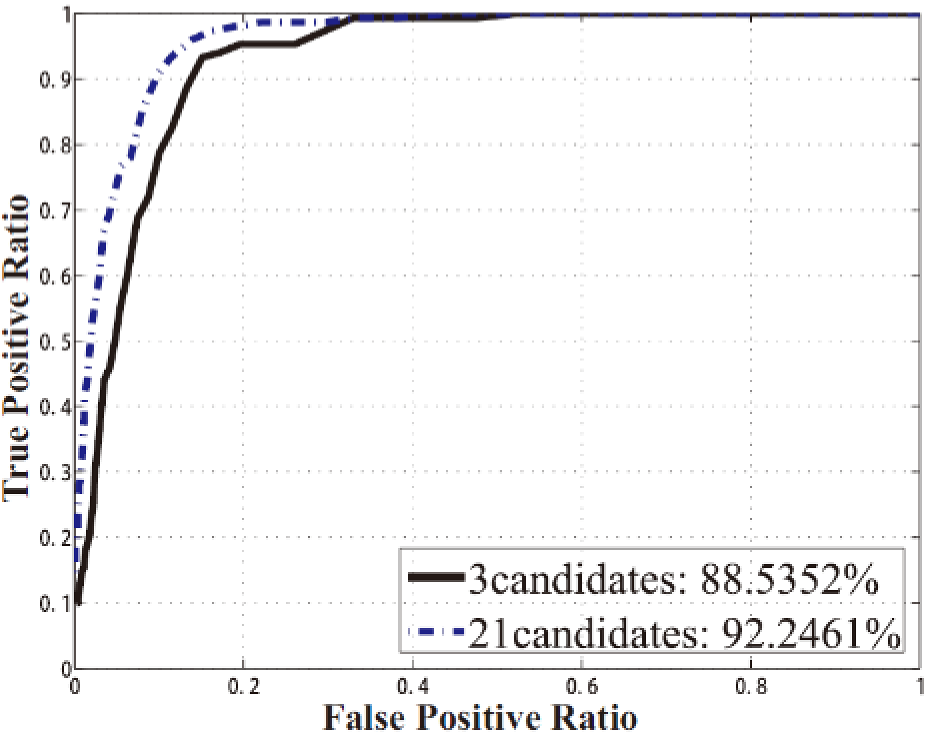


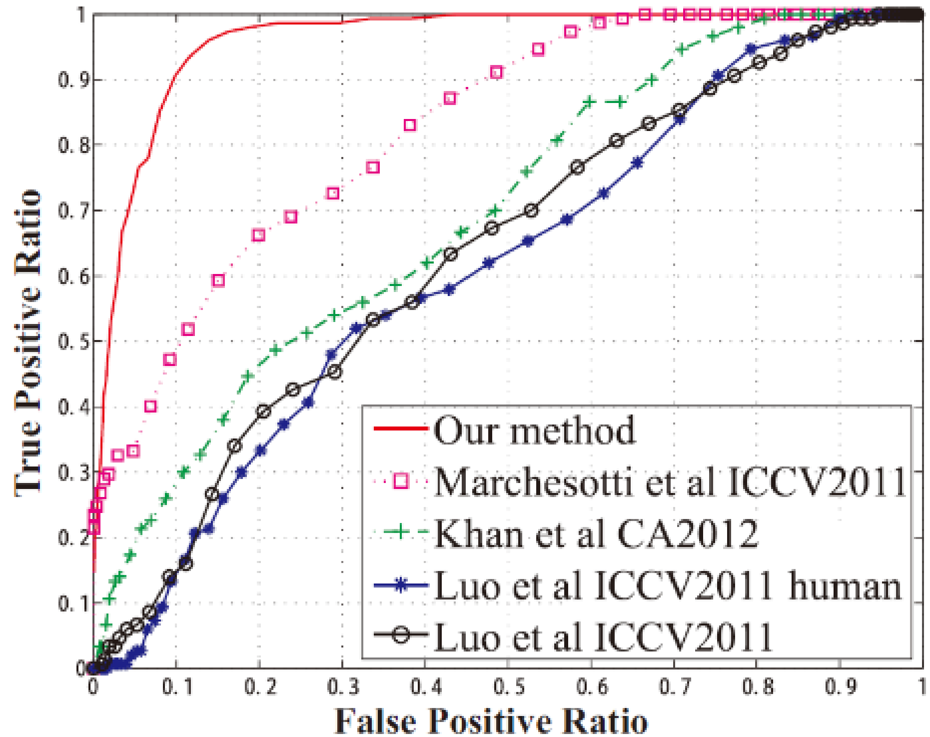
Classification of Portrait Illumination



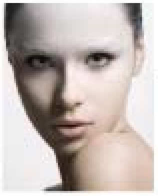
Paramount vs. Other



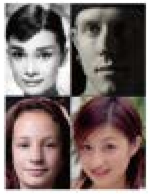


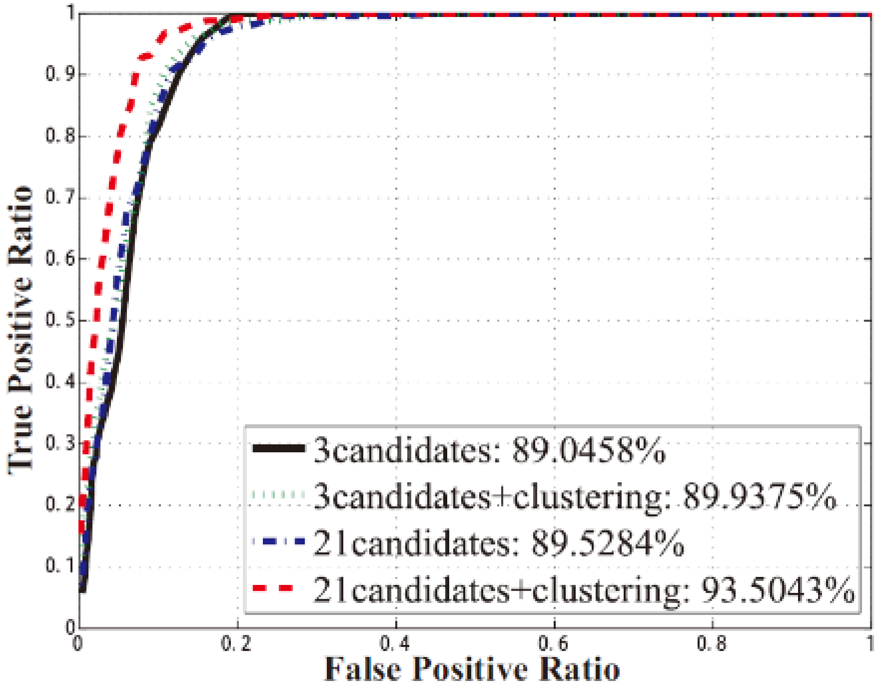


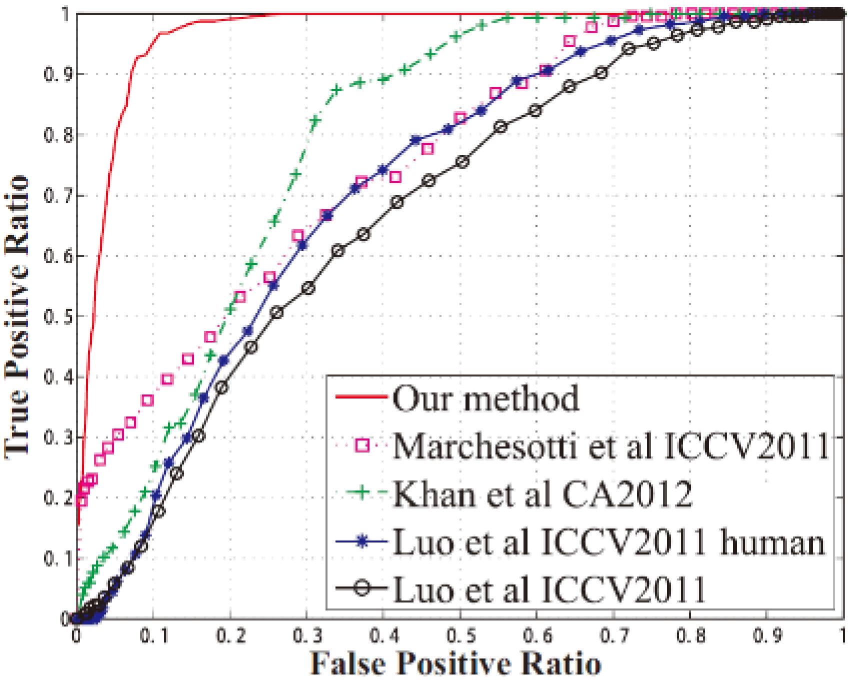
Classification of Portrait Illumination



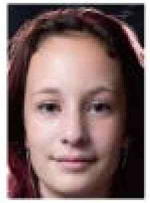
Rembrandt vs. Other



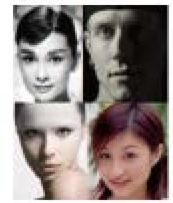


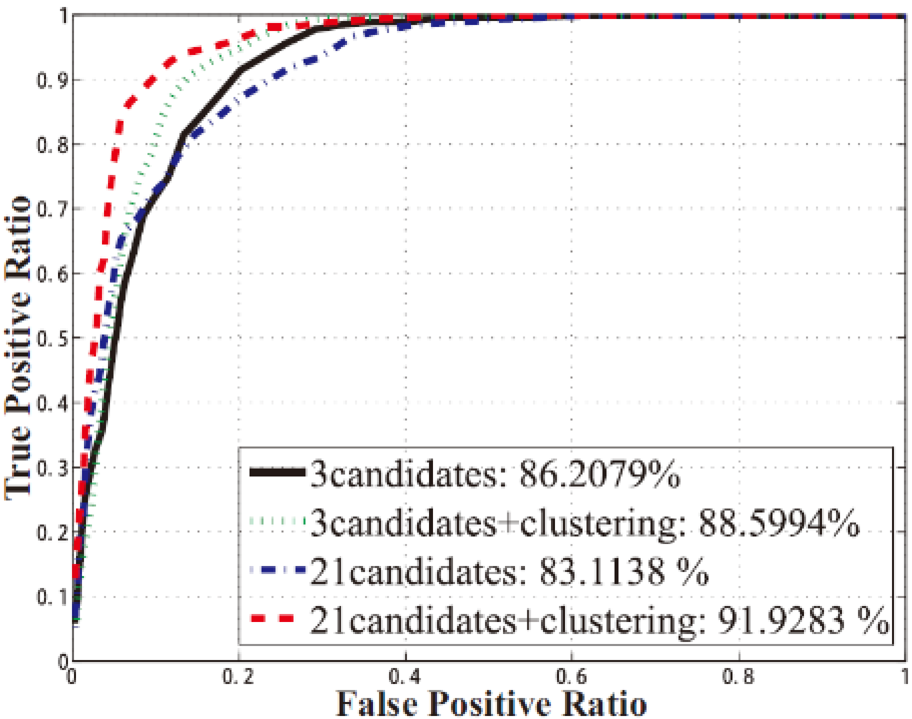


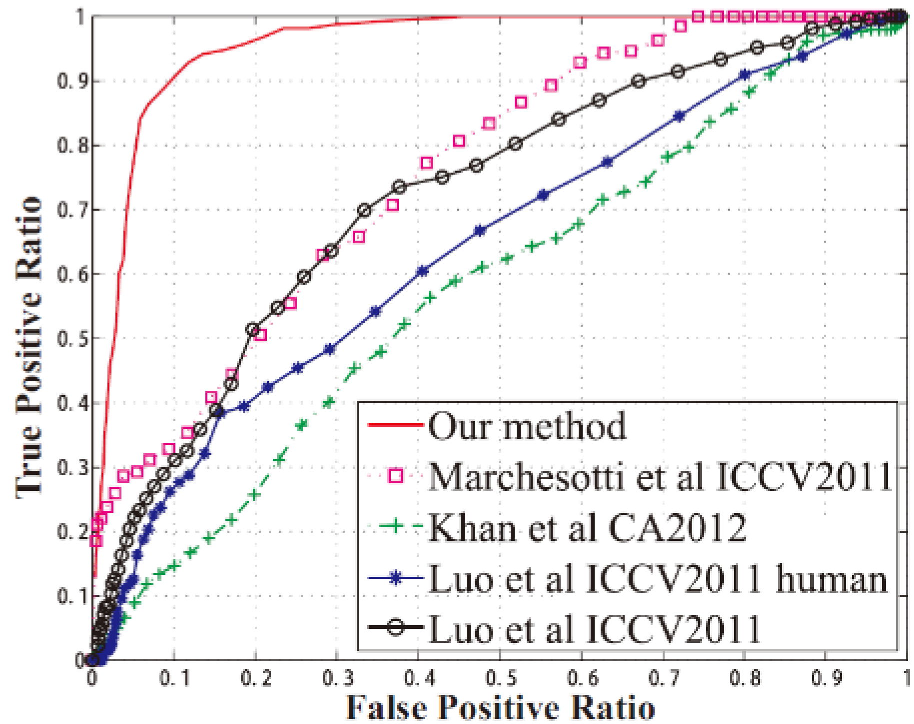
Classification of Portrait Illumination



Loop vs. Other

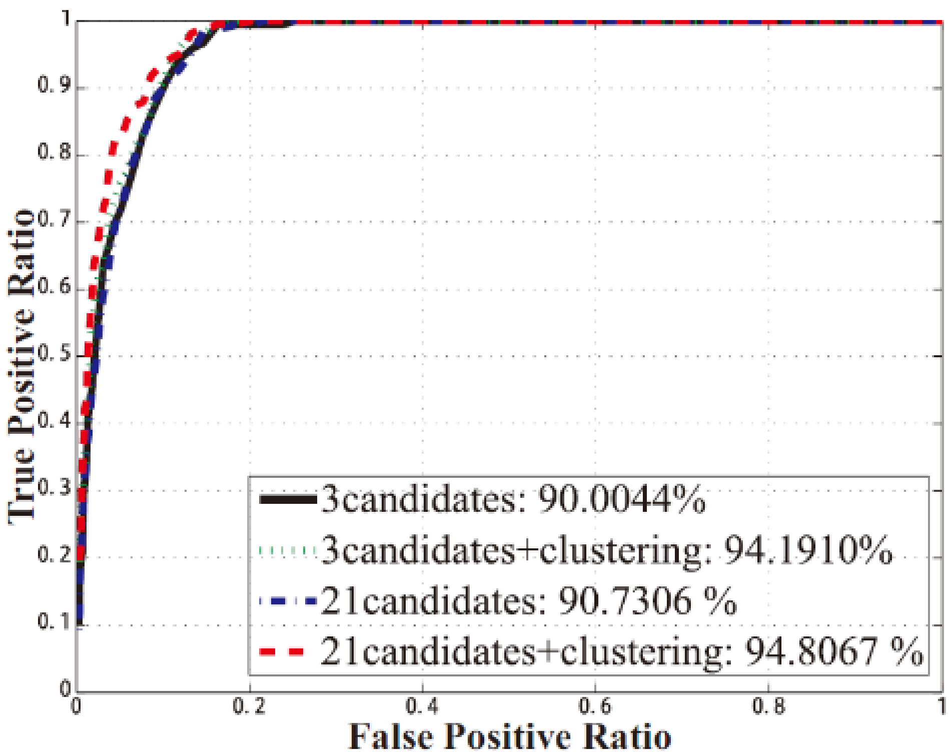


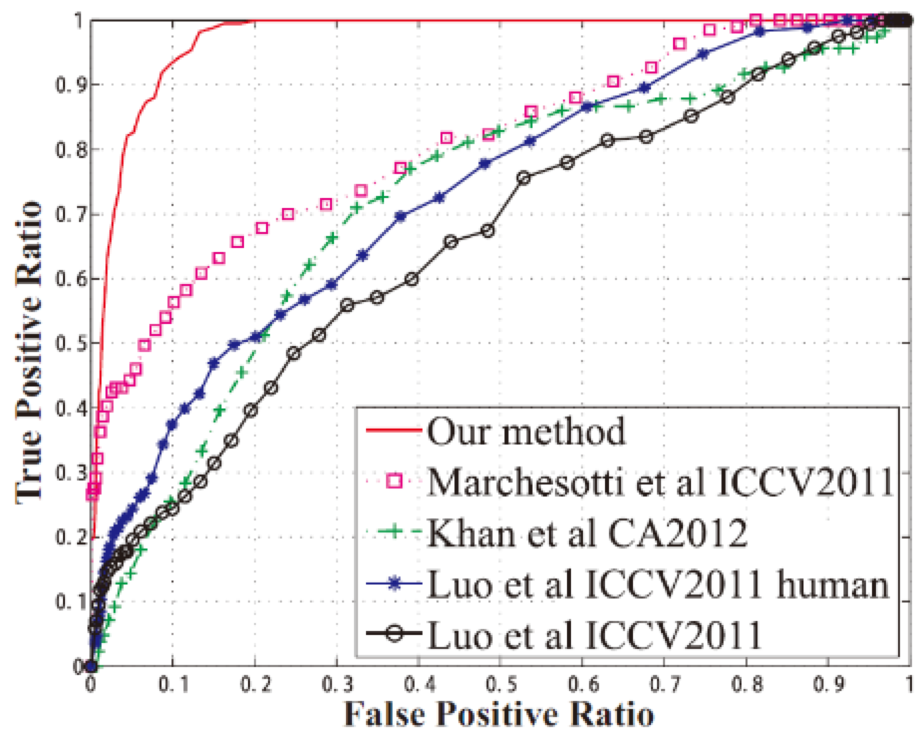




Classification of Portrait Illumination

Split vs. Other



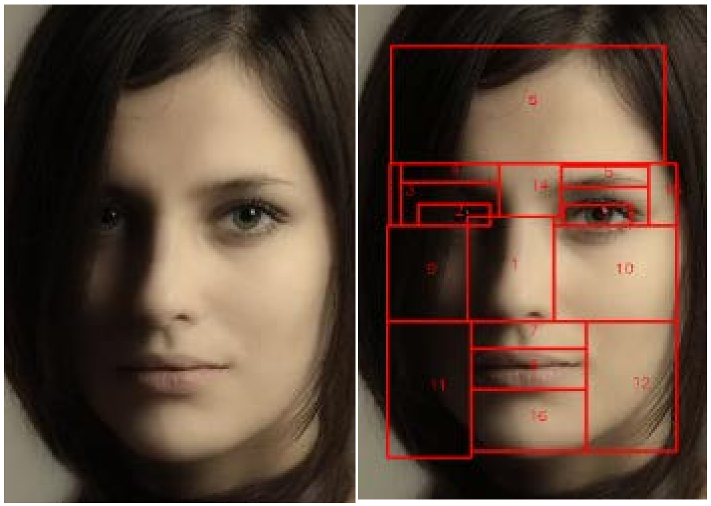


Numerical Assessment of Portrait Illumination

$$\mathit{QualityScore}(P) = p = \mathrm{E}_{f(J)}[1(P \text{ wins against } J)]$$

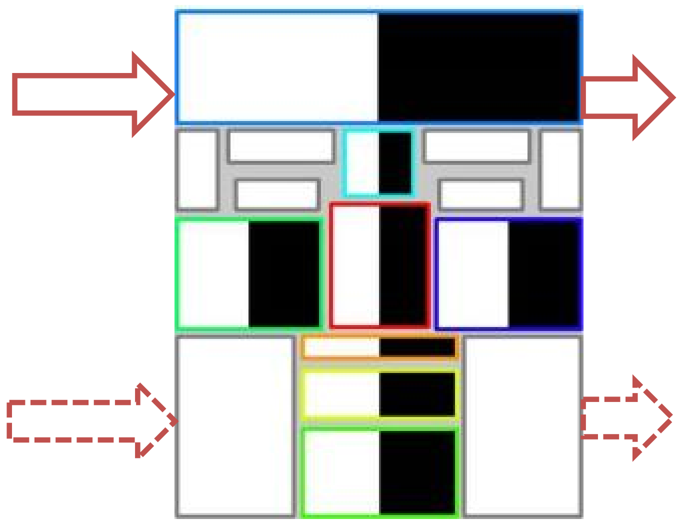
binom(n, p)

