A Two-Step Approach to Hallucinating Faces: Global Parametric Model and Local Nonparametric Model

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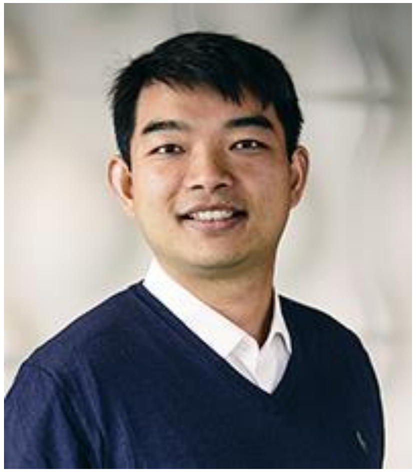

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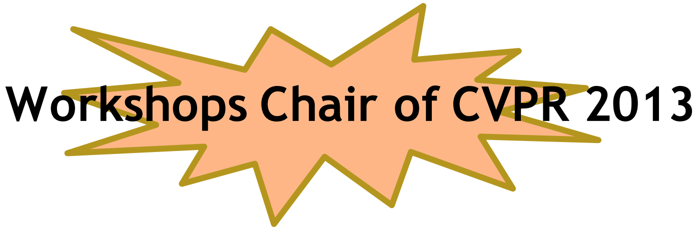


