Gaussian Mixture Models and Image Super-Resolution

Spencer Hammersten

Division of Science and Mathematics
University of Minnesota, Morris

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Introduction

- Images
  - Resolution, patches
  - Upscaling and Downscaling
- Super-resolution
  - Applications
    - Surveillance
    - Medicine
    - Entertainment
- The Gaussian Mixture Model (GMM) method
  - Machine learning
  - Applications of patches and statistics

Outline

- Background
    - Images
    - Interpolation
    - Sparse Representation
    - Gaussian Distribution
    - Mixture Models
- GMM Method
- Conclusions

Key Image

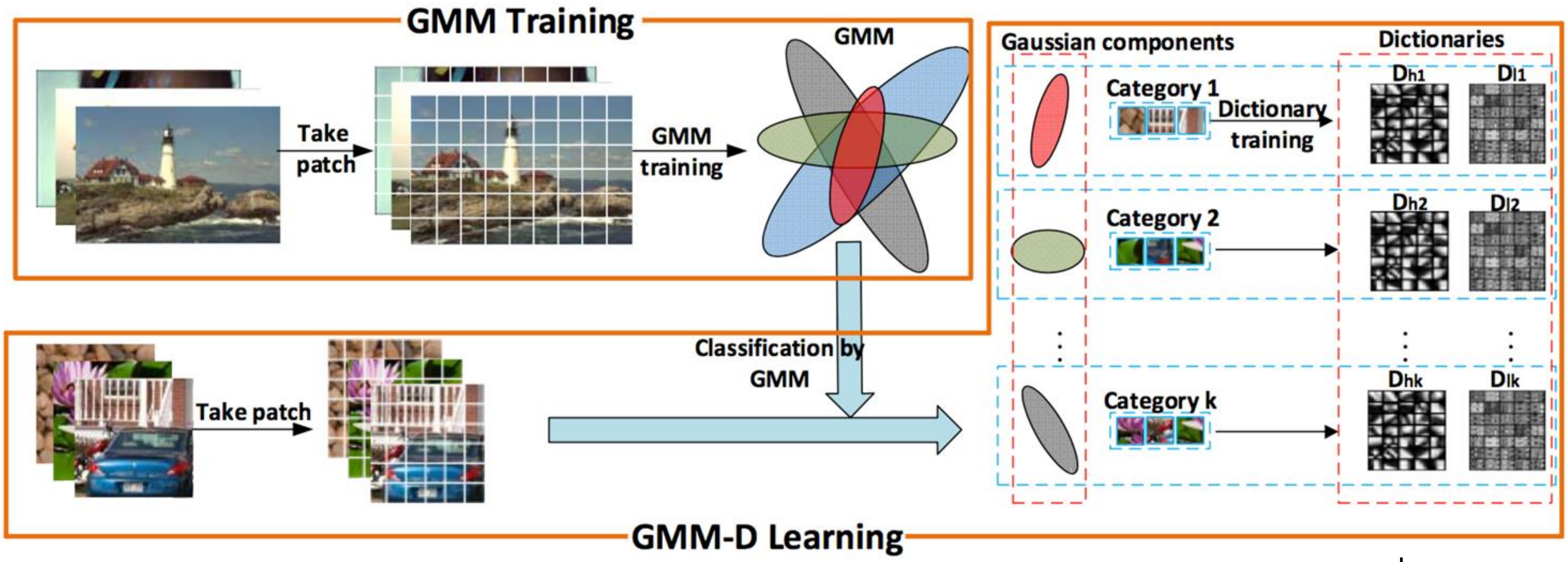


Image source:
Mei et. al

Image Formatting

- Chrominance and Luminance
  - Images composed of color and intensity
  - Used in TV signals
  - Red/Green, Blue/Yellow chrominance
- Gradient
  - Change in value between pixels