Numerical Assessment of Portrait Illumination



$$\log \frac{p}{1-p} = \sum_{k=1}^{K} (\lambda_k r_k(P) - \log z_k) = \lambda_0 + \sum_{k=1}^{K} \lambda_k r_k(P)$$

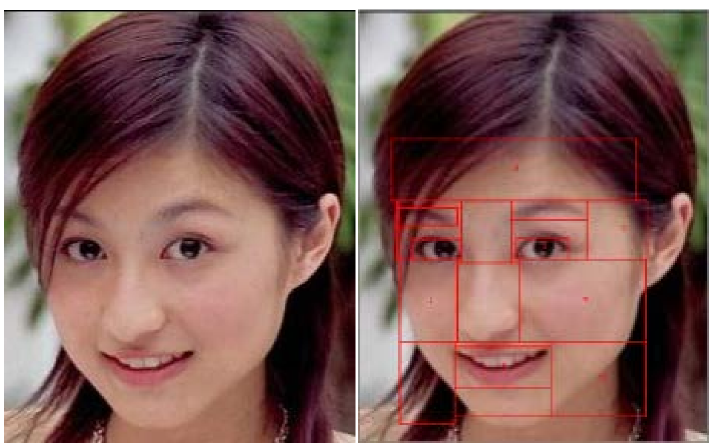
Logistic Regression



Score
0.781

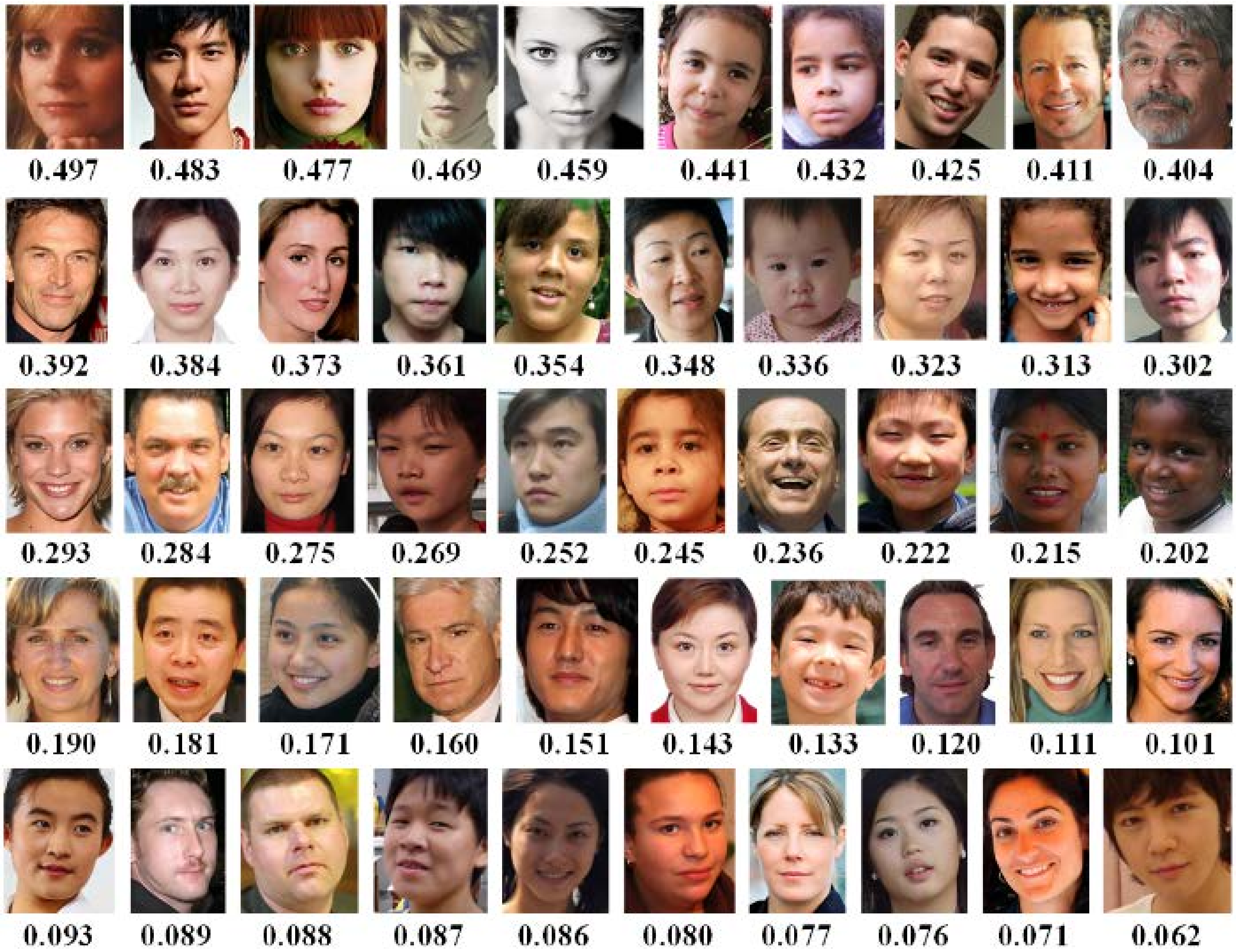
Score
0.157

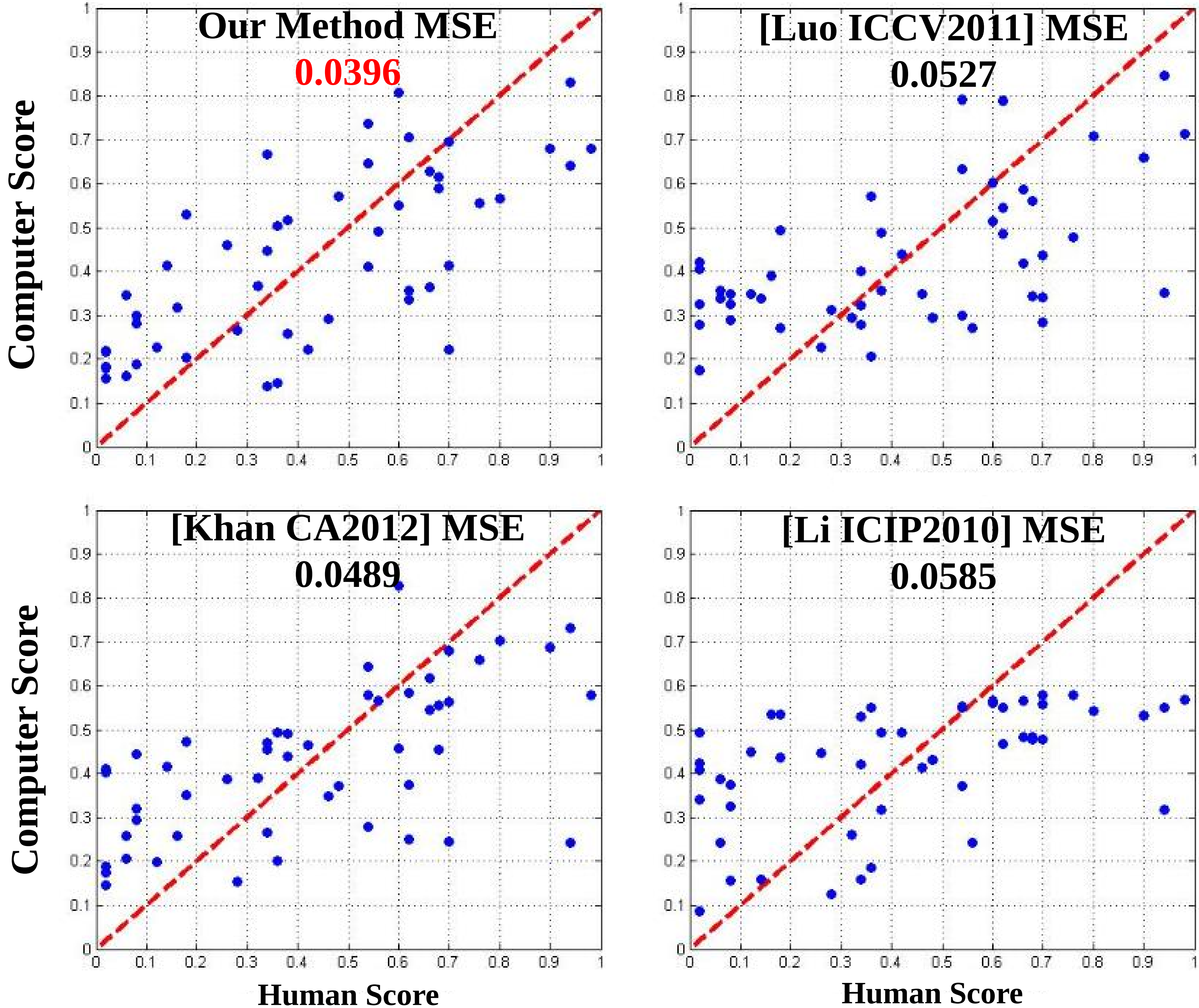
Common Template



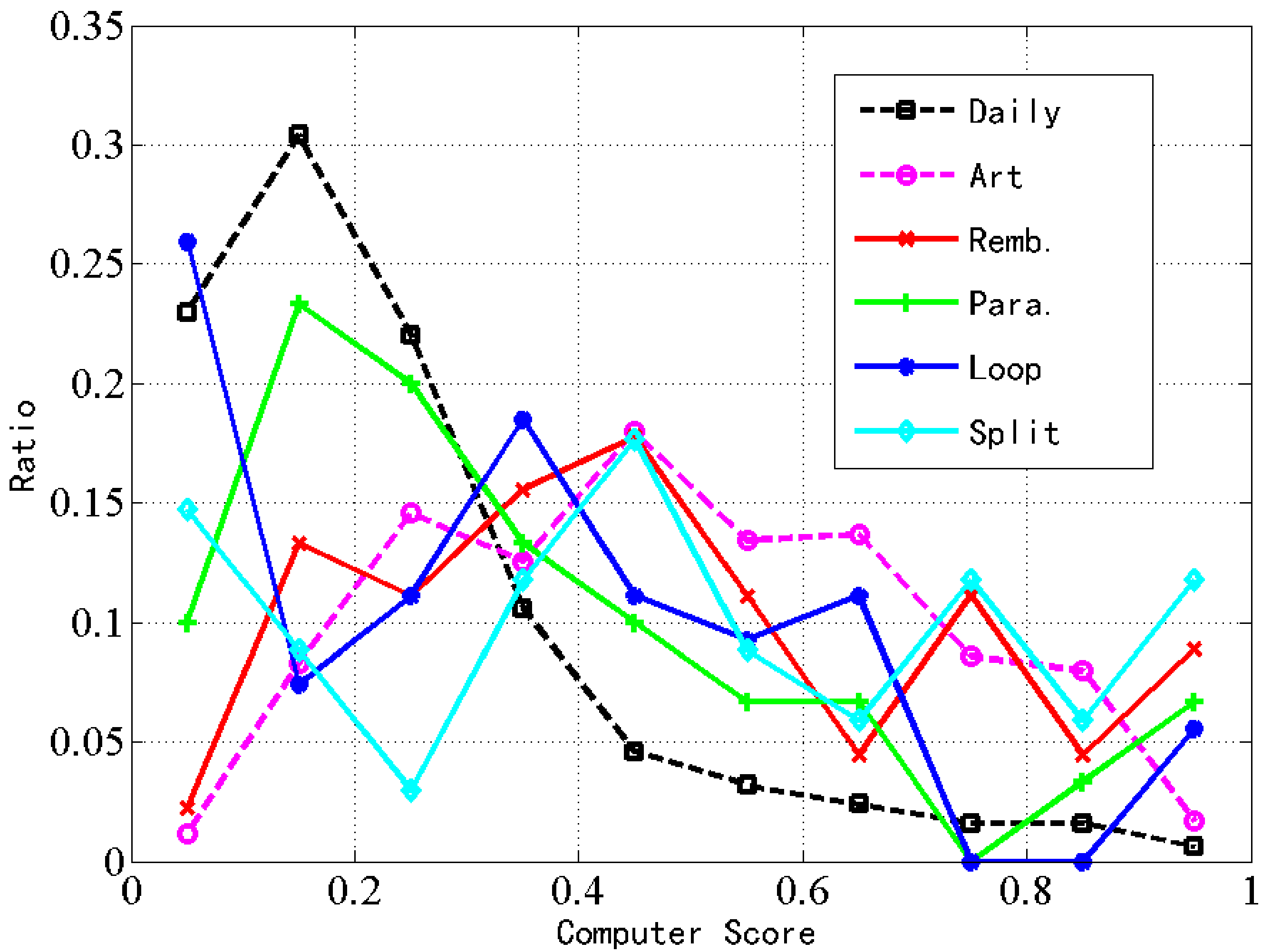
Numerical Assessment of Portrait Illumination

Numerical Assessment of Portrait Illumination




Our Method MSE
0.0396
[Luo ICCV2011] MSE
0.0527
[Khan CA2012] MSE
0.0489
[Li ICIP2010] MSE
0.0585
Computer Score
Human Score

Numerical Assessment of Portrait Illumination

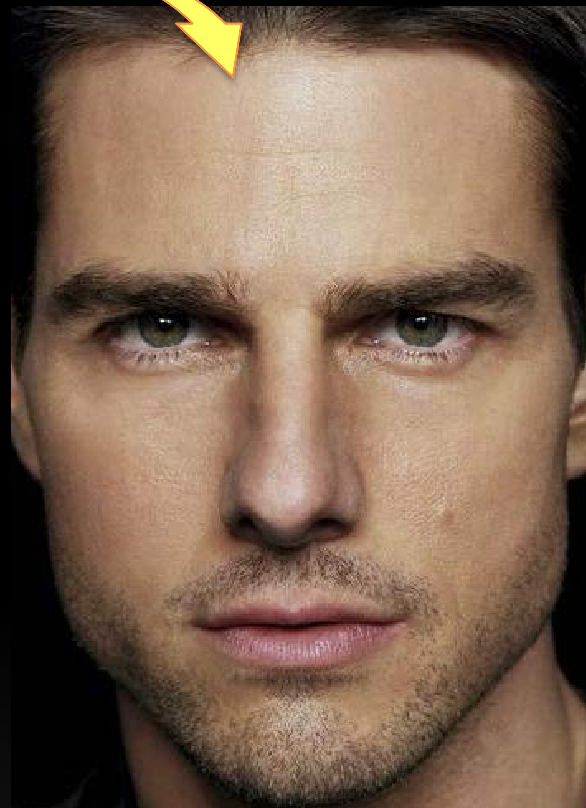


3 Questions

- Q1: Can computers assess portrait lighting automatically?
- Q2: Can we transfer good illumination to a normal lighting face ?
- Q3: How about artistic illumination from Masterpieces?

Q2: Can we transfer good illumination to a normal lighting face ?

reference face



input face

?

relit result

Related Work

1. Artistic Image Analysis
2. Artistic Image Synthesis

Related Work

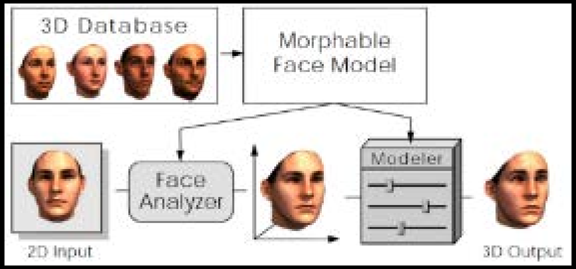
- **3D reconstruction**
  - □ Morphable Model[Blanz et al. 1999]

- **Two reference images**
  - □ Quotient Image [Riklin-Raviv et al. 1999] [Peers et al. 2007] [Chen et al. 2010]

- **A single reference image**
  - □ Logarithmic Total Variation (LTV) Model [Li et al. 2009]

Related Work

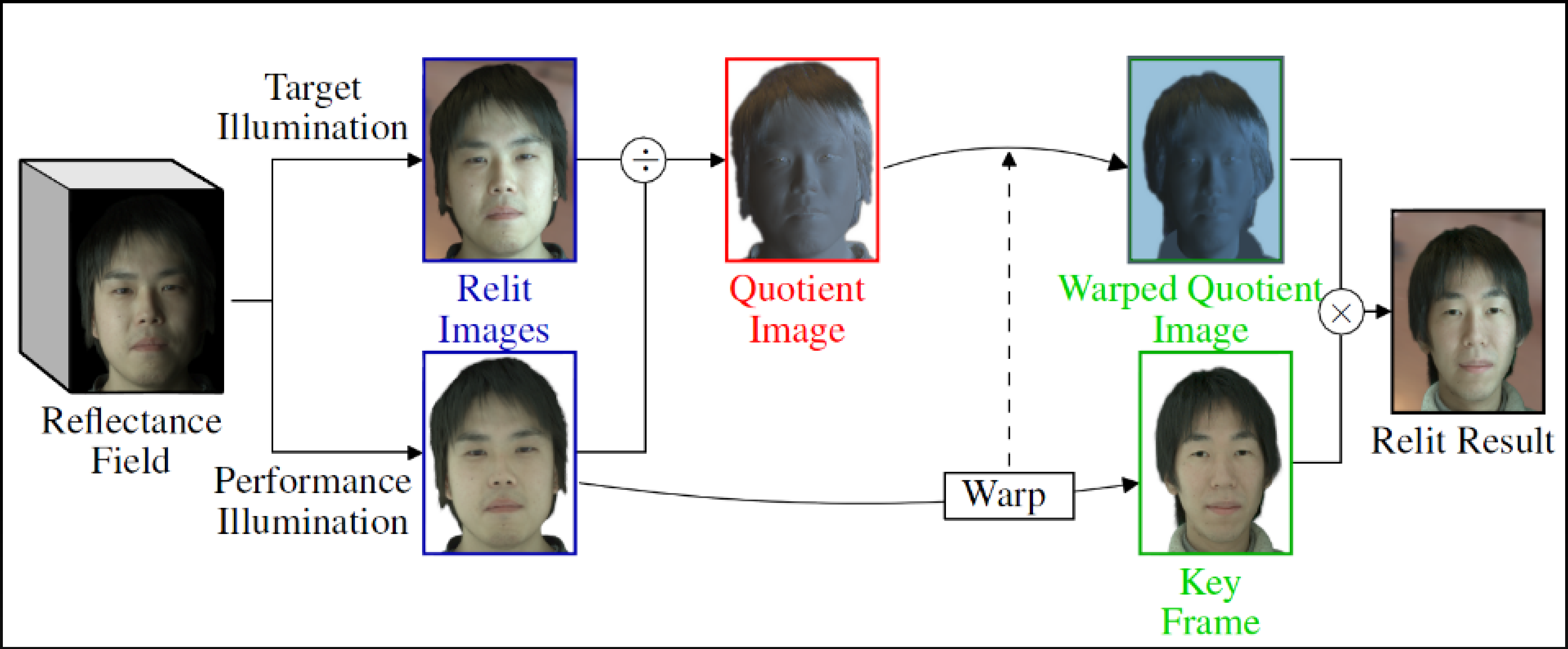
Morphable Model[Blanz *et al.* 1999]



Blanz Volker and Vetter Thomas. A morphable model for the synthesis of 3D faces. SIGGRAPH 1999.

Related Work

Quotient Image [Riklin-Raviv *et al.* 1999] [Peers *et al.* 2007] [Chen *et al. 2010*]



Peers Pieter, Tamura Naoki, Matusik Wojciech and Debevec Paul. Post-production Facial Performance Relighting using Reflectance Transfer. SIGGRAPH2007.