FACE HALLUCINATION

- Face super-resolution (FSR)
- Face sketch-photo synthesis (FSPS) techniques

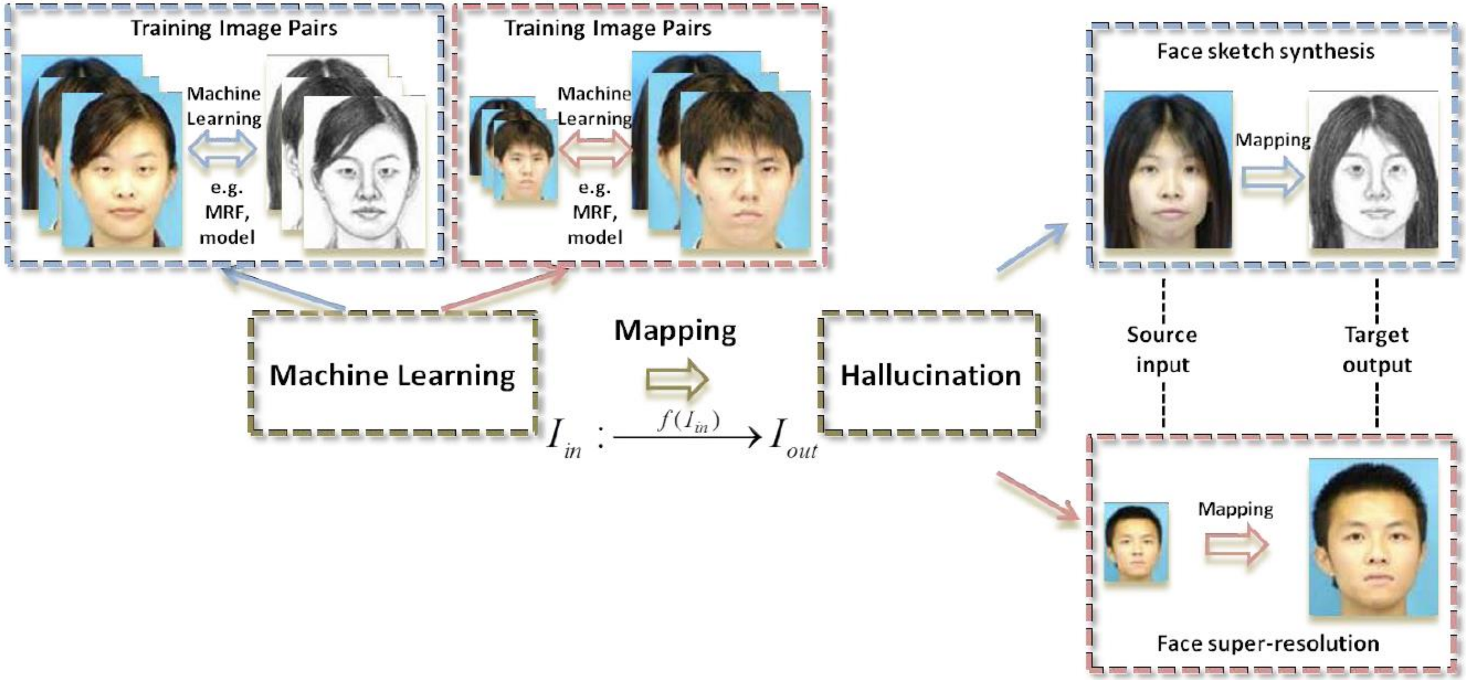


Fig. 1 Diagram of face hallucination

A Comprehensive Survey to Face Hallucination, IJCV 2013

FACE SUPER-RESOLUTION

- Reconstruction-based
  - Input images alone
- Learning-based
  - Learn by other HR & LR pairs of images (or only HR images)

CONSTRAINTS

- **Sanity constraint.** The result must be very close to the input image when smoothed and down-sampled.

- **Global constraint.** The result must have common characteristics of a human face, *e.g*. eyes, mouth and nose, symmetry, etc.

- **Local constraint.** The result must have specific characteristics of this face image with photorealistic local features.

CONSTRAINTS

- Sanity constraint
  - Easily satisfied
- Global constraint
  - Without -> noisy
- Local constraint
  - Without -> too smooth, close to average face

Two-Step Approach

- Title:
  - A **Two-Step** Approach to Hallucinating Faces: **Global** Parametric Model and **Local** Nonparametric Model

- Global + Local

Bayesian Formulation

- Smoothing and down-sampling
  - The same as averaging pooling*

$$I_L(m,n) = \frac{1}{s^2}\sum_{i=0}^{s-1}\sum_{j=0}^{s-1} I_H(sm+i, sn+j) \qquad (3)$$

- If I_L & I_H are vectors,

$$I_L = AI_H \qquad (4)$$

- Reverse it!

Bayesian Formulation

- maximum a posteriori (MAP) criterion

$$p(I_H|I_L) = \frac{p(I_L|I_H)p(I_H)}{p(I_L)}.$$

$$I_H^* = \arg\max_{I_H} p(I_L|I_H)p(I_H). \tag{5}$$

Global and Local Modeling of Face

- Global + Local

$$I_H = I_H^l + I_H^g. \quad (6)$$

- Since I_L is the low-frequency part of I_H

$$AI_H^g = AI_H, \ AI_H^l = 0. \quad (7)$$

$$p(I_H) = p(I_H^l, I_H^g) = p(I_H^l | I_H^g) p(I_H^g). \quad (8)$$

- Regard $p(I_L|I_H)$ as soft constraint to I_H

$$p(I_L | I_H) = \frac{1}{Z} \exp\{-\|AI_H - I_L\|^2 / \lambda\}, \quad (9)$$

$$p(I_L | I_H) = \frac{1}{Z} \exp\{-\|AI_H^g - I_L\|^2 / \lambda\} = p(I_L | I_H^g). \quad (10)$$

Target

$$I_H^* = \arg\max_{I_H} p(I_L|I_H)p(I_H). \quad (5)$$

$$p(I_L|I_H) = \frac{1}{Z}\exp\{-\|AI_H^g - I_L\|^2/\lambda\} = p(I_L|I_H^g). \quad (10)$$

$$I_H^* = \arg\max_{I_H^g, I_H^l} p(I_L|I_H^g)p(I_H^g)p(I_H^l|I_H^g). \quad (11)$$

$$p(I_L|I_H^g)p(I_H^g) \Uparrow \longrightarrow I_H^{g*}$$

$$p(I_H^l|I_H^g) \Uparrow \longrightarrow I_H^{l*}$$

$$\longrightarrow \quad I_H^* = I_H^{g*} + I_H^{l*}$$

The Method

- Decouple high-resolution face image to two parts

 =  + 

I_H $\qquad$ I_H^g $\qquad$ I_H^l

I_H— high resolution face image $\quad$ I_H^g — global face $\quad$ I_H^l — local face

- Two-step Bayesian inference

I_L

?

$$I_H^* = \arg\max_{I_H} p(I_L \mid I_H)p(I_H)$$
$$= \arg\max_{I_H^g, I_H^l} p(I_L \mid I_H^g, I_H^l)p(I_H^g, I_H^l)$$
$$= \arg\max_{I_H^g, I_H^l} p(I_L \mid I_H^g)p(I_H^g)p(I_H^l \mid I_H^g)$$