Image source:
Algr, Wikipedia

Background

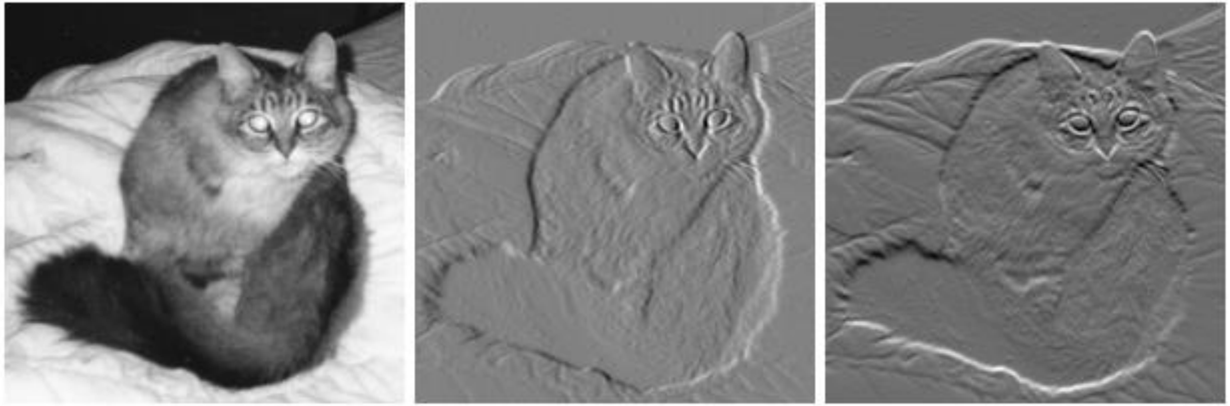
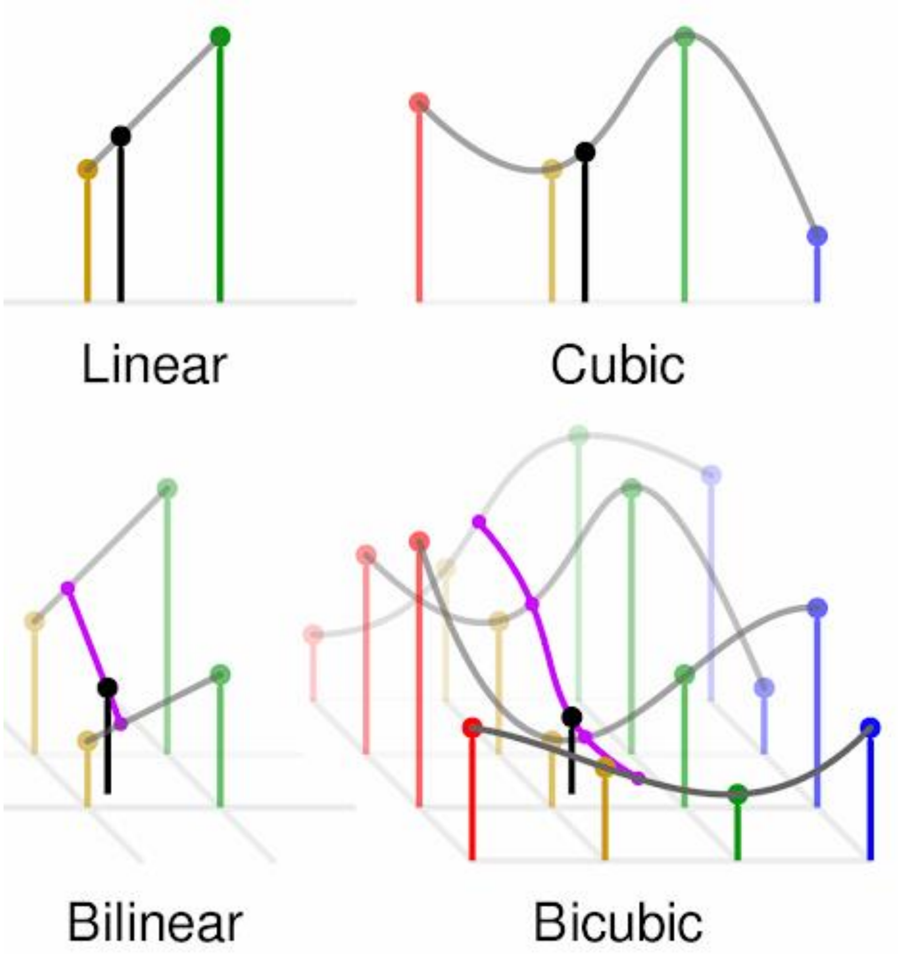