Related Work

Quotient Image [Riklin-Raviv *et al.* 2001] [Peers *et al.* 2007] [Chen *et al. 2010*]

Reference

Input

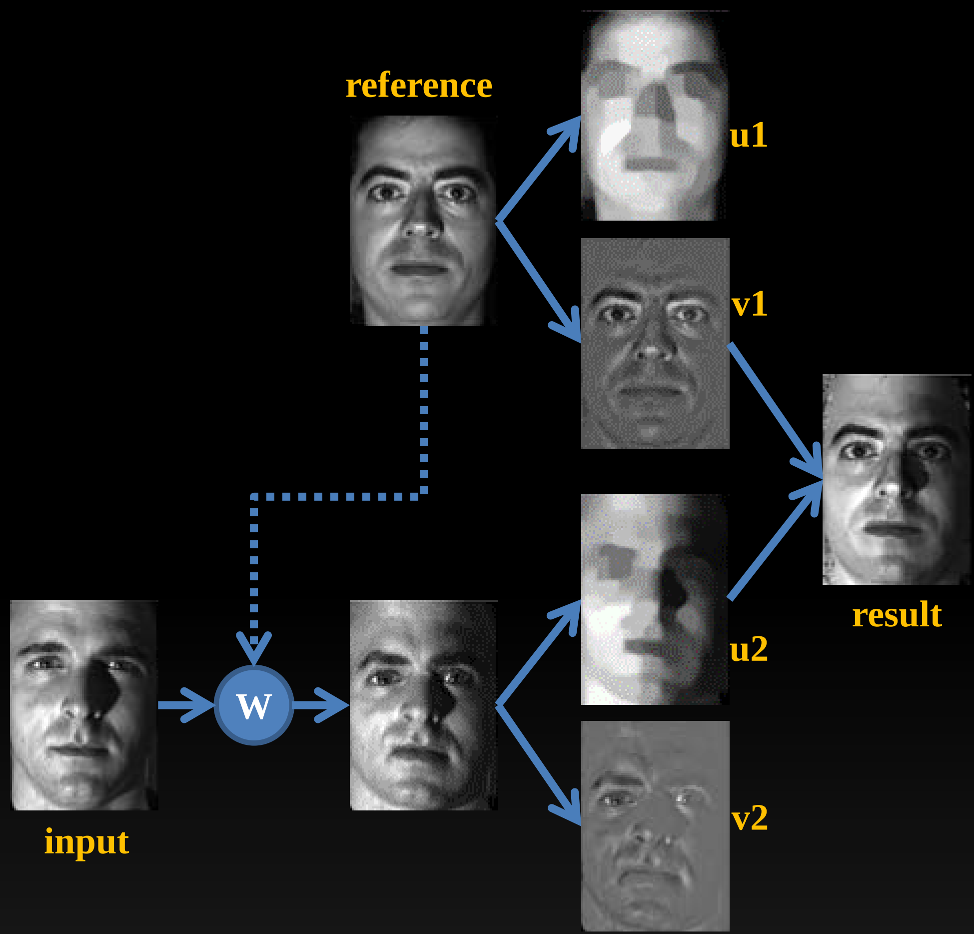
?

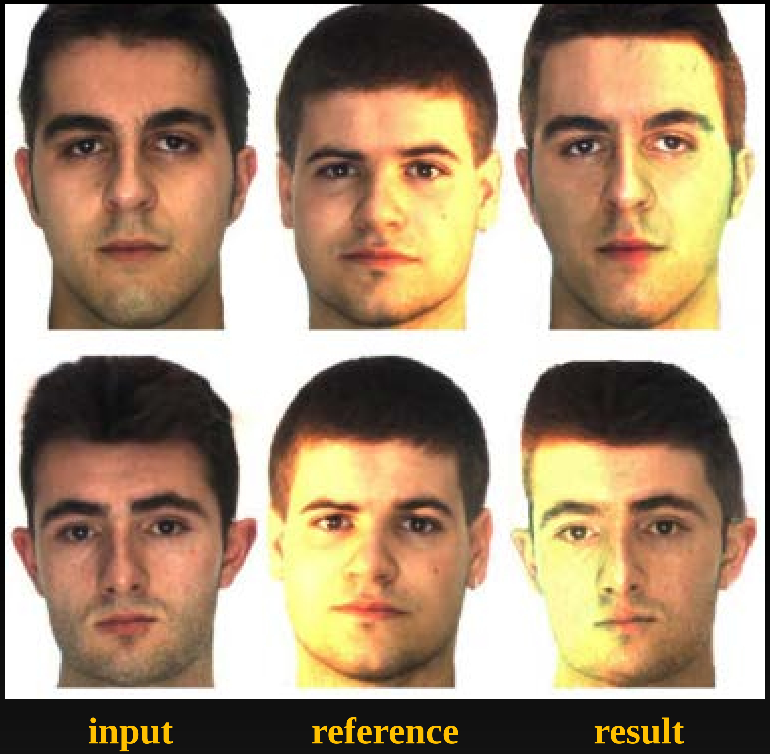
Result

If only a single reference image is available ?

Related Work

Logarithmic Total Variation (LTV) Model [Li *et al.* 2009]





Qing Li, Wotao Yin and Zhigang Deng. Image-based face illumination transferring using logarithmic total variation models. The visual computer, 2010.

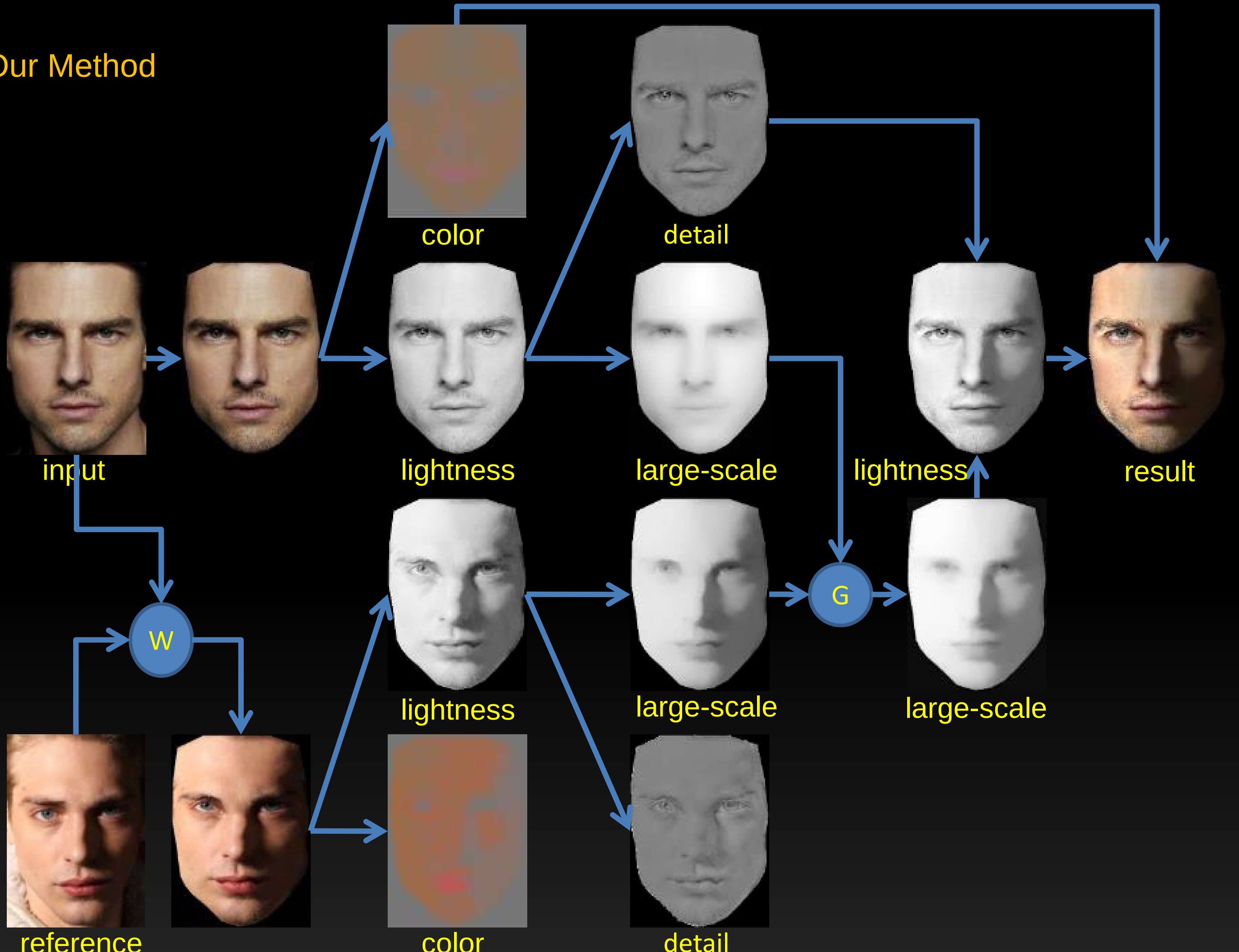
Related Work

Logarithmic Total Variation (LTV) Model [Li *et al.* 2009]

(a) reference images (b) input images (c) Li et al.

Qing Li, Wotao Yin and Zhigang Deng. Image-based face illumination transferring using logarithmic total variation models. The visual computer, 2010.

Our Method

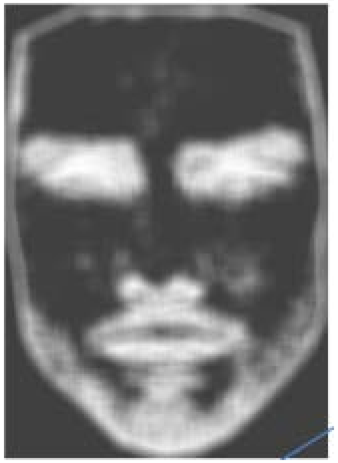

color
detail
input
lightness
large-scale
lightness
result
W
lightness
large-scale
G
large-scale
reference
color
detail

WLS Filter with Adaptive Filter

$$E = |l - s|^2 + H(\nabla s, \nabla l)$$

$$H(\nabla s, \nabla l) = \sum_p \left(\boxed{\lambda(p)} \left(\frac{(\partial s/\partial x)_p^2}{(\partial l/\partial x)_p^\alpha + \epsilon} + \frac{(\partial s/\partial y)_p^2}{(\partial l/\partial y)_p^\alpha + \epsilon} \right) \right).$$

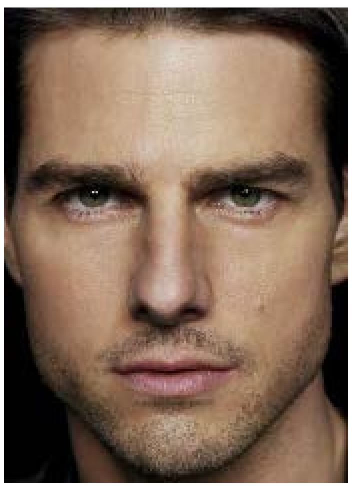
$$\gamma(p) = \sum_{i \in \omega_p} \left(\sqrt{(\partial l/\partial x)_i^2 + (\partial l/\partial y)_i^2} \geq t_1 \right)$$



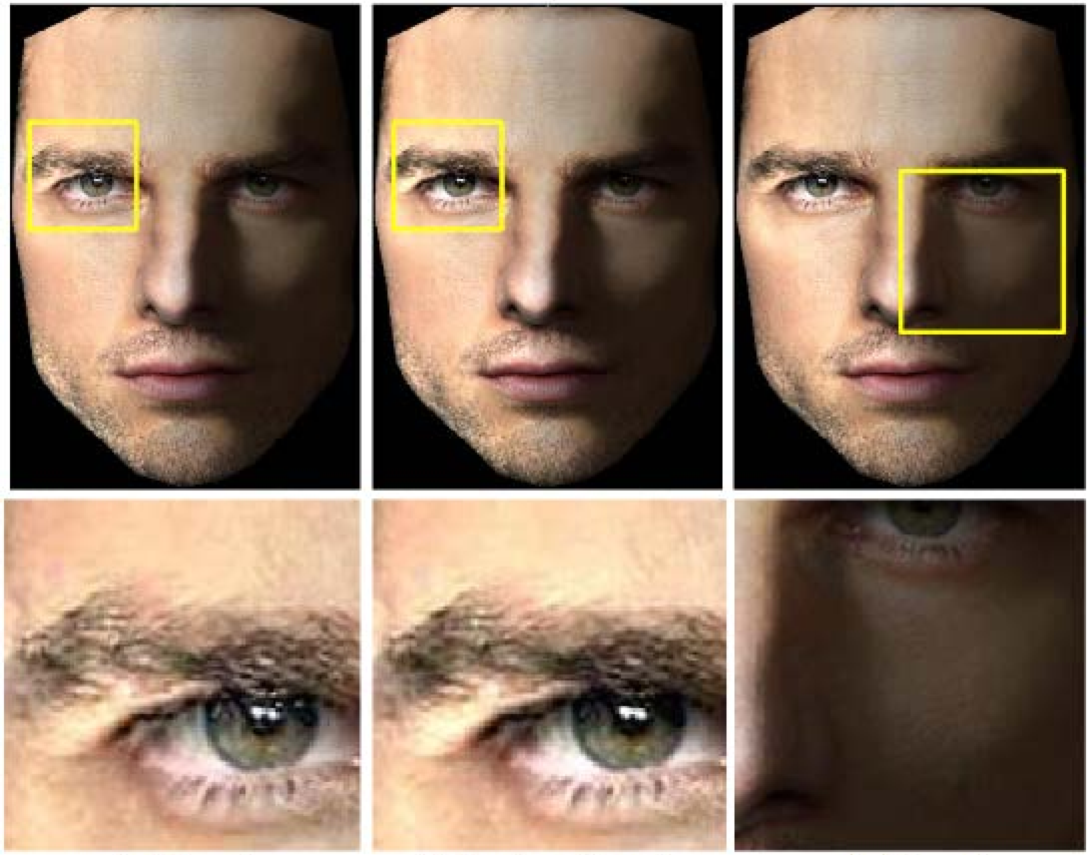
$$\lambda(p) = \lambda_s + (\lambda_l - \lambda_s) * \gamma(p)$$

WLS Filter with Adaptive Filter

Reference



Input



(a) $\lambda = 1$ (b) adaptive λ (c) $\lambda = 4$

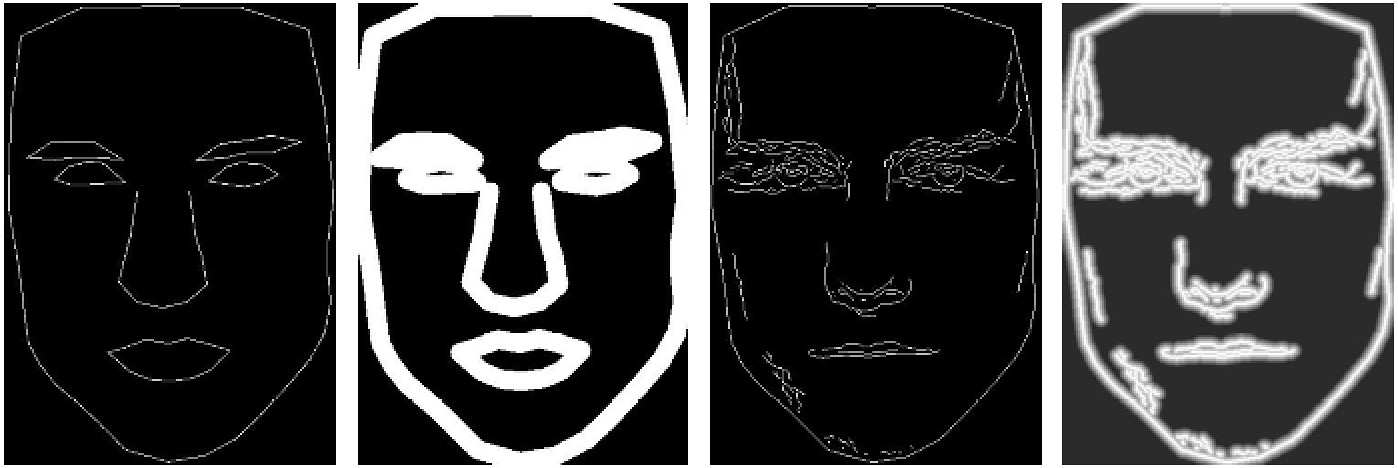
Guided Filter with Adaptive Filter

$$q_i = a_k I_i + b_k, \forall i \in w_k$$

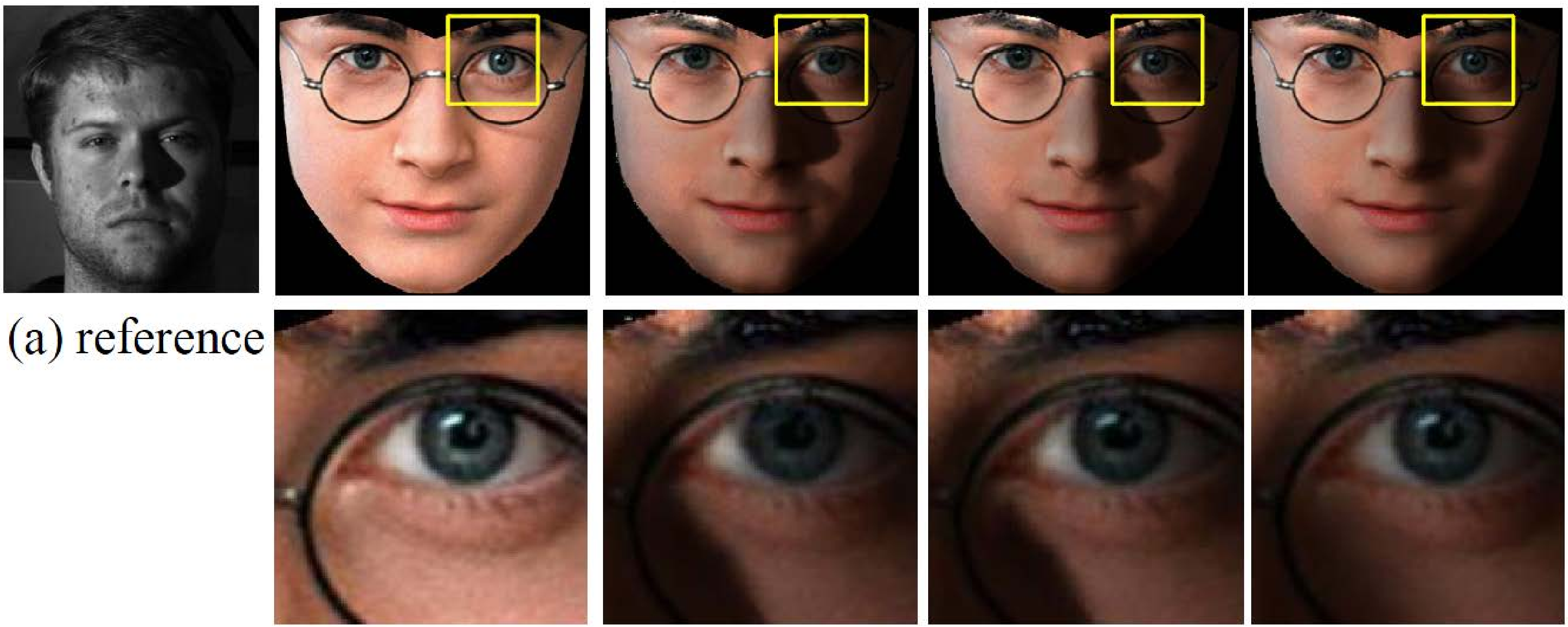
$$E(a_k, b_k) = \sum_{i \in w_k} ((a_k I_i + b_k - P_i)^2 + \epsilon a_k^2)$$

$$dist(p) = |p - q(\min_q(|q - p|))|$$

$$r(p) = \begin{cases} \frac{dist(p)}{T_d} r_0 + (1 - \frac{dist(p)}{T_d}) r_1 & \text{if } dist(p) \le T_d \\ r_0 & \text{else} \end{cases}$$