1. Inferring global face

$$I_H^{g*} = \arg\max_{I_H^{g*}} p(I_L \mid I_H^g)p(I_H^g)$$

2. Inferring local face

$$I_H^{l*} = \arg\max_{I_H^{l*}} p(I_H^l \mid I_H^{g*})$$

Finally adding them together $I_H^* = I_H^{l*} + I_H^{g*}$

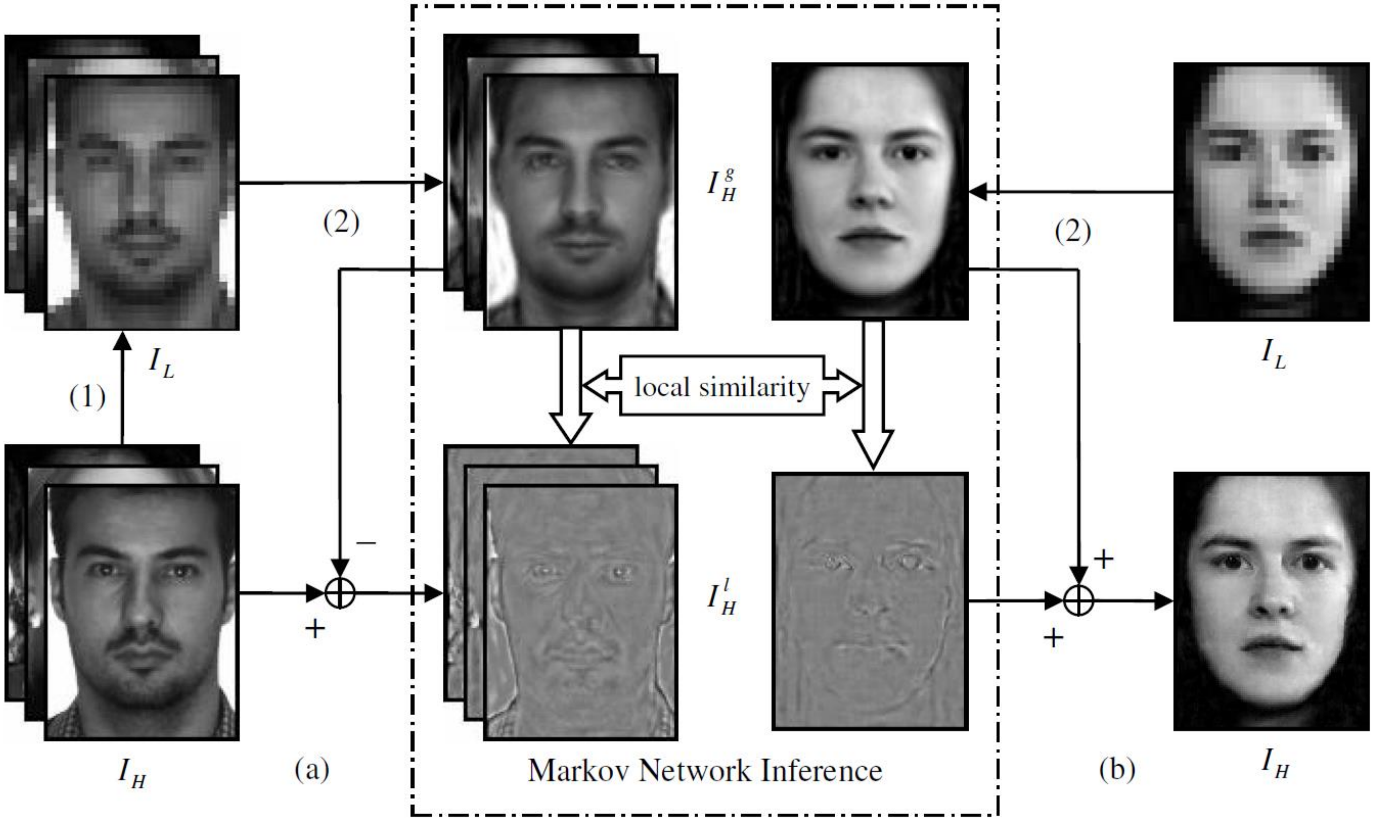


Figure 2. The function of Markov network in our model. (a) is the training process and (b) the hallucinating process. (1): smooth and down-sampling. (2): MAP inference to get the optimal global face I_H^{g*}. The Markov network finds the optimal local feature image I_H^{l*} by energy minimization.