Image source:
Njw000, Wikipedia

Interpolation

- What is it
  - Find values between points
  - Mathematical formulas
    - Linear, cubic, etc
- Applications
  - Fill in pixels
  - Approaches:
    - Nearest neighbor
    - Bilinear
    - Bicubic



Background

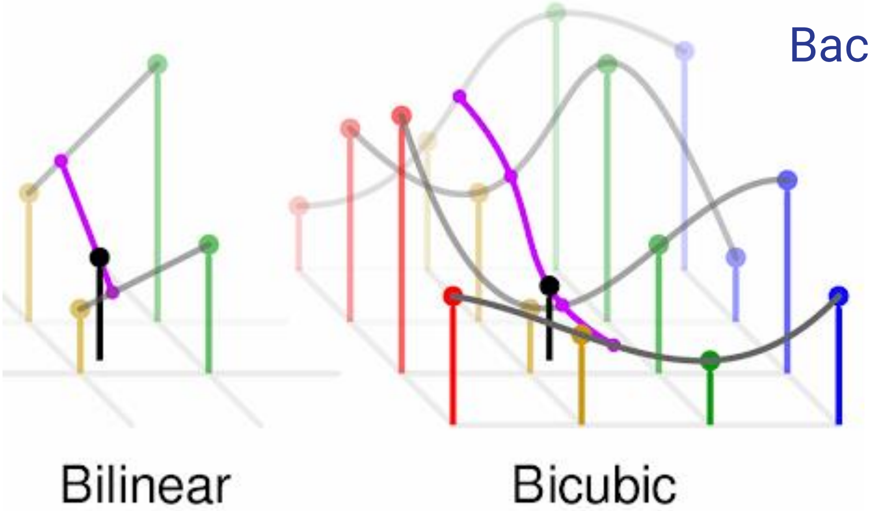


Image source:
Cmglee, Wikipedia

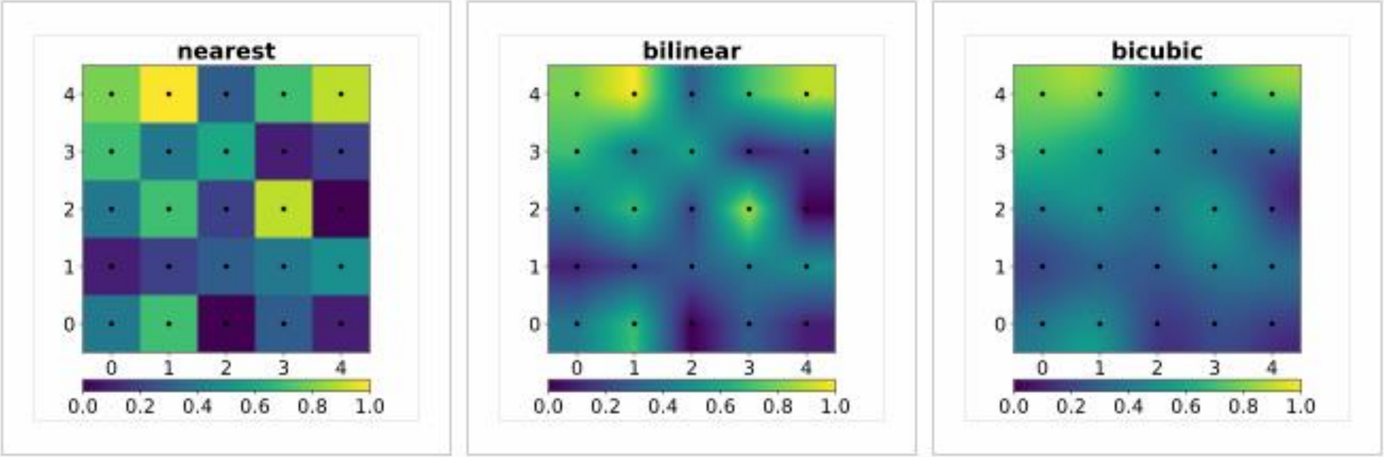
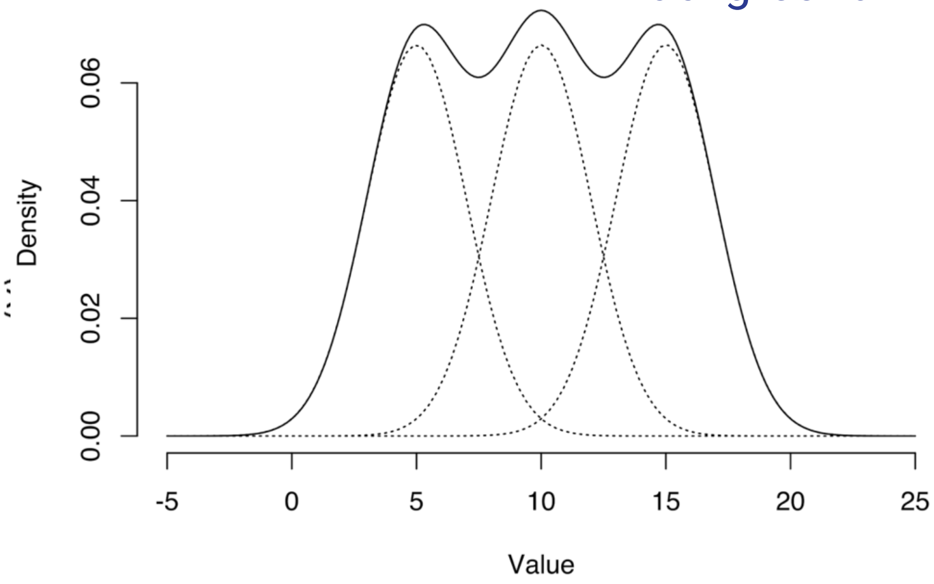