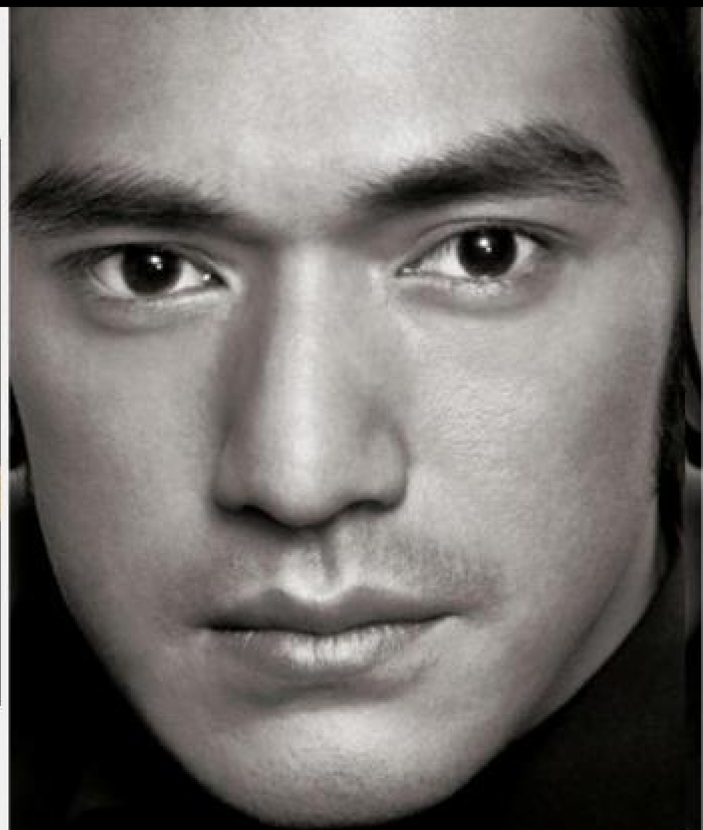
Guided Filter with Adaptive Filter



(a) reference

(b) input (c) $r = 3$ (d) adaptive r (e) $r = 18$

reference face



input face

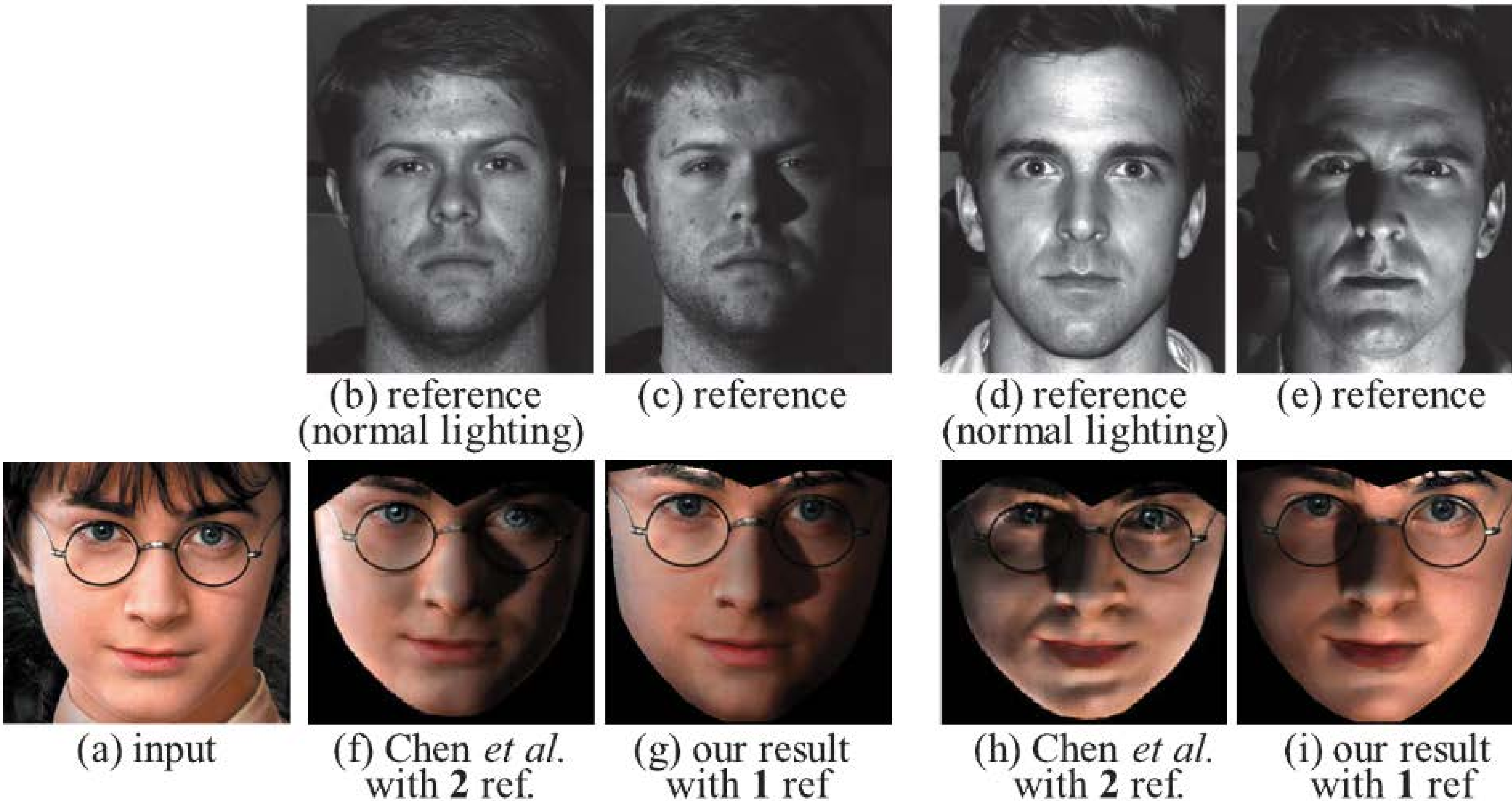
relit result


GIFAK.NET

Comparison with Previous Work

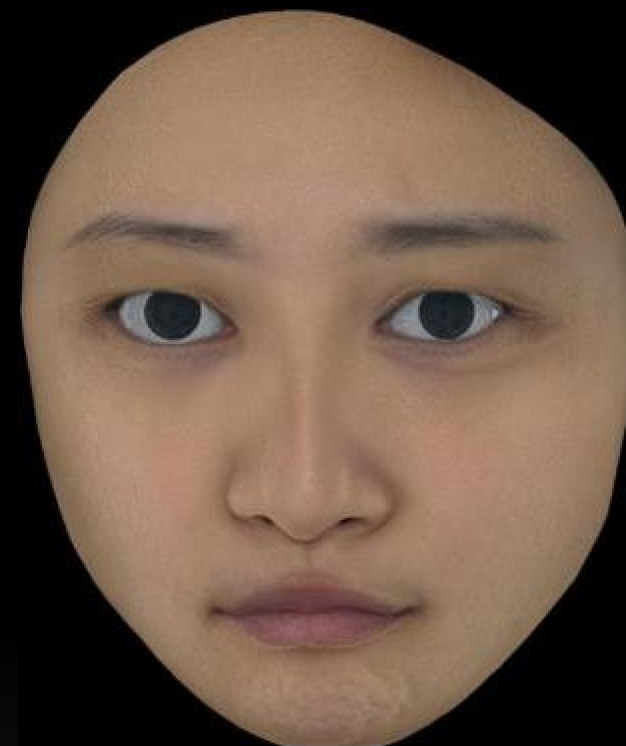
(a) reference images (b) input images (c) Li et al. (d) our results

Comparison with Previous Work



Illumination Normalization ?

Input Image



Normalized

Illumination Normalization ?

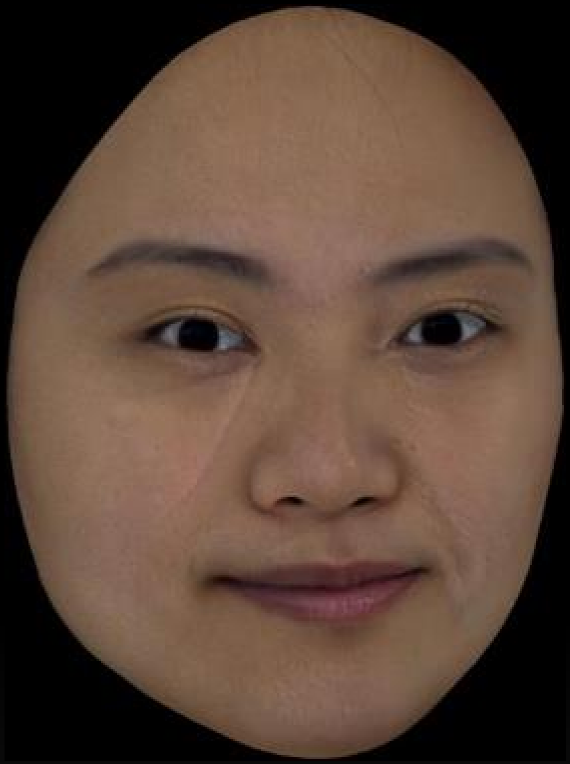
Input Image

?

Normalized

Illumination Normalization ?

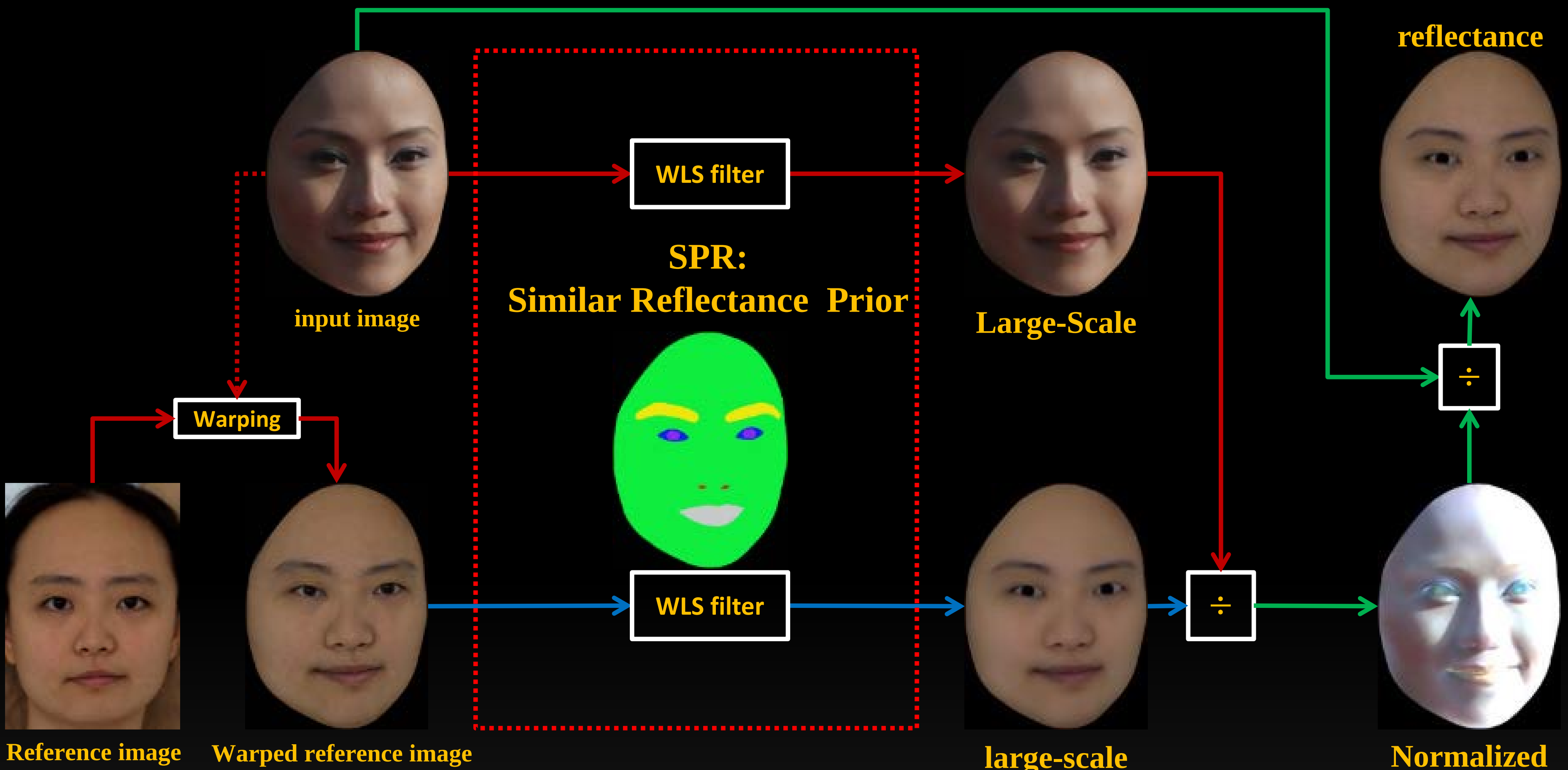
Input Image



Normalized

Use the Above Illumination Transfer Workflow

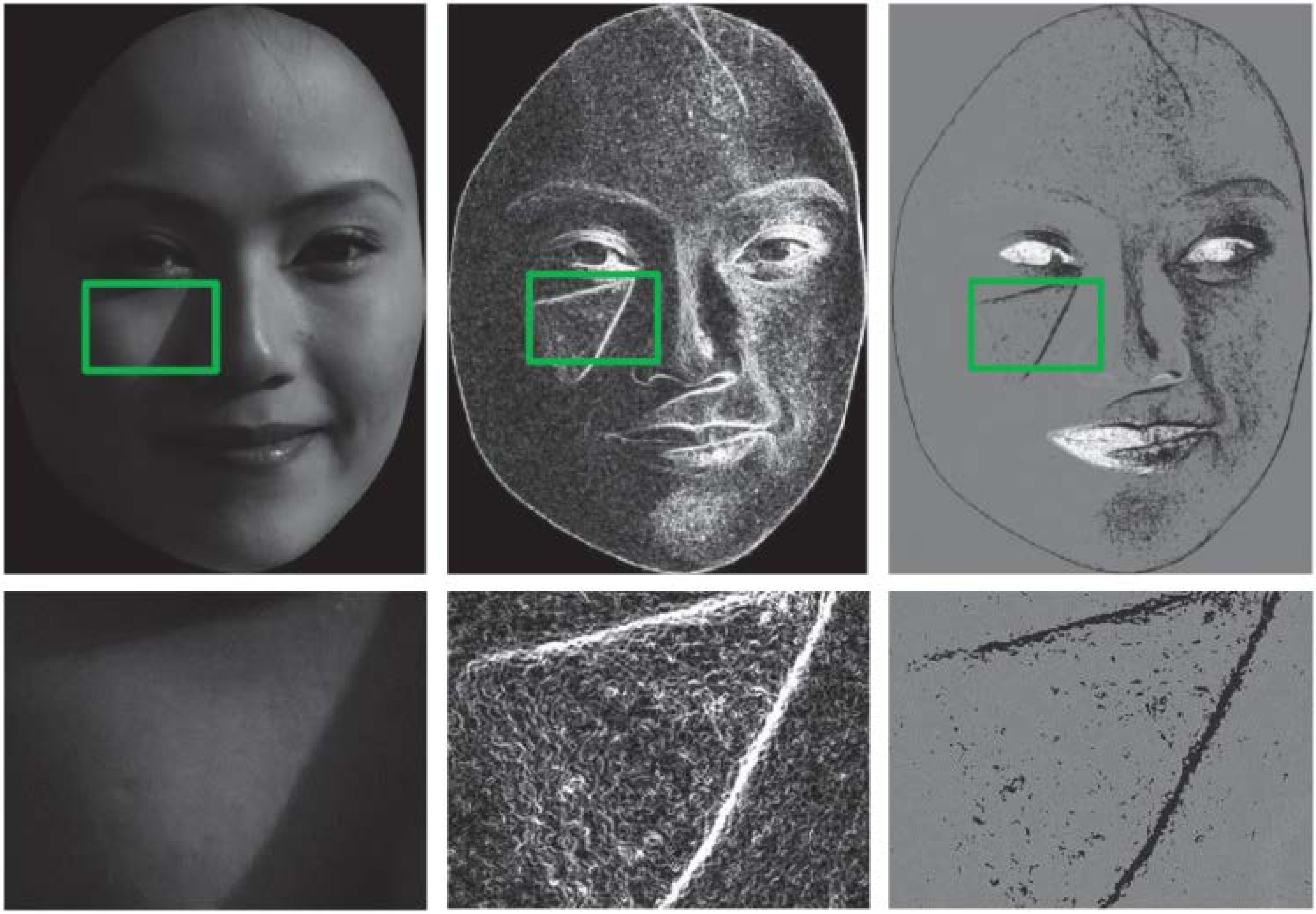
WLS + Guided Filter with Adaptive Parameters



$$\lambda(p) = \begin{cases} C_s & \text{if } ga(p) \geq T_g \\ ga(p) & \text{others} \end{cases}$$

$$ga(p) = \sqrt{(\partial l/\partial x)_i^2 + (\partial l/\partial y)_i^2}$$

Comparison with Previous Work



Input Image | Gradient | Adaptive λ with SPR

Comparison with Previous Work

Input

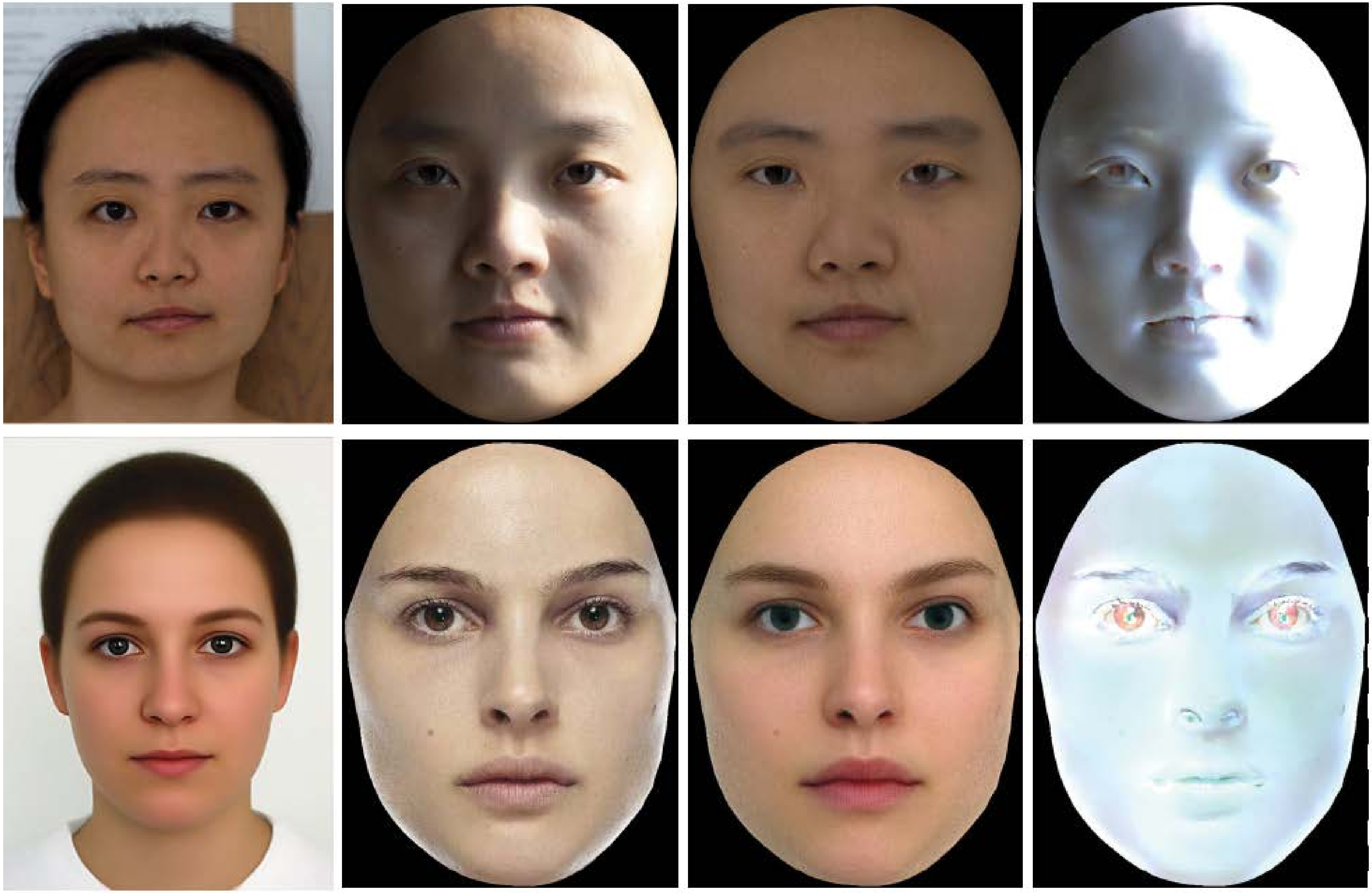
Without SPR + Guide Filter
Illumination Transfer