Global Modeling

- Apply PCA to training face image $\{I_H^{(i)}\}_{i=1}^k$

$$I_H^g = BX + \mu, X = B^T(I_H - \mu), \qquad (12)$$

$$p(I_L|I_H^g)p(I_H^g) \longleftrightarrow p(I_L|X)p(X)$$

$$p(X) = \frac{1}{Z'}\exp\{-X^T\Lambda^{-1}X\}, \qquad (13)$$

$$p(I_L|X) = \frac{1}{Z}\exp\{-\|A(BX+\mu)-I_L\|^2/\lambda\}. \qquad (14)$$

Global Modeling

$$\text{maximize } p(I_L|X)p(X)$$

$$X^* = \arg\min_X \lambda X^T \Lambda^{-1} X + \|A(BX+\mu)-I_L\|^2, \qquad (15)$$

$$X^* = (B^T A^T A B + \lambda\Lambda^{-1})^{-1} B^T A^T (I_L - A\mu). \qquad (16)$$

$$I_H^{g*} = BX^* + \mu$$

- I_H^{g*} is very close to human face with some smoothness
- Calculate quickly using input I_L

Local Modeling

- Patch-based nonparametric Markov network
- Square patch size: $w \times w$ & h overlap
- $\vec{v}$ means (i, j)
- Δ_x means (1,0)
- Δ_y means (0,1)

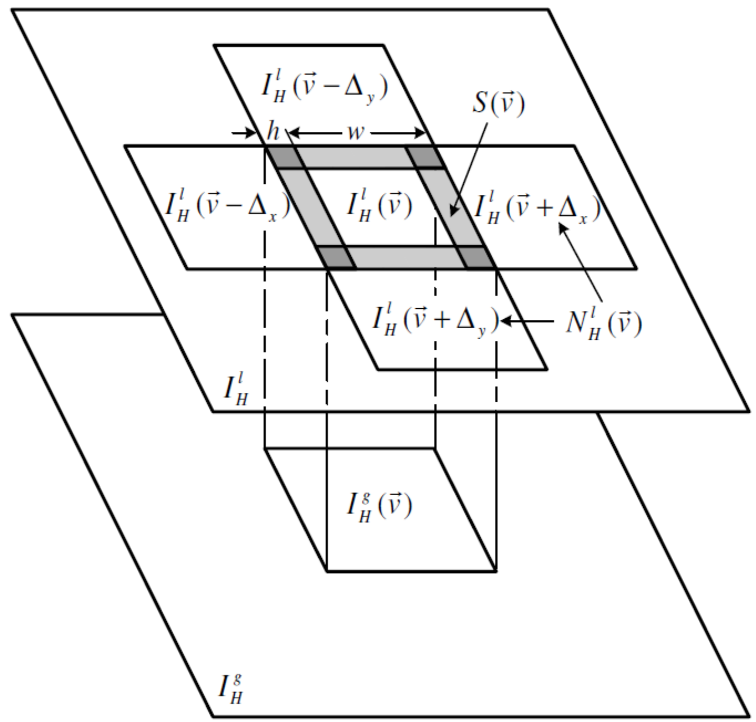


Figure 3. Illustration of the patch-based Markov network.

Local Modeling

- Assume that the above network is a Markov network

$$p(I_H^l(\vec{v})\,|\,I_H^{l-}(\vec{v}), I_H^g) = p(I_H^l(\vec{v})\,|\,N_H^l(\vec{v}), I_H^g(\vec{v})), \qquad (17)$$

- Suppose $p(I_H^l(\vec{v})\,|\,N_H^l(\vec{v}), I_H^g(\vec{v}))$ Gibbs distribution

$$p(I_H^l(\vec{v})\,|\,N_H^l(\vec{v}), I_H^g(\vec{v})) \propto \exp\{-E_G(I_H^l(\vec{v}), N_H^l(\vec{v}), I_H^g(\vec{v}))\} \quad (18)$$

where $E_G(\cdot)$ is the Gibbs potential function to describe how likely a patch $I_H^l(\vec{v})$ connects to $I_H^g(\vec{v})$ and is surrounded by $N_H^l(\vec{v})$.