Image source:
Zykure, Wikipedia

Gaussian Distribution

- Most common statistical distribution
- Shape defined by mean, variance
- Single-variable or multivariate



Gaussian Mixture Models

- Represent data described by multiple Gaussian distributions
- Individual distribution: “component”
- Group data into sets, find most likely trend

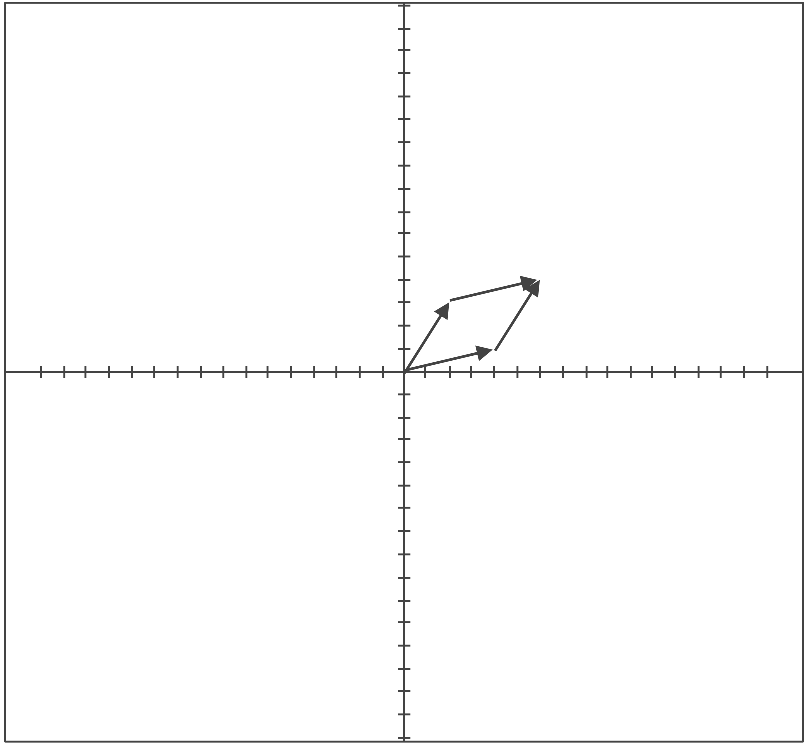
Image sources:
Smason79, Wikipedia
Bscan, Wikipedia

