Epitomic Image Colorization

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Outline

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   - Epitome
   - Robust Patch Dissimilarity Measure via Epitome

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Image Colorization

- A process of adding color to grayscale images
  - Increasing the visual appeal of images
  - Information illustration in scientific images
- Manual colorization is time consuming and tedious.
- We focus on automatic image colorization that transfers color from the reference image to the grayscale target image.
**Figure 1:** Colorize the Nano Mushroom-like structure by our method. From left to right: the reference image, the target image, the colorized target image.
Related Work

- Transferring Color to Greyscale Images (Welsh et al., 2002)
  - Pixel-level matching by luminance value and neighborhood statistics
  - Suffers from spatial inconsistency

- Image Colorization Using Similar Images (Gupta et al., 2012)
  - A cascade feature matching scheme for matching the target superpixels to the reference superpixels
  - Lacks robust to change in pose or orientation
Contribution

- We propose a new automatic image colorization method by epitome, called Epitomic Image Colorization
  - Achieve feature matching robust to both noise and the large change in the pose or orientation of the objects
  - Epitome is a generative model which summarizes raw image patches into a condensed representation.
- A new robust patch dissimilarity measure by epitome and the MRF inference.
Epitome (Jojic, Frey, & Kannan, 2003) is a generative model which summarizes raw image patches into a condensed representation similar to Gaussian Mixture Models (GMMs).

In contrast to traditional GMMs, the Gaussian components of epitome can be overlapping with each other.

**Figure 2:** Examples of the learned epitome
Introduction to Epitome

- The epitome $e$ is obtained by maximizing the log likelihood function:

$$
\hat{e} = \arg \max_{\hat{e}} \log p \left( \{Z_k\}_{k=1}^Q | \hat{e} \right),
$$

(1)

Figure 3: Learn the epitome from the reference image. $Z_k$: patch from the reference image; $T_k$: hidden mappings that maps the image patch $Z_k$ to the epitome patch.
Heterogeneous Feature Epitome

- We learn the pixel epitome $e^{YIQ}$, the dense SIFT epitome $e^{SIFT}$ and the LBP epitome $e^{LBP}$ jointly from the raw pixel, the dense SIFT feature (Lazebnik, Schmid, & Ponce, 2006) and the rotation invariant Local Binary Pattern (LBP) (Ojala, Pietikainen, & Maenpaa, 2002) of the reference image.
- The heterogeneous feature epitome $e = (e^{YIQ}, e^{SIFT}, e^{LBP})$
Robust Patch Dissimilarity Measure via Epitome

In order to match the target patch to the reference patch for color transfer, we need a robust patch dissimilarity measure.

We propose a robust dissimilarity measure between the target patch $\hat{Z}_i$ and the reference patch $Z_j$ with the heterogeneous feature epitome $e$ learned from the reference image:

$$D_e (\hat{Z}_i, Z_j) = 1 - p(\hat{T}_i^* | Z_j, e)$$  \hspace{1cm} (2)

where $\hat{T}_i^*$ is the most probable hidden mapping for $\hat{Z}_i$:

$$\hat{T}_i^* = \arg \max_{\hat{T}_i} p (\hat{T}_i | \hat{Z}_i, e)$$  \hspace{1cm} (3)
Robust Patch Dissimilarity Measure via Epitome

- This dissimilarity measure is robust to noise and the large change in the pose or orientation of the objects.

Figure 4: Colorize the cheetah
Epitomic Image Colorization

- Use the robust patch dissimilarity measure via epitome to find similar reference patches for each target patch
- Transfer color from the similar reference patch to the target patch
- Use MRF inference to obtain a smooth colorization result

Figure 5: Comparison between colorizing the Nano image with MRF inference (left) or not (right).
Parameter Setting

- The area of the heterogeneous feature epitome is no more than $\frac{1}{4}$ of that of the reference images.
- The patch size is $9 \times 9$ or $12 \times 12$. 
Colorization Results

learned epitome  reference image  target image

Welsh et al.  Gupta et al.  our result.
Colorization Results Cont.

- **learned epitome**
- **reference image**
- **target image**

- Welsh et al.
- Gupta et al.
- our result.
Colorization Results Cont.

learned epitome  reference image  target image

Welsh et al.  Gupta et al.  our result.
Colorization Results Cont.

learned epitome  reference image  target image

Welsh et al.  Gupta et al.  our result.
Colorization Results Cont.

learned epitome  reference image  target image

Welsh et al.  Gupta et al.  our result.
Colorization Results Cont.
Thank you!