With SPR + Guided Filter

With SPR – Guide Filter

Comparison with Previous Work

(a) λ = 0.01 | (b) λ = 4 | Without SPR + Guided Filter Illumination Transfer | With SPR + Guided Filter | With SPR – Guide Filter

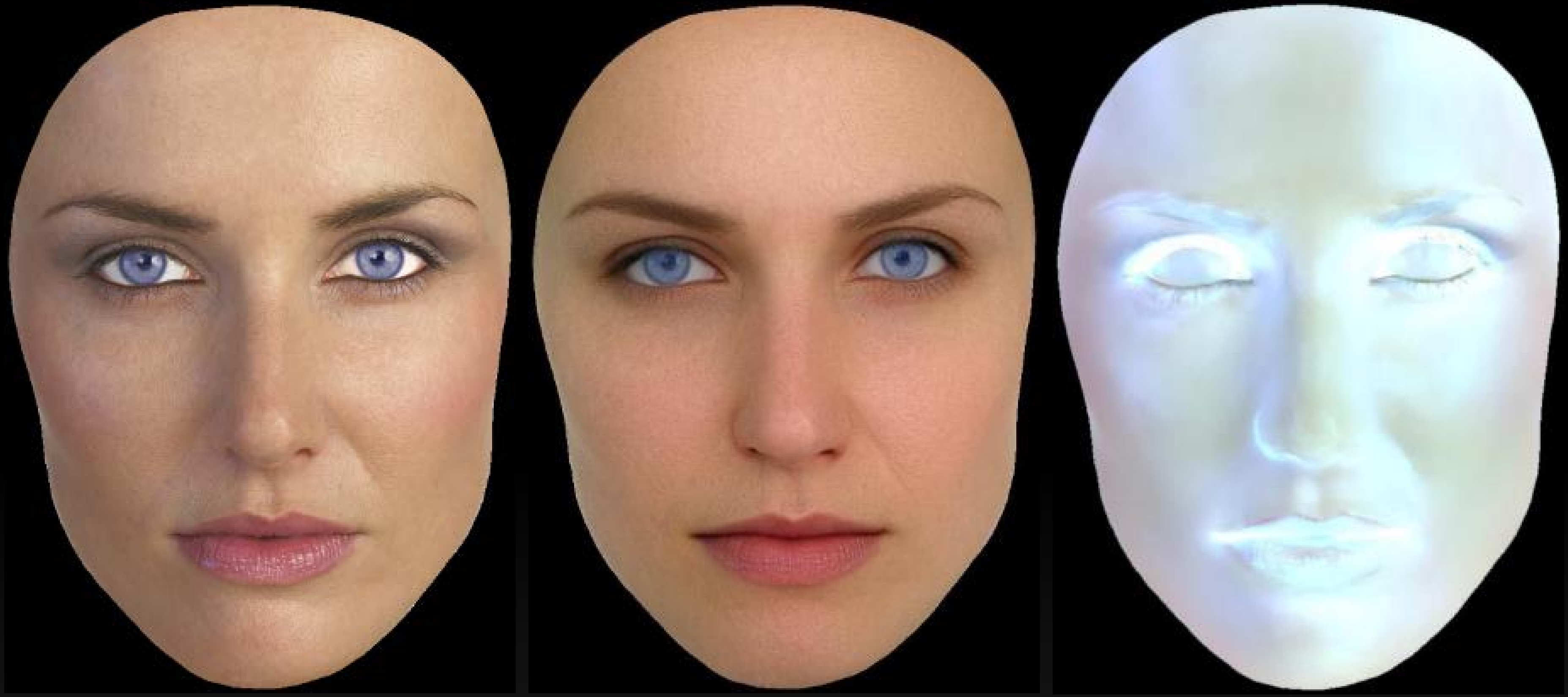


(a) reference (b) input (c) normalized (d) illumination

Additional results

reference images

Additional results



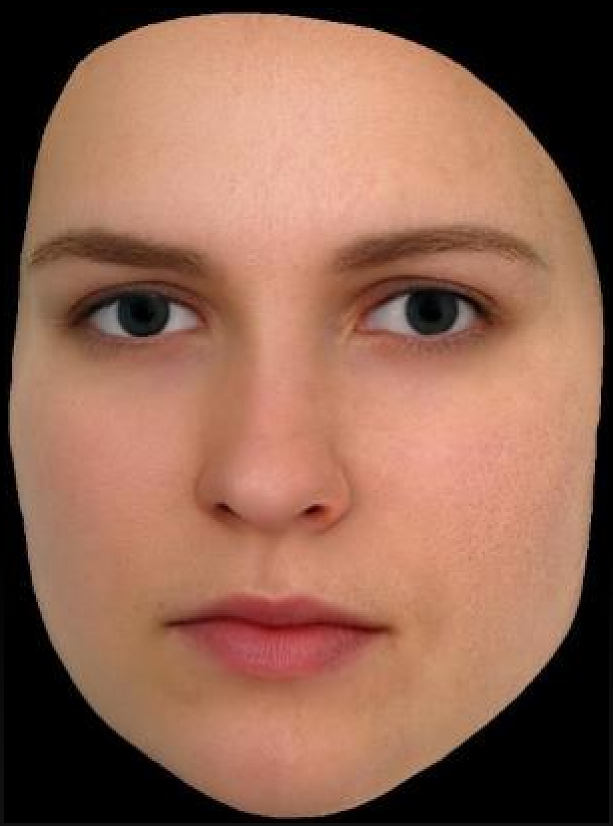
input image

normalized

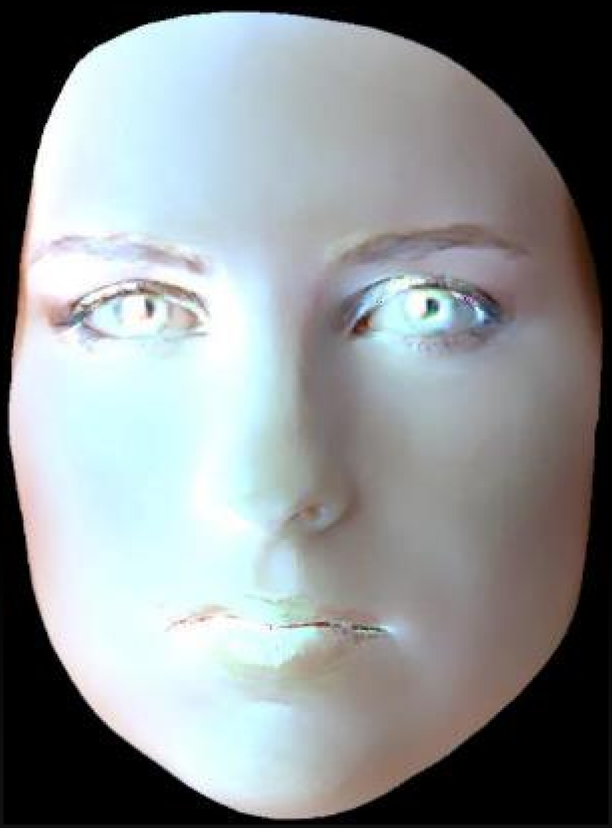
illumination

Additional results

input image



normalized



illumination

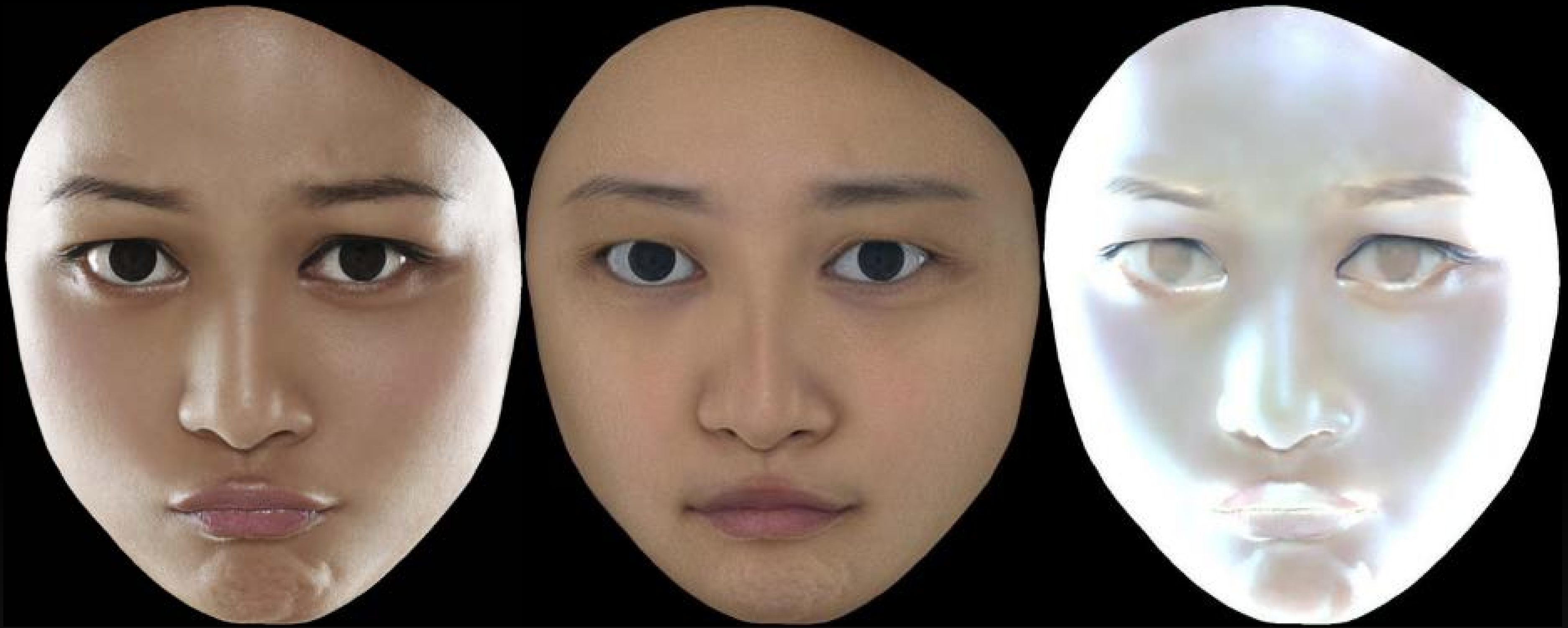
Additional results

input image

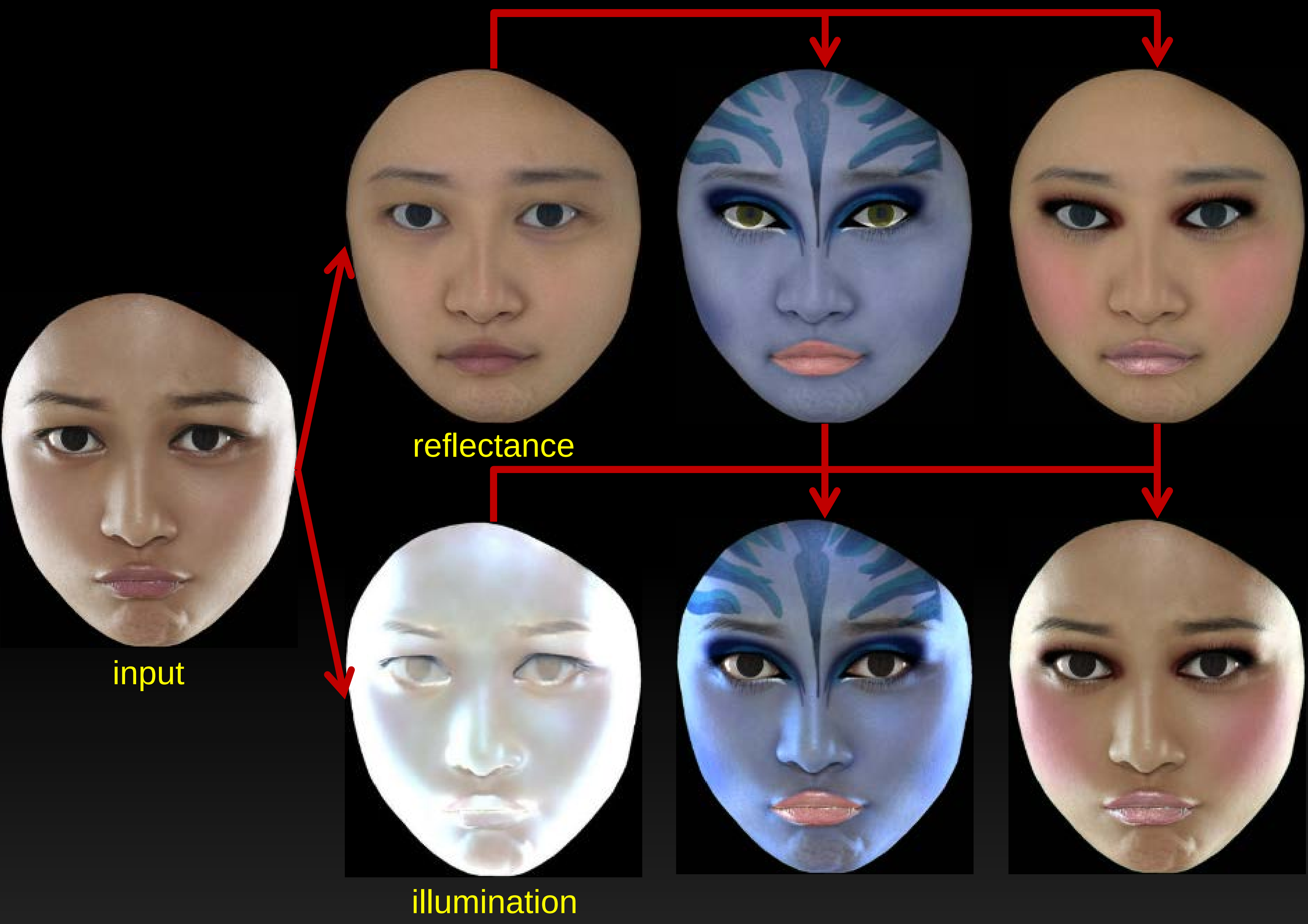
normalized

illumination

Additional results



input image normalized illumination


reflectance
input
illumination

Comparison with Previous Work

(a) input images (b) Bousseau *et al.* (c) Shen *et al.* (d) our method

Illumination Changing

reference | input | directly transfer | normalized | relit result

3 Questions

- Q1: Can computers assess portrait lighting automatically?
- Q2: Can we transfer good illumination to a normal lighting face ?
- Q3: How about artistic illumination from Masterpieces?

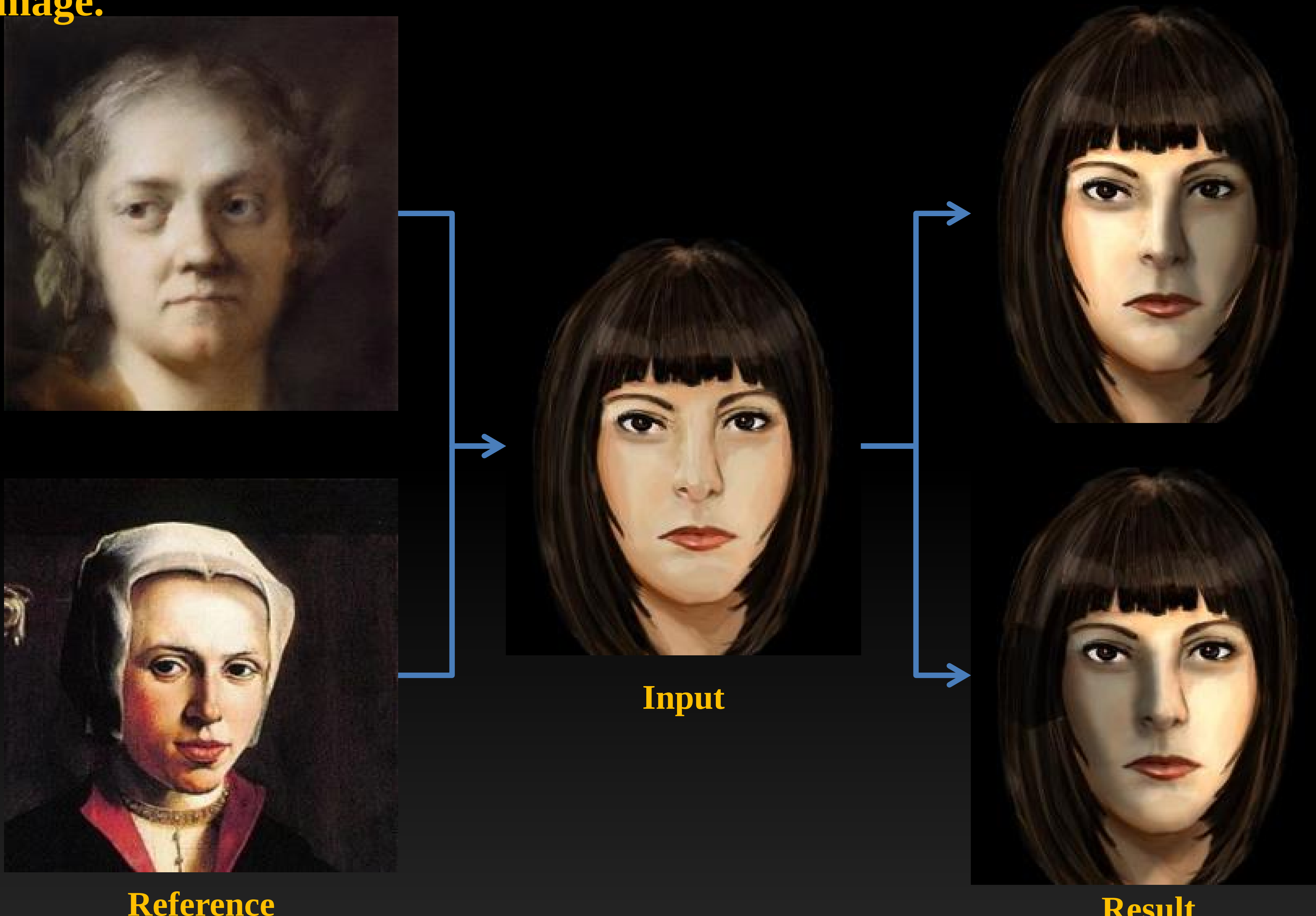
Q3: How about artistic illumination from Masterpieces?

Self portrait of Rembrandt

Mona Lisa

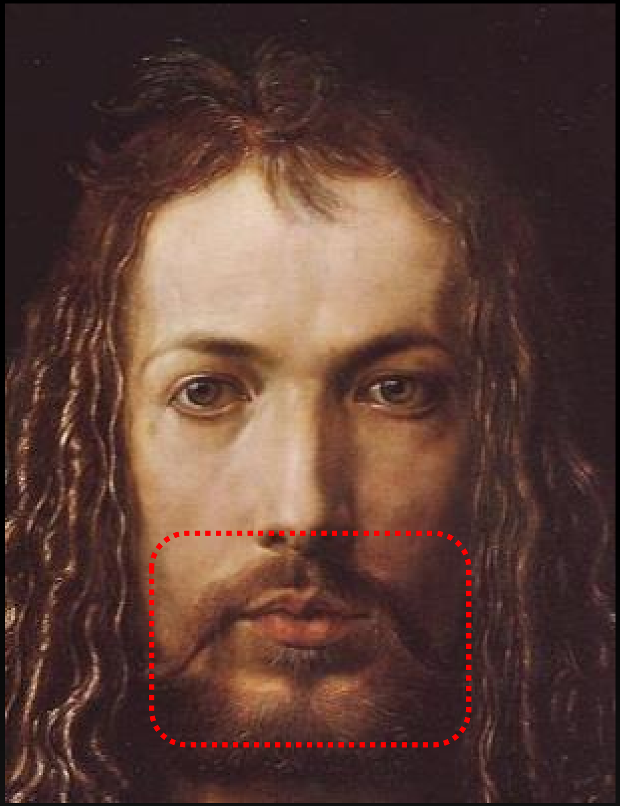
Motivation

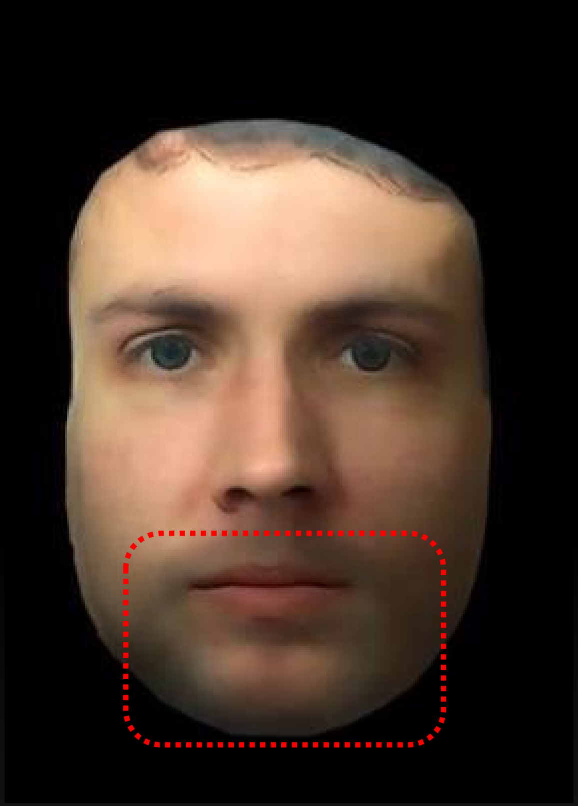
Transfer the artistic illumination from the reference image to the input image.