Local Modeling

$$p(I_H^l(\vec{v})|N_H^l(\vec{v}), I_H^g(\vec{v})) \propto \exp\{-E_G(I_H^l(\vec{v}), N_H^l(\vec{v}), I_H^g(\vec{v}))\} \quad (18)$$

$N_H^l(\vec{v})$ and $I_H^g(\vec{v})$ independently.

$$\begin{aligned} & E_G(I_H^l(\vec{v}), N_H^l(\vec{v}), I_H^g(\vec{v})) \\ = \; & E_G^{int}(I_H^l(\vec{v}), N_H^l(\vec{v})) + E_G^{ext}(I_H^l(\vec{v}), I_H^g(\vec{v})) \\ \equiv \; & E_G^{int}(\vec{v}) + E_G^{ext}(\vec{v}) \end{aligned} \qquad (19)$$

Local Modeling

- $E_G^{ext}(\vec{v})$
- Training pairs $\{I_H^{l(i)}(\vec{v}), I_H^{g(i)}(\vec{v})\}_{i=1}^{k}$

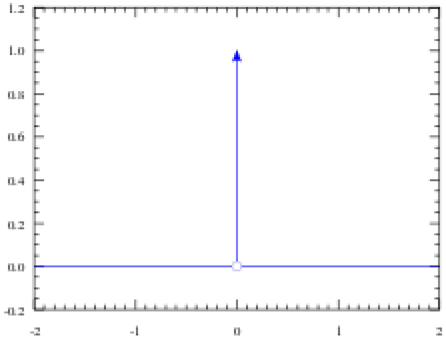
$$E_G^{ext}(\vec{v}) = \frac{1}{\lambda'} \sum_{i=1}^{k} \delta[I_H^l(\vec{v}) - I_H^{l(i)}(\vec{v})] d^2[I_H^g(\vec{v}), I_H^{g(i)}(\vec{v})], \quad (20)$$

$d(\cdot)$ is the distance metric between two patches in I_H^g

- Laplacian image L_H^g of I_H^g

$$d^2[I_H^g(\vec{v}), I_H^{g(i)}(\vec{v})] = \|L_H^g(\vec{v}) - L_H^{g(i)}(\vec{v})\|^2. \qquad (21)$$

$\delta(\cdot)$ is the dirac function



Local Modeling

- $E_G^{int}(\vec{v})$

$$E_G^{int}(\vec{v}) = \frac{1}{\lambda''} \sum_{\mathbf{u} \in S(\vec{v})} [\, I_H^l(\mathbf{u}) - N_H^l(\mathbf{u}) \,]^2, \qquad (22)$$

- Total Energy

$$E_{MN} = \sum_{\vec{v}} (E_G^{int}(\vec{v}) + E_G^{ext}(\vec{v})).$$

$p(I_H^l | I_H^{g*})$

$$I_H^{l*} = \arg\min_{I_H^l} E_{MN}. \qquad (24)$$

Simulated Annealing

MinimizeMarkovNetworkEnergy

Loop until $T < \epsilon$

Loop $\vec{v}$ *sequentially visiting all patches*

compute the energy of each patch $I_H^{l(i)}(\vec{v})$

set $I_H^l(\vec{v}) = I_H^{l(i)}(\vec{v})$ *with probability* (25)

decrease T

$I_H^{l*} = I_H^l$

$$exp\{-(E_G^{int}(\vec{v}) + E_G^{ext}(\vec{v}))/T\}, \qquad (25)$$

Experimental Results

- Database
  - FERET data set
  - AR data set
  - Other collections
- Align the face image