Machine Learning:

- Use data analysis to accomplish task
- Trained on input data
- Several types
  - Dictionary Learning
    - Find sparse representation of data set
    - Dictionary represents input range
    - Good for image de-noising and compression, etc.
  - Clustering
    - Group data based on traits
    - Use statistics to classify
    - Good for pattern recognition
- Training
  - Dictionary trained on vectors
  - GMM Trained by collecting data points
    - Data shows clusters
    - EM Algorithm to get components

Linear Combinations

- Linear Combination
  - Represent vector as combination of several
    - (2x + 3y) + (4x + y) = (6x + 4y)
  - Any number of vectors/dimensions
  - Can multiply vectors
    - 2(2x + 3y) + 3(4x + y) = (16x + 9y)
- Sparsely representing a space
  - Two vectors span 2D plane
  - More = over-representation
  - Trade-off
    - Sparsity vs accuracy



Sparse Dictionary Learning

- Dictionary
  - Set of data that spans a given input space
  - Luminance values of pixels as vectors
- Think of images as vectors
  - Pixel = variable
  - Color = value or coefficient
- Linear combinations
  - Represent image space
- Sparse representation
  - Use as few vectors as possible
  - Trade-off, sparsity vs. accuracy

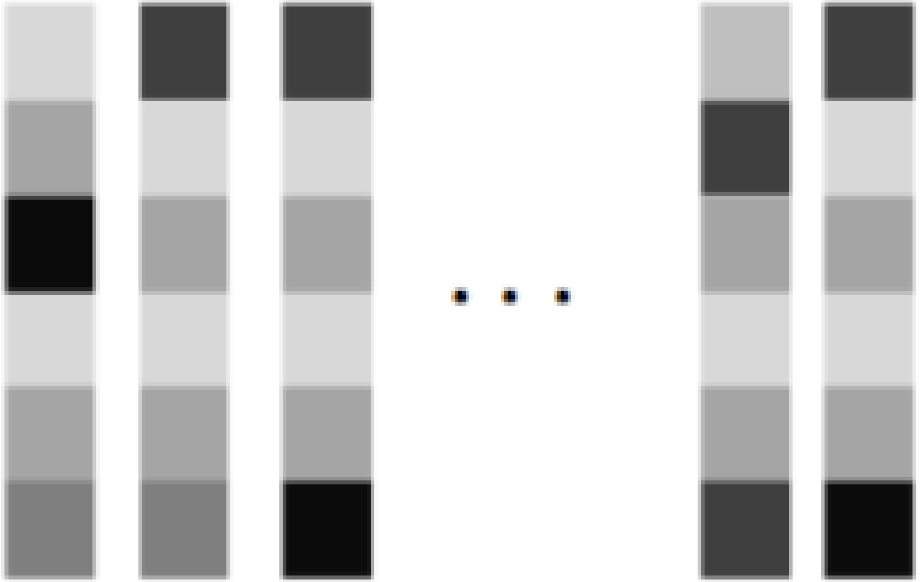


Image source:
Mei et. al

Patch Classification

- Break images into patches
- Use GMM to classify patches

Image source:
Mei et. al

Training Multi-Pairs

- Extract feature vectors
  - Patches -> Luminance data
  - Luminance Data -> Gradients
- Train a **pair** of dictionaries GMM-D
  - High resolution, low resolution
  - Train dictionaries for patch categories
  - Find sparse representation of category