Related Work

Edge-Preserving Filters [Chen *et al.* 2011]





Reference Input Result

Template Drawing

Beauty Check Project Web set: http://www.beautycheck.de

Reference

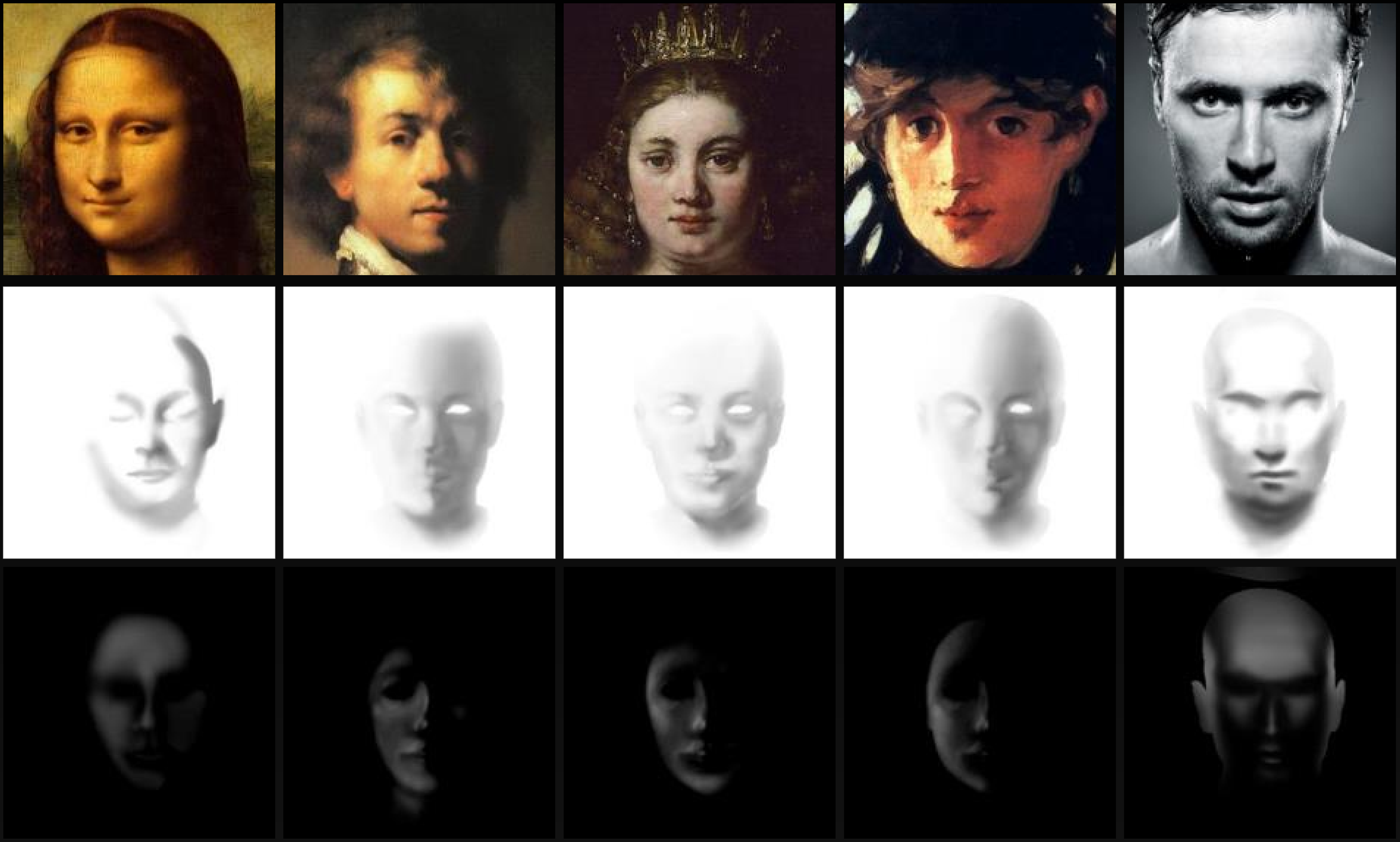
Light Template

Average Face

Shadow Template

+

Artistic Illumination Templates

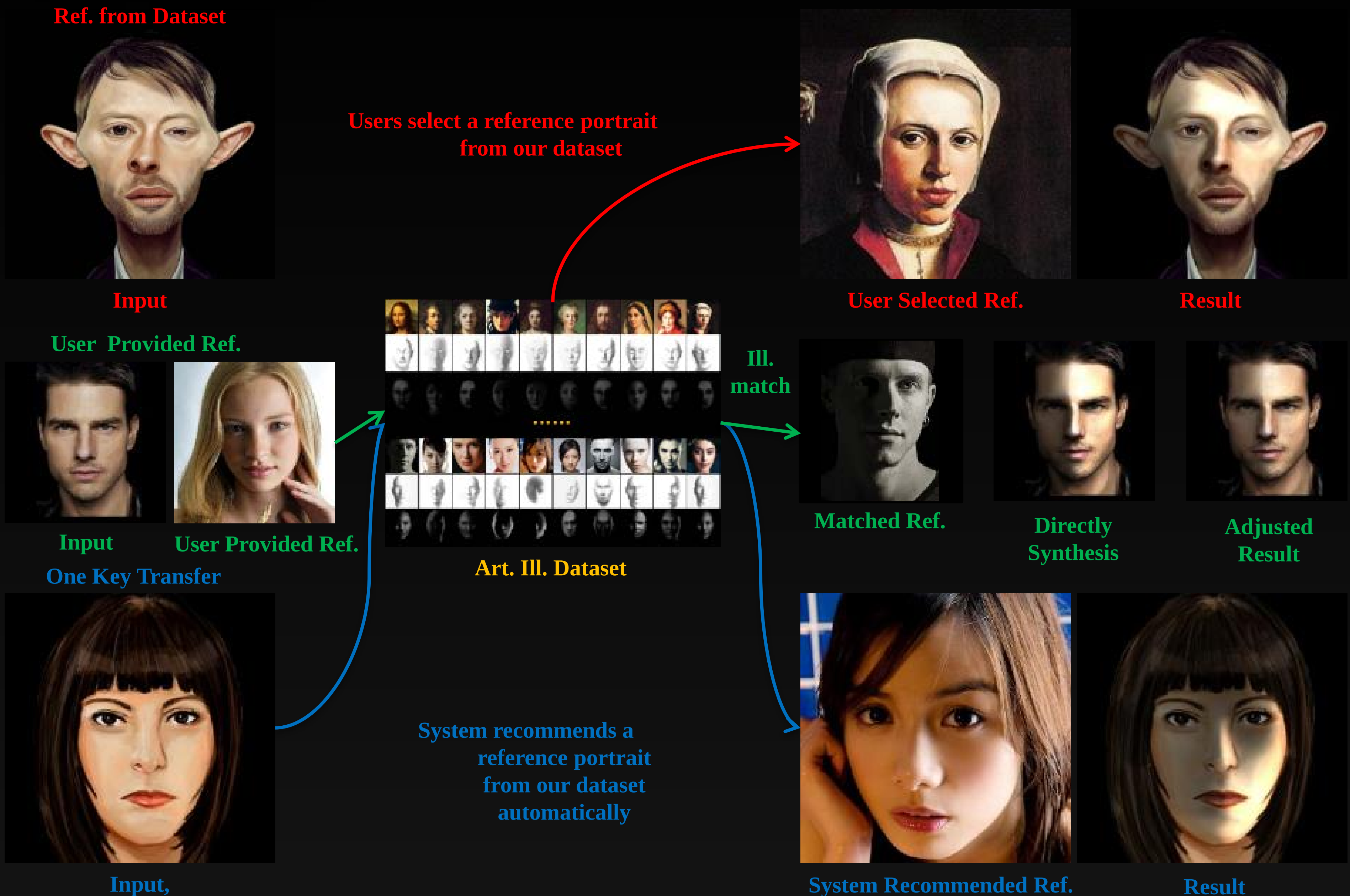


Butterfly Triangle Loop Spit Btf.+Side

Artistic Illumination Templates

Tri. + Side Loop+Side Split+Side Bottom 3/4 Side

Our System



Ref. from Dataset
Users select a reference portrait from our dataset
Input
User Selected Ref.
Result
User Provided Ref.
Ill. match
Input
User Provided Ref.
Art. Ill. Dataset
Matched Ref.
Directly Synthesis
Adjusted Result
One Key Transfer
System recommends a reference portrait from our dataset automatically
Input,
System Recommended Ref.
Result

The Basic Transfer Workflow

---Choose Reference from Our Database

Reference

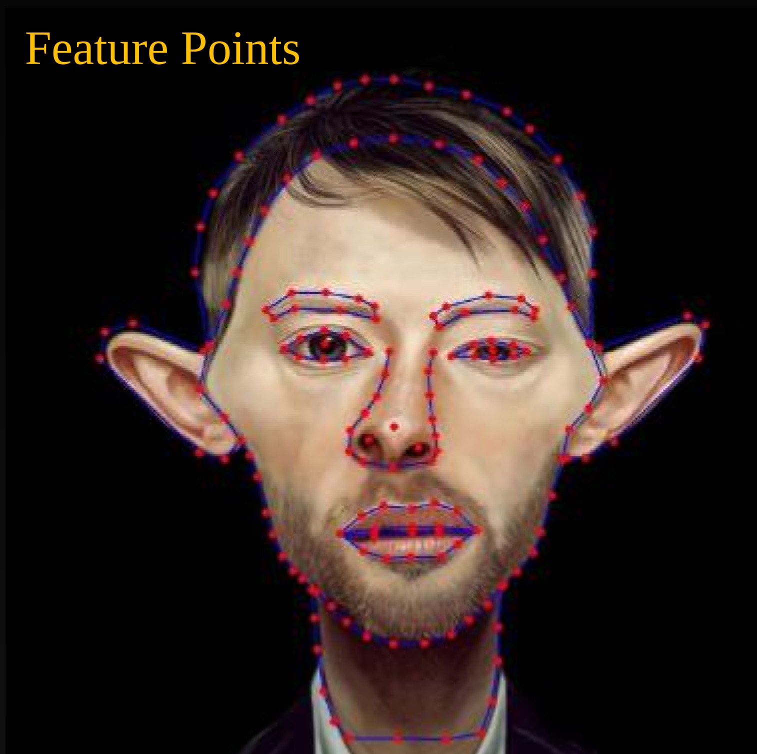
Shadow Template

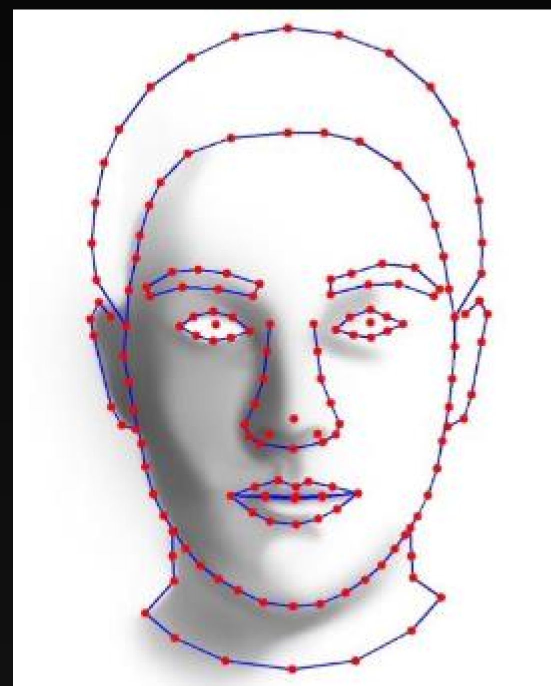
Light Template

The Basic Transfer Workflow

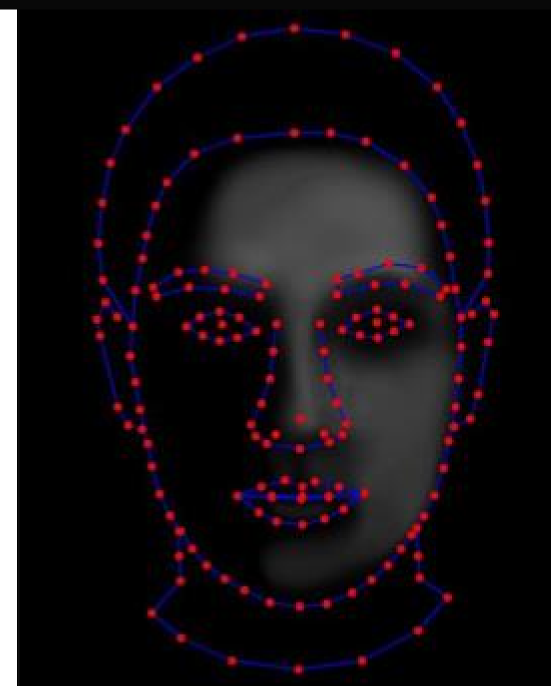
---Choose Reference from Our Database

Reference





Shadow Template



Light Template

S. Milborrow and F. Nicolls. Locating Facial Features with an Extended **Active Shape Model**. ECCV 2008

The Basic Transfer Workflow

---Choose Reference from Our Database

Final Result

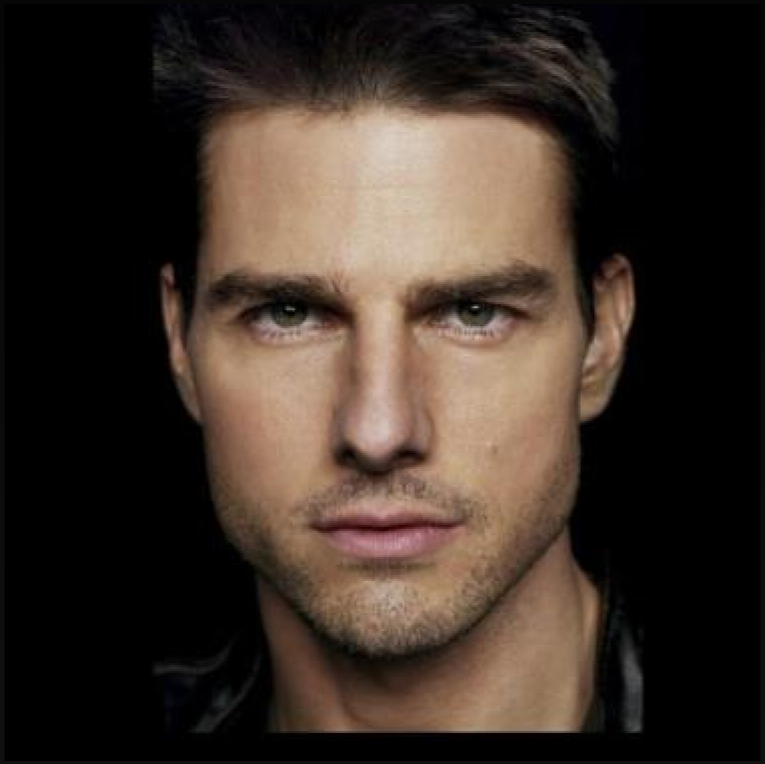
Warped Shadow Template

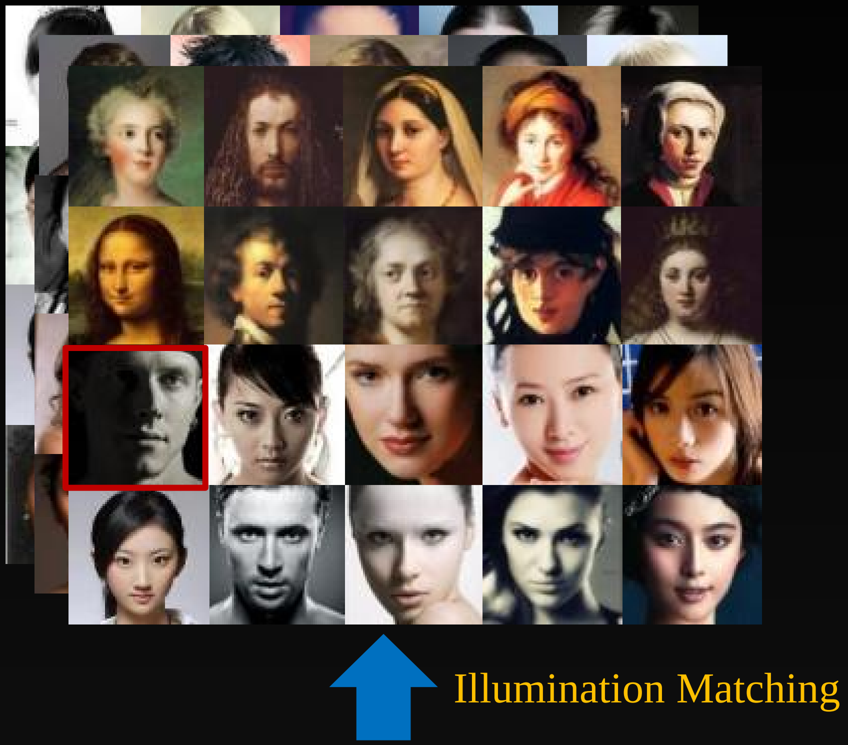
Warped Light Template

Seungyong Lee, George Wolberg, Kyung-Yong Chwa, and Sung Yong Shin. Image Metamorphosis with Scattered Feature Constraints. TVCG 1996.

The Extended Transfer Workflow

---User-provided Reference Portraits

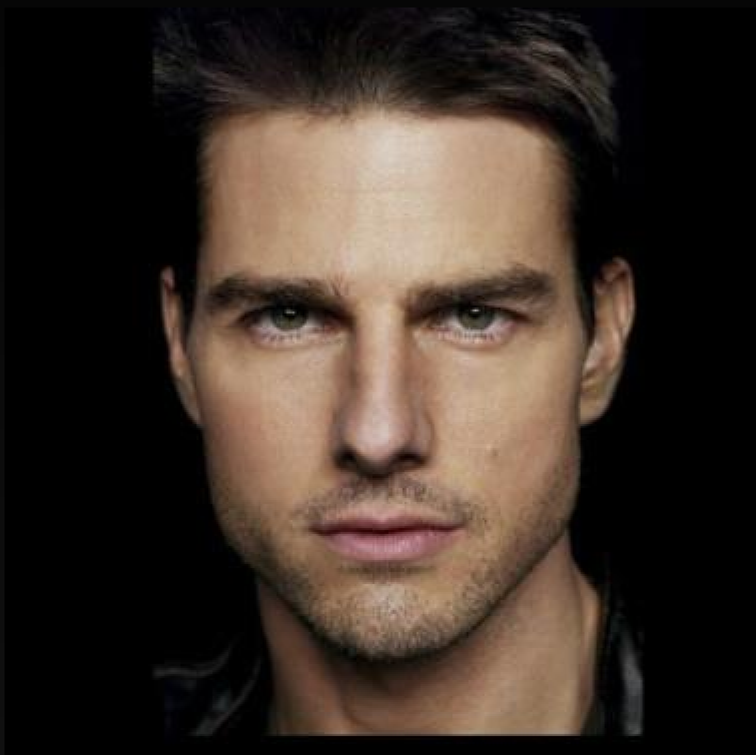


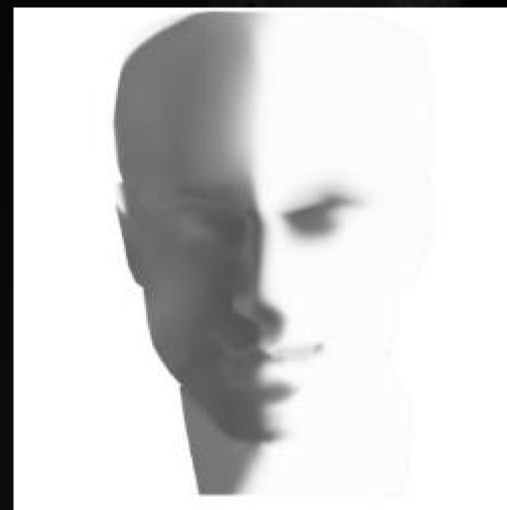


User Provided Ref.