Experimental Results

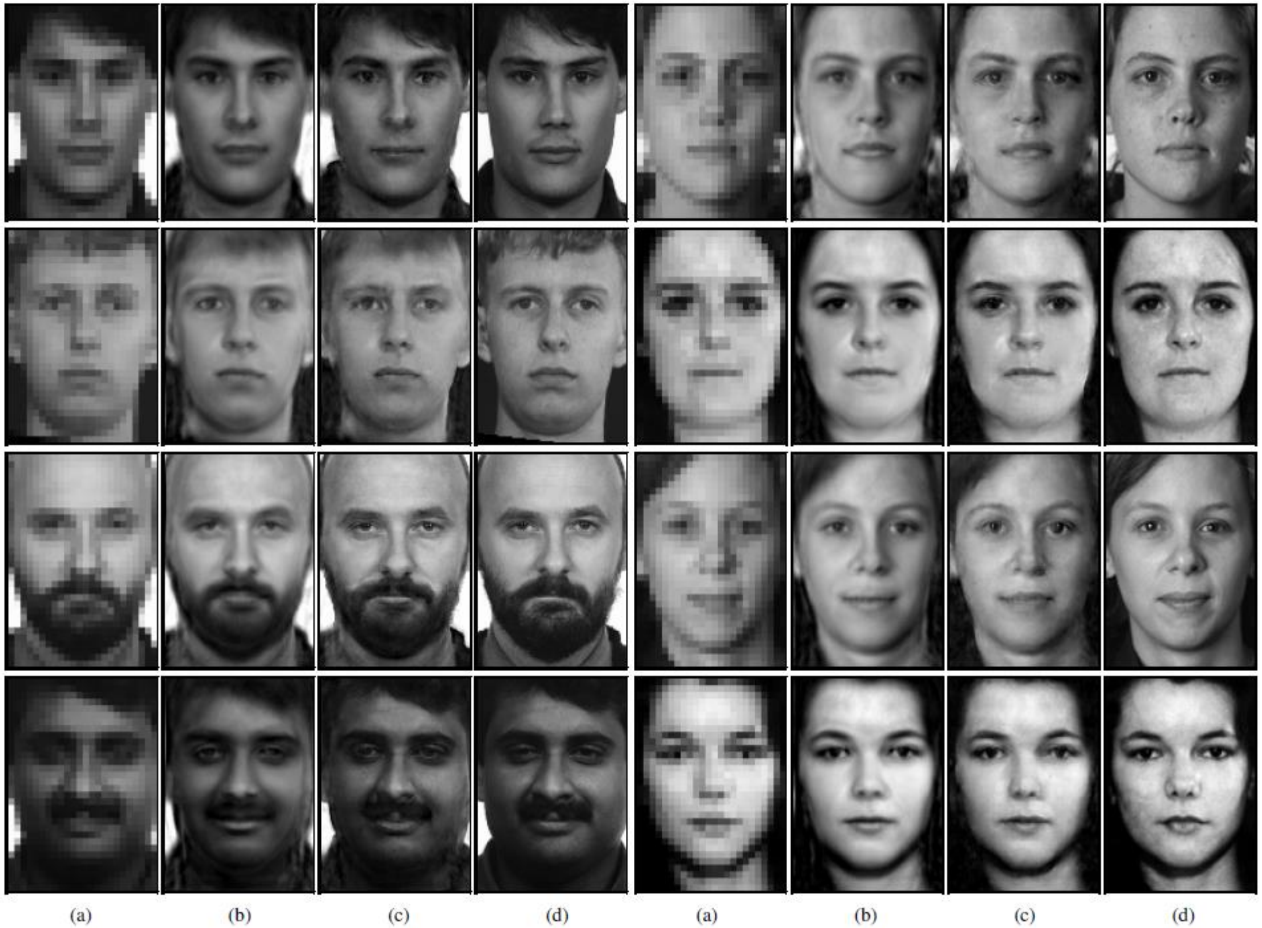


Figure 4. The hallucination results. (a) is the low-resolution 24×32 input. (b) is the inferred global face I_H^{g*} from (a). (c) is the final result $I_H^* = I_H^{g*} + I_H^{l*}$. I_H^{l*} is inferred from I_H^{g*} by Markov network. (d) is the original high-resolution 96×128 image.

Experimental Results

- Compete with other paper

(a) Input 24×32 (b) Our method (c) Cubic B-Spline (d) Hertzmann et al. (e) Baker et al. (f) Original 96×128

Figure 5. Comparison between our method and others.

Conclusion

- Combine global and local constrains
  - robustness and efficiency
- Why not complex model
  - the error can be compensated in the local model
- Patch-based nonparametric Markov network
  - Nonparametric -> accuracy
  - patch-based -> high efficiency
- Simulated Annealing
  - Similar to Gibbs sampling but converges more quickly
- Generalization -> Other super-resolution problem

The End

THANK YOU!

Q&A