Key Image (reprise)

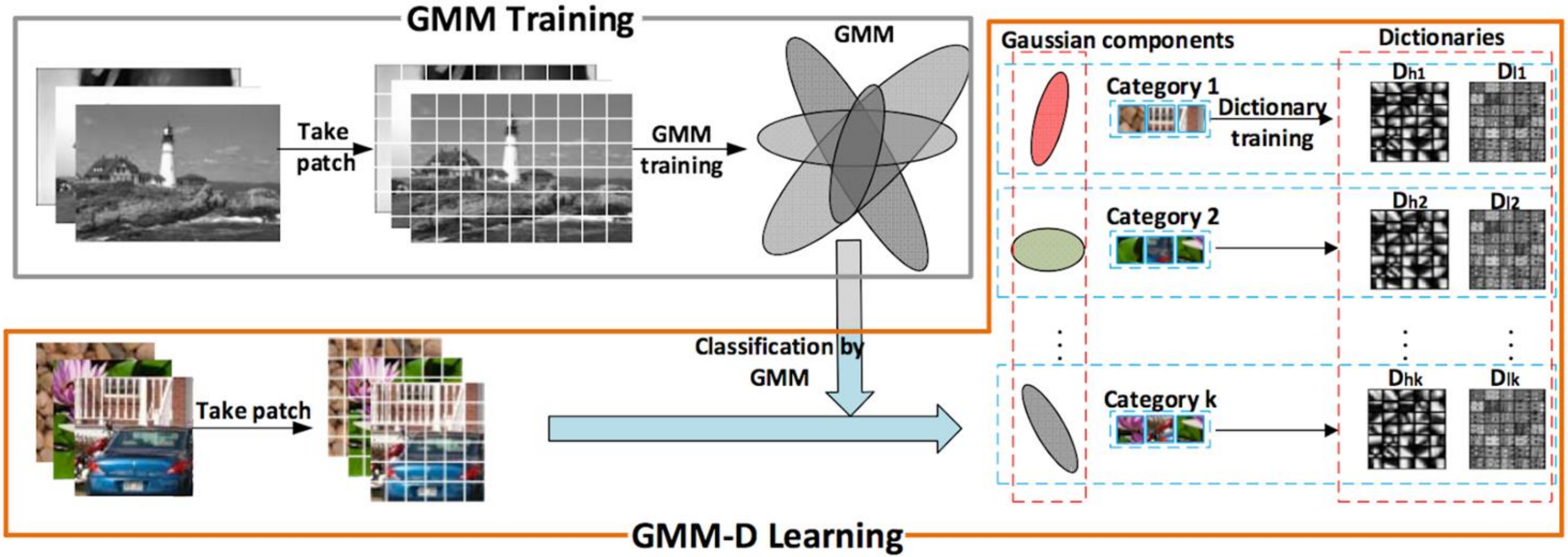


Image source: Mei et. al

Upscaling an image

1. Linear combination of LR training patches for patch type -> LR input patch
2. Same combination of HR training data + interpolated LR input patch -> HR output patch
3. Interpolated chrominance input data -> HR output patch -> Final output patch
4. Final output patches -> Final HR image