The Extended Transfer Workflow

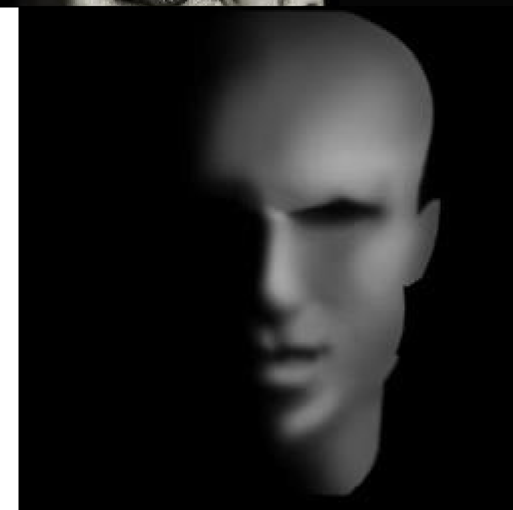
---User-provided Reference Portraits





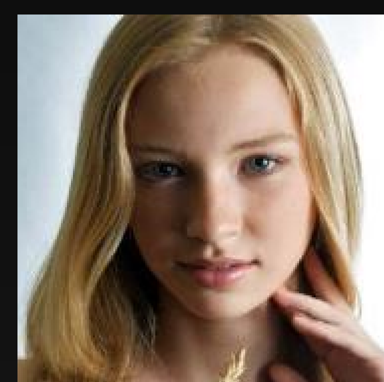
Warped Shadow Template

Shadow Template



Warped Light Template

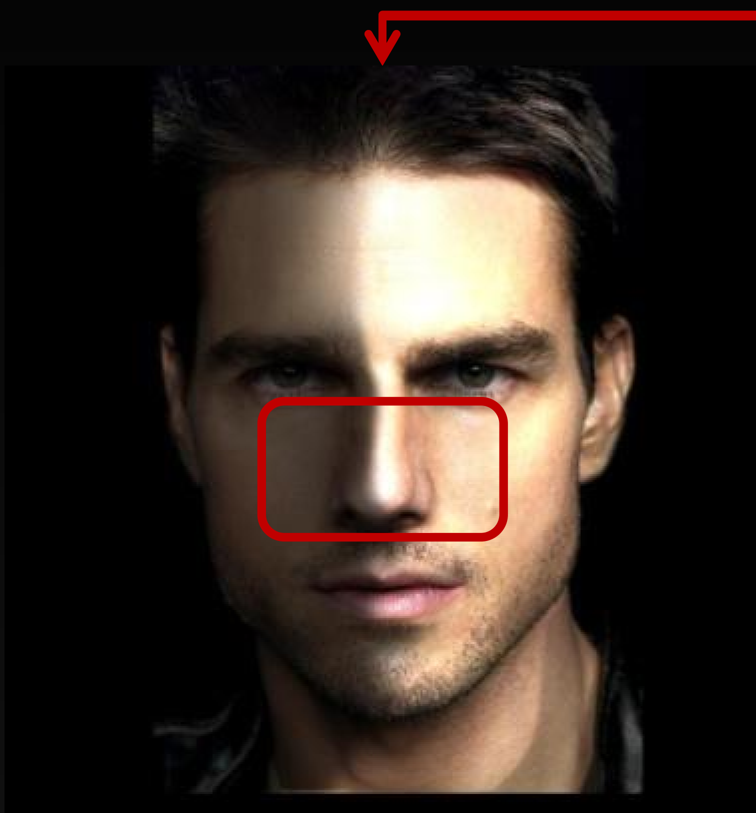
Light Template

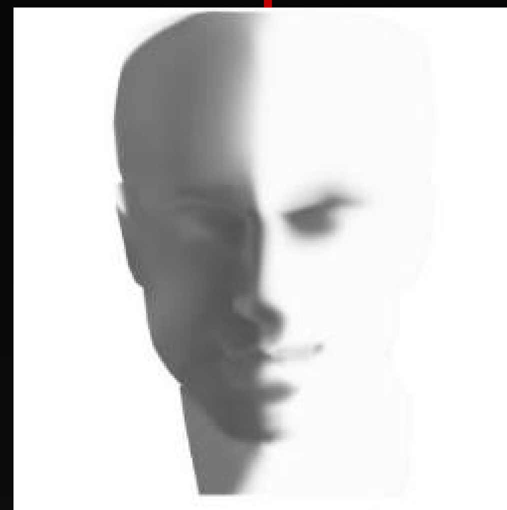


User Provided Ref.

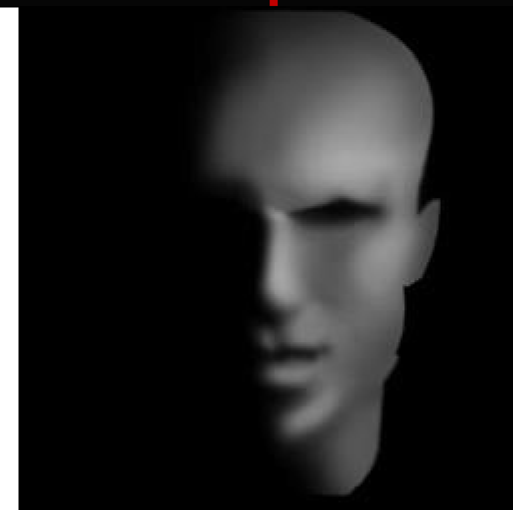
The Extended Transfer Workflow

---User-provided Reference Portraits

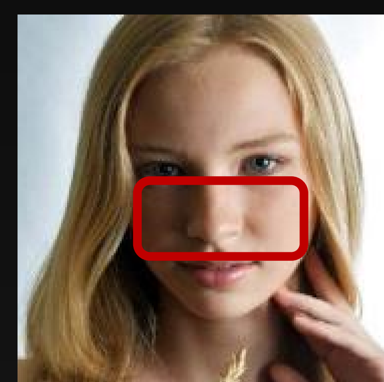




Warped Shadow Template



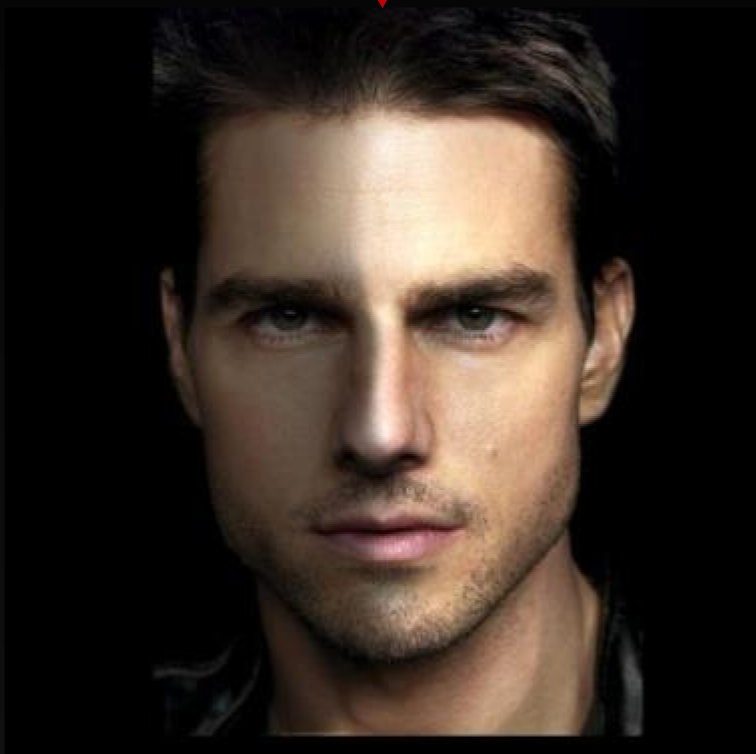
Warped Light Template

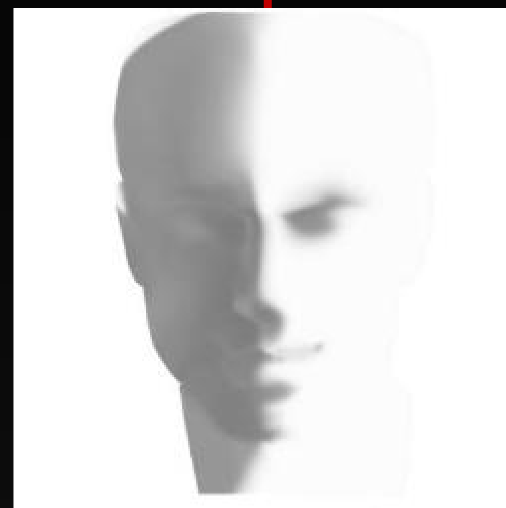


User Provided Ref.

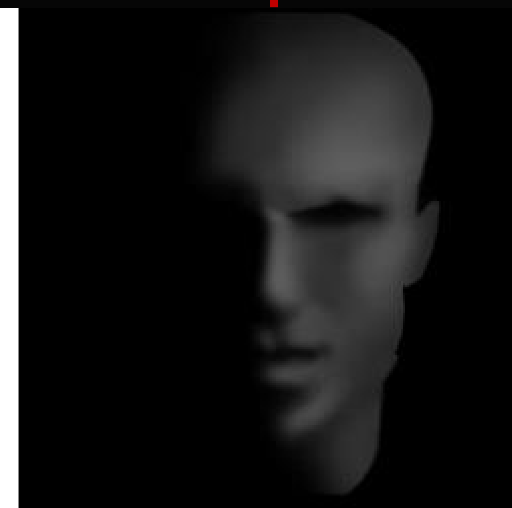
The Extended Transfer Workflow

---User-provided Reference Portraits





Adjusted Shadow Template



Adjusted Light Template

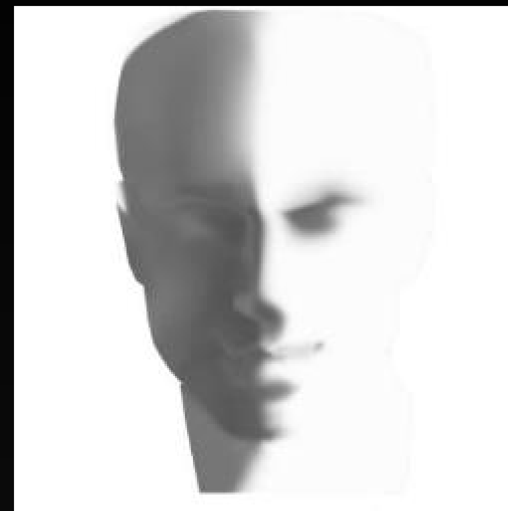
User Provided Ref.

The Extended Transfer Workflow

---User-provided Reference Portraits

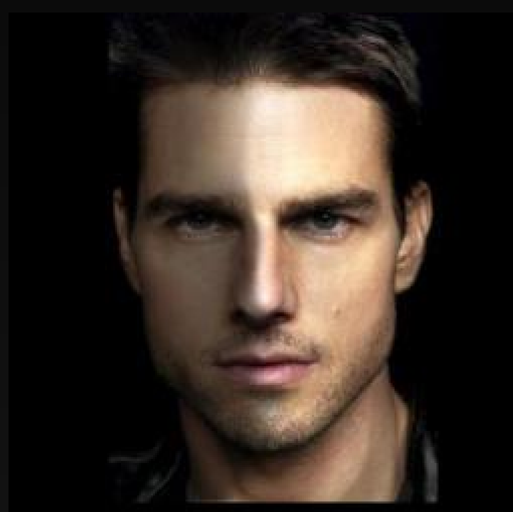
User Custom Ref.

Before Adjustment

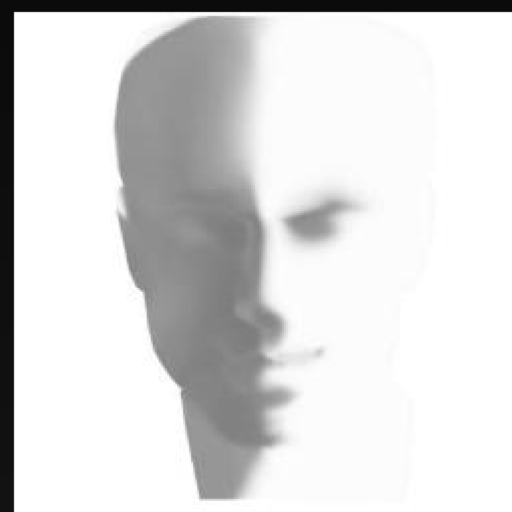


Shadow Template

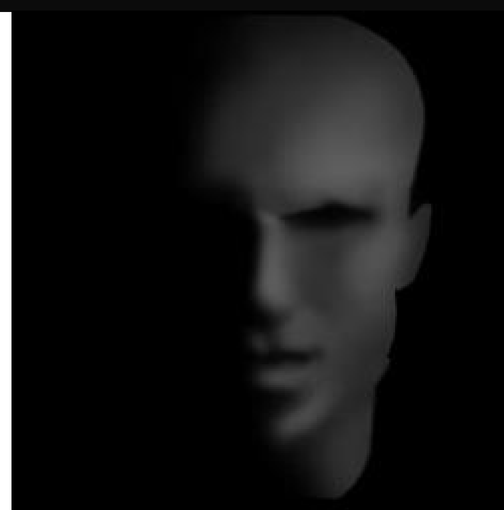
Light Template



After Adjustment



Adjusted Shadow Template



Adjusted Light Template

The Extended Transfer Workflow

---User-provided Reference Portraits

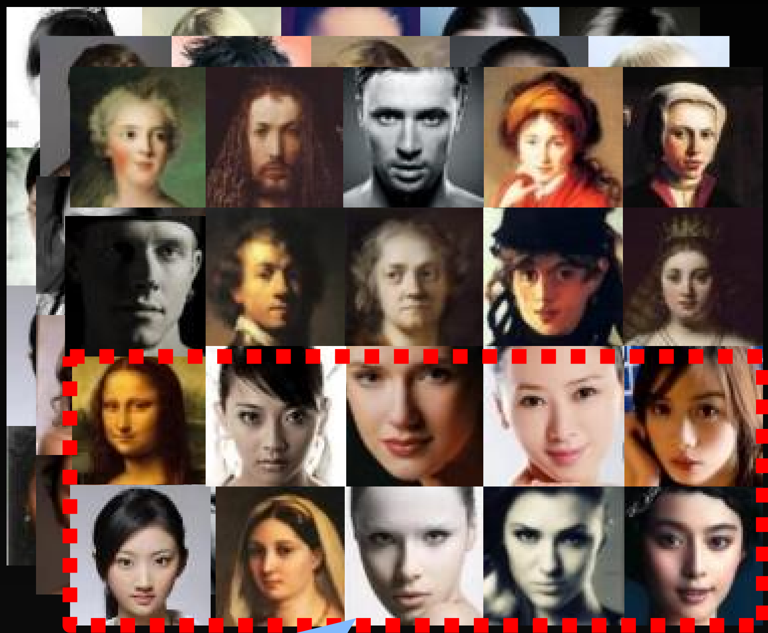
The Extended Transfer Workflow

---User-provided Reference Portraits

(a) User-provided (b) Input (c) Ill. Matched (d) Result of (b) (e) Adjusted Result

