Exploring the Effect of Sparse Recovery on the Quality of Image Superresolution

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Problem Statement

- Image super-resolution (S-R) is widely used to enhance the resolution and quality of a low-resolution (LR) image, to obtain a higher-resolution (HR) version without hardware improvement.
- S-R based on dictionary learning, a method used in signal processing to find a way to represent data in a more concise and meaningful manner, has been used successfully in variety of S-R applications.
- **Challenges:** S-R based on dictionary learning relies on sparse recovery. There are many existing sparse recovery methods, but their effects on the quality of S-R are not well studied.

SR based on Coupled Dictionary Learning

- **Training phase:** two dictionaries are trained using a dataset of paired HR and LR images.
- **Testing phase:** LR images are used to recover the shared sparse vector, which then is used to reconstruct the HR image

Algorithm 1 (SR via Sparse Representation).

1: **Input:** training dictionaries $\boldsymbol{D}_h$ and $\boldsymbol{D}_l$, a low-resolution image $\boldsymbol{Y}$.
2: **For** each 3×3 patch $\boldsymbol{y}$ of $\boldsymbol{Y}$, taken starting from the upper-left corner with 1 pixel overlap in each direction,
- Compute the mean pixel value m of patch $\boldsymbol{y}$.
- Solve the optimization problem with $\tilde{\boldsymbol{D}}$ and $\tilde{\boldsymbol{y}}$ defined in (8): $\min_{\boldsymbol{\alpha}} \|\tilde{\boldsymbol{D}}\boldsymbol{\alpha} - \tilde{\boldsymbol{y}}\|_2^2 + \lambda\|\boldsymbol{\alpha}\|_1$.
- Generate the high-resolution patch $\boldsymbol{x} = \boldsymbol{D}_h\boldsymbol{\alpha}^*$. Put the patch $\boldsymbol{x} + m$ into a high-resolution image $\boldsymbol{X}_0$.

3: **End**
4: Using gradient descent, find the closest image to $\boldsymbol{X}_0$ which satisfies the reconstruction constraint

$$\boldsymbol{X}^* = \arg\min_{\boldsymbol{X}} \|SH\boldsymbol{X} - \boldsymbol{Y}\|_2^2 + c\|\boldsymbol{X} - \boldsymbol{X}_0\|_2^2.$$

The Effect of Sparse Recovery on SR Quality in the Testing Phase

- There are various algorithms to solve the optimization problem in Step 2 in the image S-R algorithm based on coupled dictionary learning
- For an optimal performance, it is helpful to know what sparse recovery algorithm we should use.

Empirical Exploration

- We study the effect of sparse recovery on the quality of S-R using five sparse recovery algorithms.
- We prepare a small dataset of representative images and report the performance of S-R using these algorithms on our dataset.

Results

- We perform experiments for 5 images
- We report PSNR (Peak Signal-to-Noise Ratio) values for different methods

Method	Lena	Boat	Cameraman	Butterfly	Bridge	Average
QP						
SL0	32.531 dB	12.064 dB	11.823 dB	19.579 dB		
OMP						
BP						
LASSO						

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