The Process

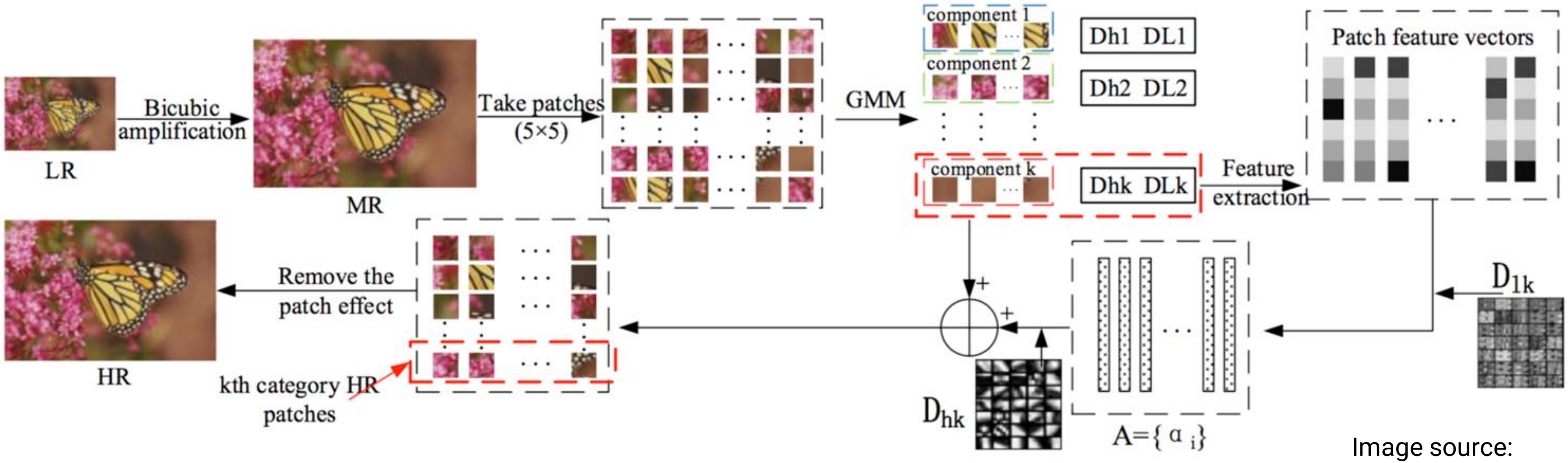
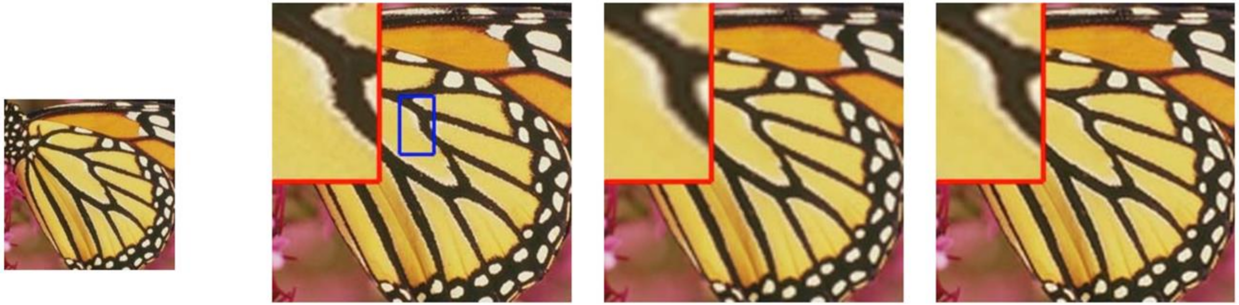


Image source:
Mei et. al

Results



(a) LR image (b) Original (c) Bicubic (d) Zeyde

(e) NCSR (f) ANR (g) Yang (h) Our

Image source:
Mei et. al

Conclusions

- GMMs are effective for patch classification
- Sparse learning on patches recovers considerable detail
- Questions?

References

- D. Mei, X. Zhu, C. Yue, Q. Cao, L. Wang, L. Zhang, and Q. Song. Image super-resolution based on multi-pairs of dictionaries via patch prior guided clustering. In 2018 Eighth International Conference on Image Processing Theory, Tools and Applications (IPTA), pages 1–6, Nov 2018.