The Extended Transfer Workflow

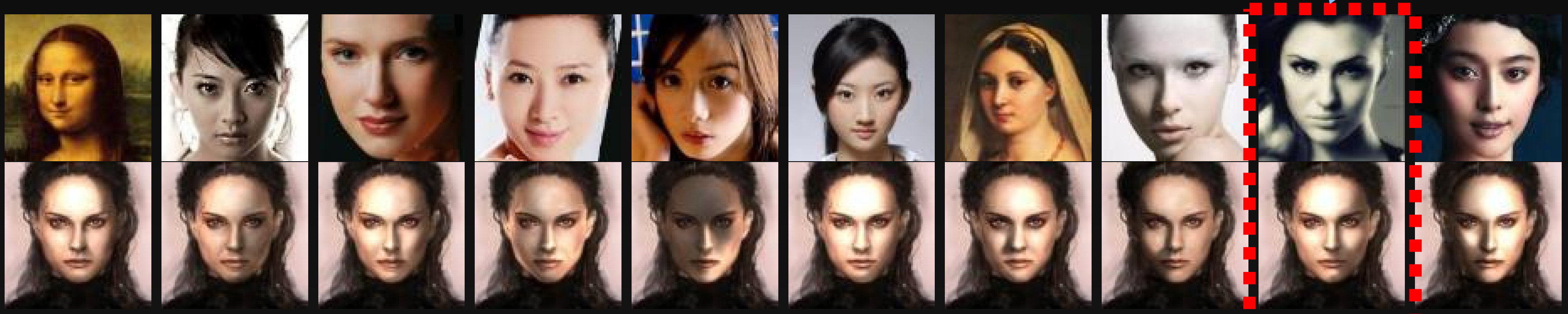
---One Key Transfer



10 most similar shapes and facial part distributions

Highest Score

The shape context distance metric



0.309 0.359 0.402 0.239 0.379 0.299 0.401 0.207 0.409 0.406

The Extended Transfer Workflow

---One Key Transfer

Input，0.179

Recommended References

Output，0.478

Additional Results with Artistic Illumination Score

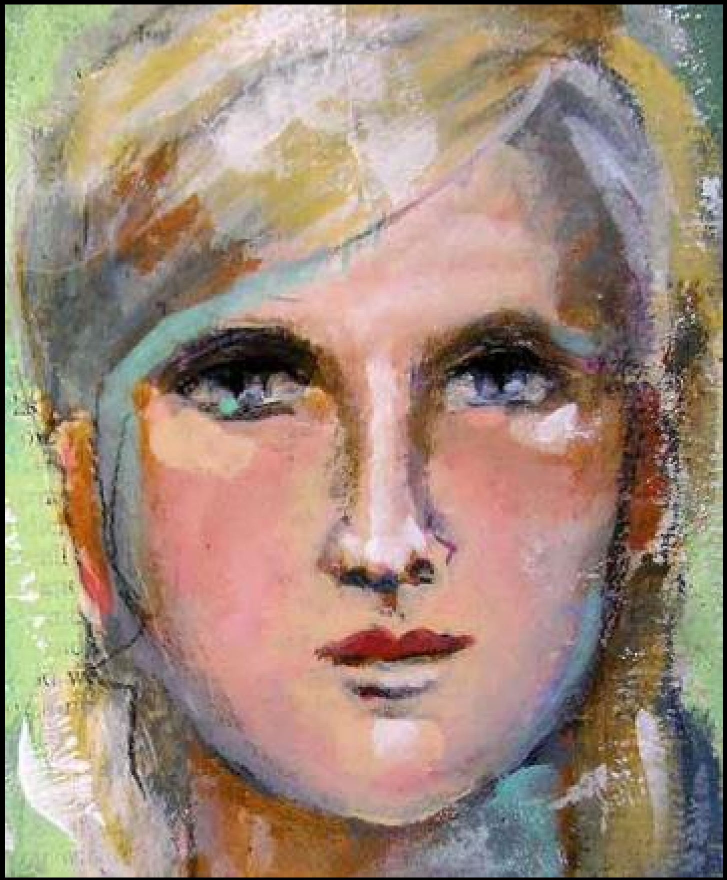
Reference

Input: 0.18897

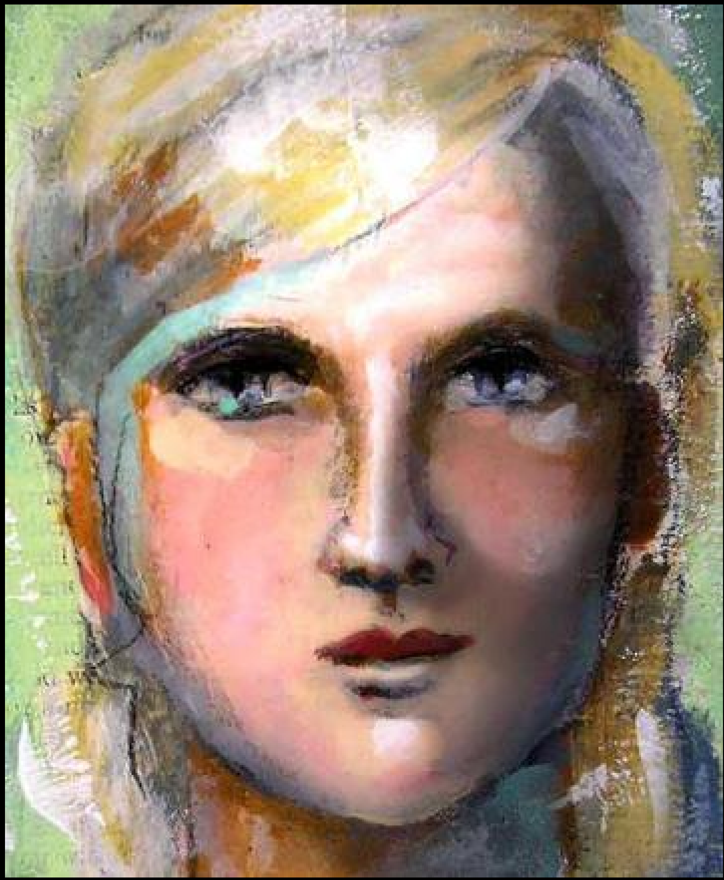
Result: 0.306477

Additional Results with Artistic Illumination Score

Reference



Input: 0.0786715



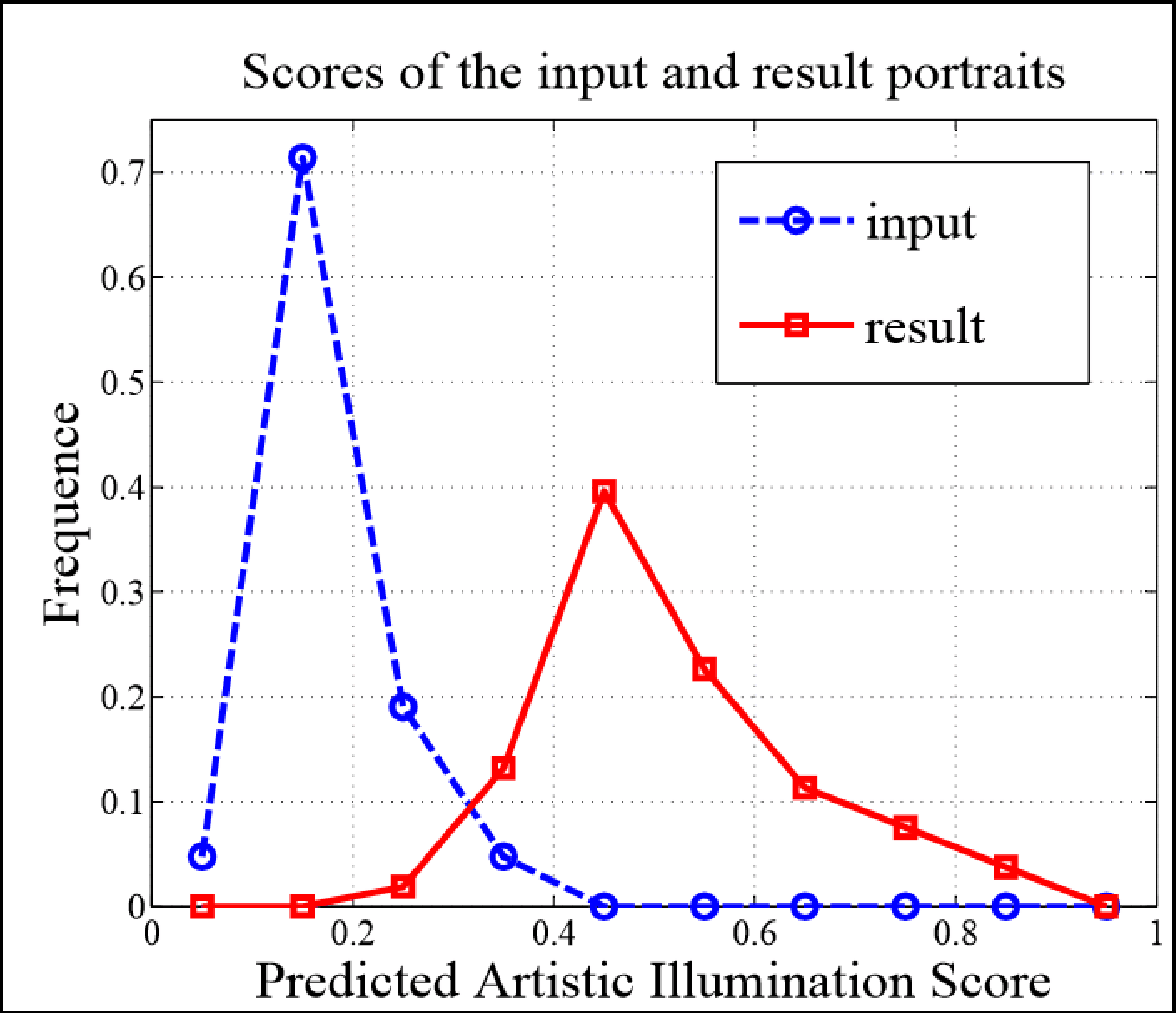
Result:0.308704

Additional Results with Artistic Illumination Score

Reference

Input: 0.182544

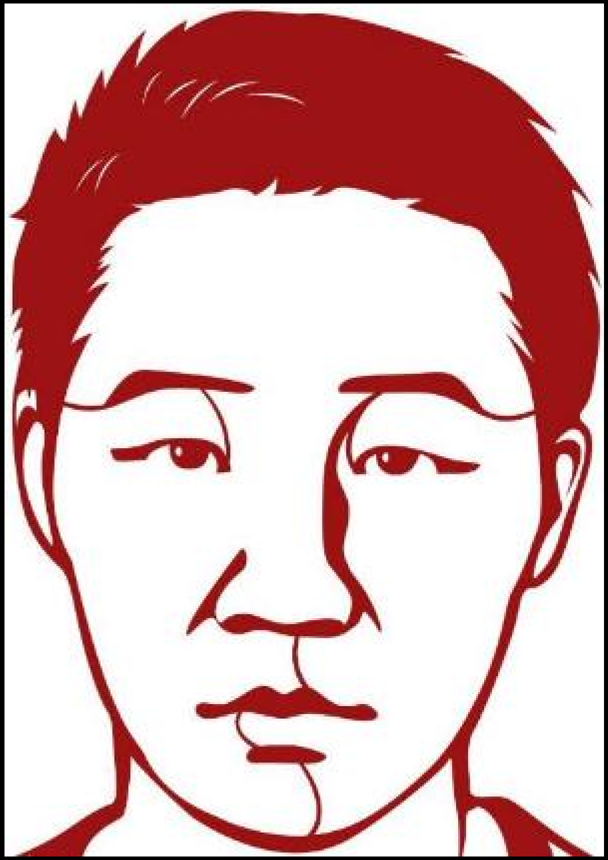
Result:0.511106



Scores of the input and result portraits
input
result
Frequence
Predicted Artistic Illumination Score
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0
0.2
0.4
0.6
0.8
1

Additional Results: Paper-cut

Reference



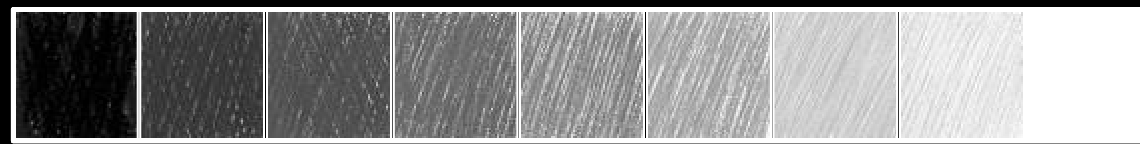
Input

Result

Paper-cut: **Meng Meng, Zhao Mingtian, Song-Chun Zhu. Artistic Paper-cut of Human Portraits. ACM Multimedia 2010**

Additional Application: Sketch

Hatching
Art Map



Reference

Input Sketch

Result

Additional Results: Sketch

Reference

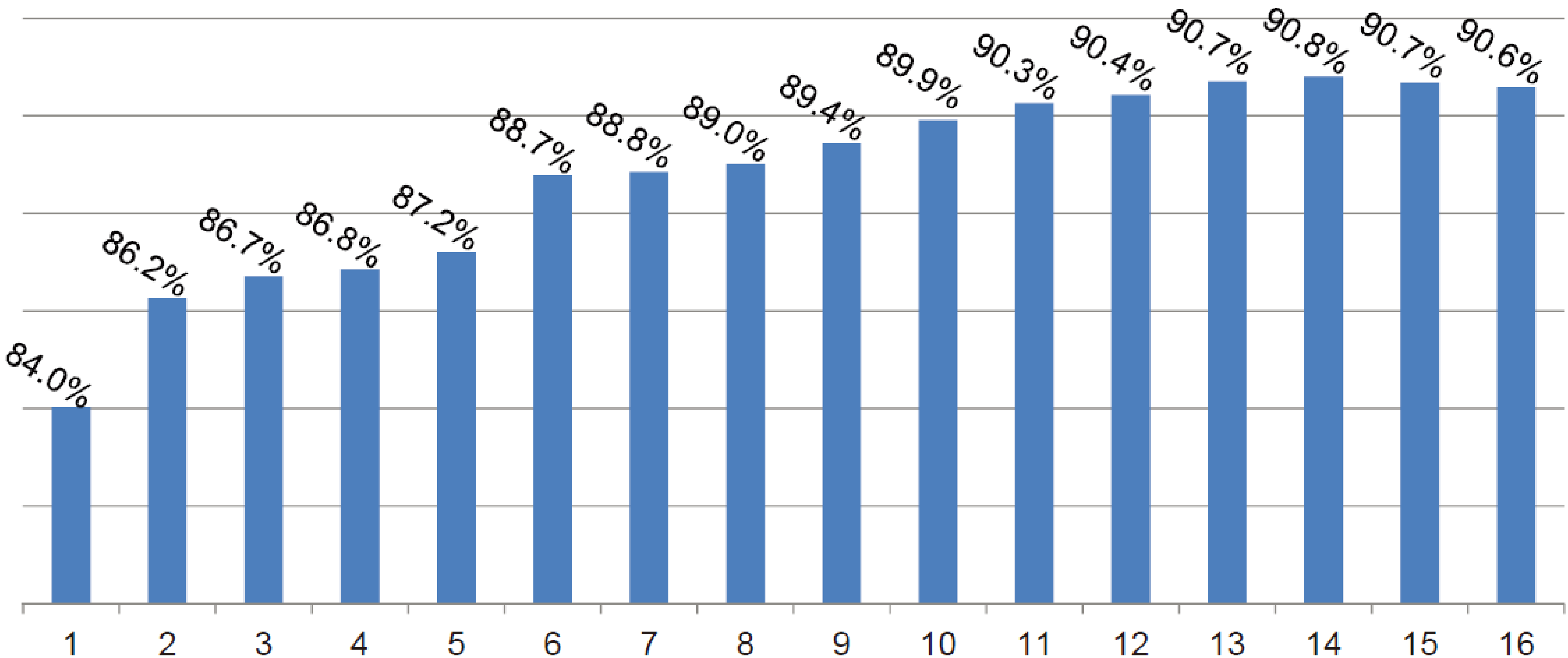
Input

Result

End
Q&A

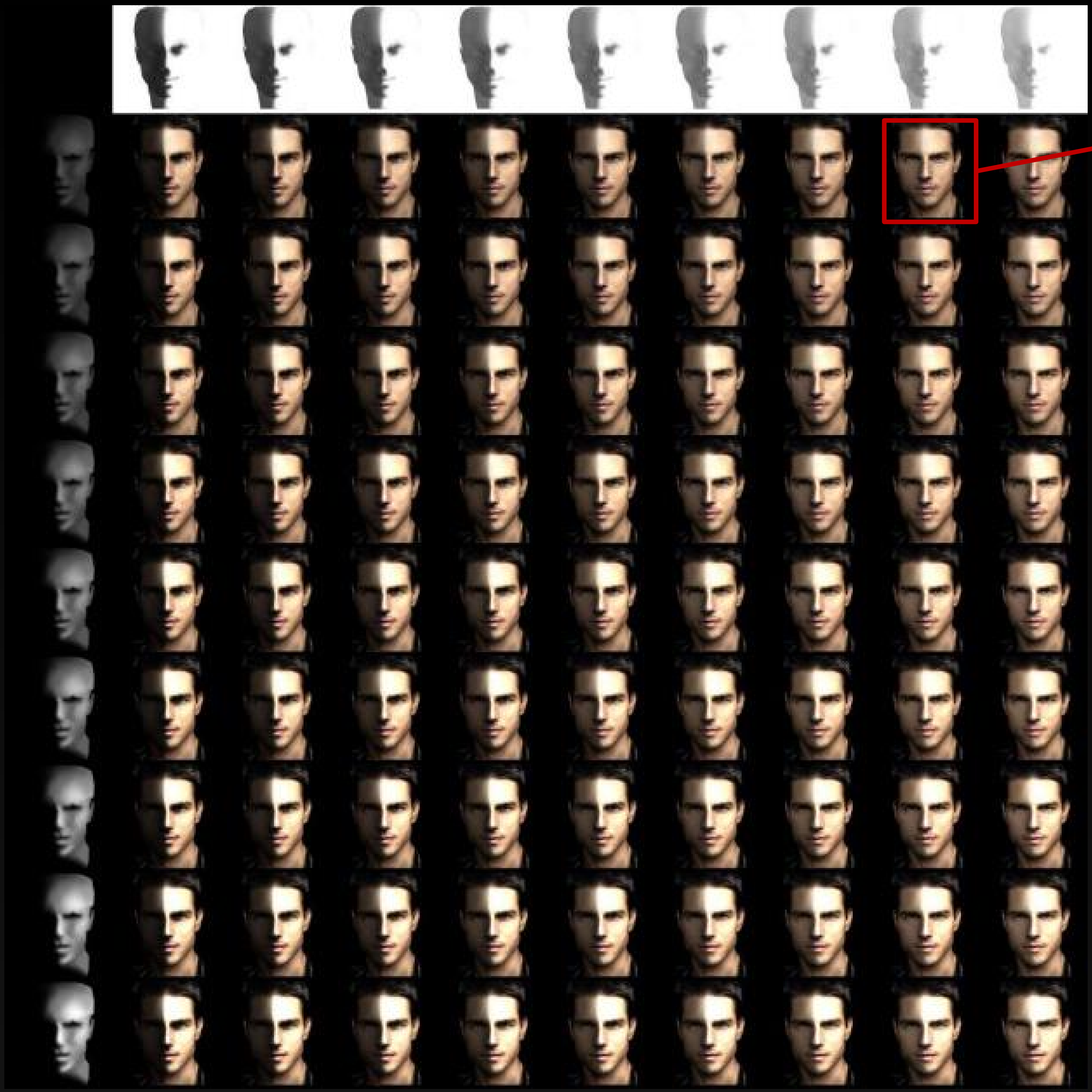
Classification of Portrait Illumination

5 times 5 folds Cross Validation



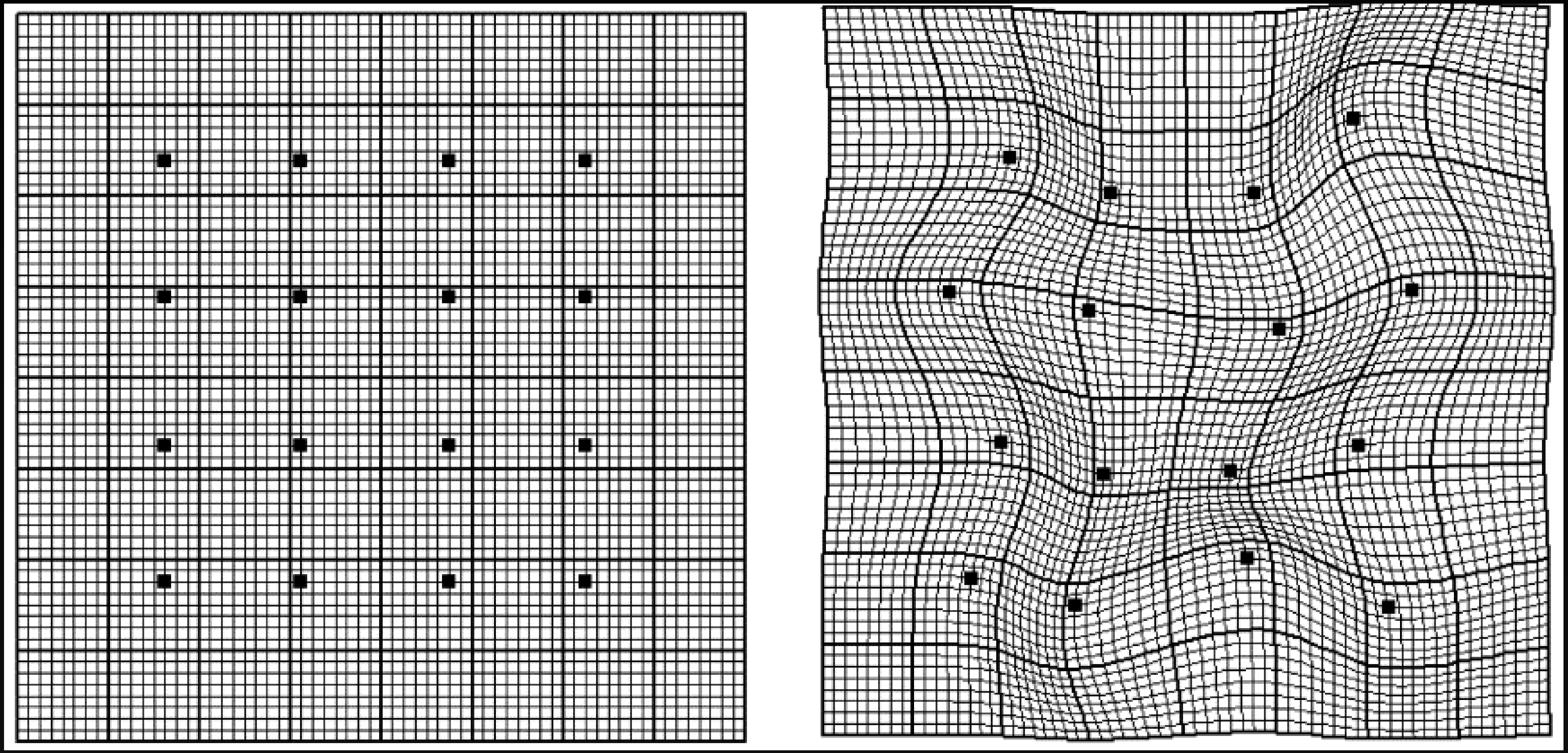
Classification accuracy with the number of local contrast features

Appendix: Template Adjustment



User Provided Ref.

Appendix：Face Image Warping



MFFD: Multilevel Free-From Deformation

Seungyong Lee, George Wolberg, Kyung-Yong Chwa, and Sung Yong Shin. Image Metamorphosis with Scattered Feature Constraints. TVCG 1996.

Appendix： Original Portrait of Paper-cut

Meng Men, Zhao Mingtian, Song-Chun Zhu. Artistic Paper-cut of Human Portraits. ACM Multimedia 2010

Appendix：Original of Computer Generated Paintings

Original

Computer Generated Painting

Kang, Henry, LeeSeungyong and Chui, Charles K. Flow-based image abstraction. TVCG2009