Single Image Super-resolution using Deformable Patches

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Motivation

The dictionary may not contain the desired HR patch exactly.

A basic patch can be deformed to a potential patch to fit the input LR patch.

The dictionary could express more patterns using finite basic patches via deformation.

Contribution

Propose a deformable patches model for single image SR problem, making the dictionary more expressive.

Develop an effective patch matching strategy to select the best basic patch for deformation.

Extend the model of single patch to a weighted combination of several deformed candidates for more reliable HR estimation.

Deformation Model

Deformation of Basic Patch:

$$\boldsymbol{B}_r = \alpha\phi(\boldsymbol{B}_h) + \beta$$

Taylor Expansion:

$$\begin{aligned}\phi(\boldsymbol{B}_h) &\approx \boldsymbol{B}_h(\boldsymbol{x}+\boldsymbol{u}, \boldsymbol{y}+\boldsymbol{v}) \\ &= \boldsymbol{B}_h + diag(\boldsymbol{B}_{hx})\boldsymbol{u} + diag(\boldsymbol{B}_{hy})\boldsymbol{v}\end{aligned}$$

Energy Function:

$$E(\boldsymbol{u},\boldsymbol{v}) = ||\boldsymbol{DHB}_r - \boldsymbol{P}_l||^2 + \psi(\boldsymbol{u},\boldsymbol{v})$$

Method

Deformation Similarity for Patch Matching:

$$\boldsymbol{B}_h = \underset{\boldsymbol{B}_h}{\operatorname{argmin}}\ \boldsymbol{P}_d^\top \boldsymbol{P}_d - \boldsymbol{P}_d^\top \boldsymbol{G}(\boldsymbol{G}^\top\boldsymbol{G}+\boldsymbol{\Gamma})^{-1}\boldsymbol{G}^\top\boldsymbol{P}_d$$

Optimizing for Energy Function:

$$E(\boldsymbol{M}) = ||\boldsymbol{P}_d + \boldsymbol{GM}||^2 + \boldsymbol{M}^\top\boldsymbol{\Gamma}\boldsymbol{M}$$

$$\boldsymbol{M} = -(\boldsymbol{G}^\top\boldsymbol{G}+\boldsymbol{\Gamma})^{-1}\boldsymbol{G}^\top\boldsymbol{P}_d$$

Weighted Combination:

$$\boldsymbol{B}_d^k = \sum_{i=1}^{M}\omega_i^k\boldsymbol{B}_{di}^k$$

$$\boldsymbol{B}_d = \phi(\boldsymbol{B}_h) \quad \omega_i^k = \frac{1}{Z}\exp(-(\boldsymbol{B}_{di}^k - \mu_k)^2/2\sigma_k^2)$$

Patch Reconstruction

$$\begin{bmatrix}\alpha\\ \beta\end{bmatrix} = (\boldsymbol{A}^\top\boldsymbol{A})\boldsymbol{A}^\top\boldsymbol{P}_l \quad \boldsymbol{A} = [\boldsymbol{DHB}_d \quad \boldsymbol{1}]$$

$$\boldsymbol{B}_r = \alpha\boldsymbol{B}_d + \beta$$

Where:

$$\boldsymbol{P}_d = \boldsymbol{DHB}_h - \frac{\boldsymbol{P}_l - \beta}{\alpha} \qquad \boldsymbol{M} = \begin{bmatrix}\boldsymbol{u}\\ \boldsymbol{v}\end{bmatrix}$$

$$\boldsymbol{P}_x = \boldsymbol{DH}diag(\boldsymbol{B}_{hx}) \qquad \boldsymbol{P}_y = \boldsymbol{DH}diag(\boldsymbol{B}_{hy}) \qquad \boldsymbol{G} = [\boldsymbol{P}_x \quad \boldsymbol{P}_y]$$

$$\boldsymbol{\Gamma} = \mu + \lambda\begin{bmatrix}-\nabla^2 & 0\\ 0 & -\nabla^2\end{bmatrix} + \eta\begin{bmatrix}(\nabla^2)^2 & 0\\ 0 & (\nabla^2)^2\end{bmatrix}$$

Evaluations on Deformation

3×, dictionary size 30000 and overlap 0.

Undeformed Patch(UP), Deformed Patch(DP), Weighted combined Undeformed Patch(UP+W) and Weighted combined Deformed Patch(DP+W)

PSNR(dB) 3×, dictionary size 30000 and overlap 0.

Image	UP	DP	UP+W	DP+W
lena	29.3259	29.6104	30.4901	**30.8557**
zebra	22.5464	23.0735	24.4748	**25.0028**
cameraman	24.539	24.7518	25.4206	**25.6633**
oldman	27.914	28.1613	29.2855	**29.6448**
child	28.1921	28.4638	29.5217	**29.8793**

UP: undeformed patch, DP: deformed patch, W: weighted combination

Evaluations on Visual Quality

PSNR(dB) of the final super-resolved test images (3×, dictionary size 30000 and overlap 6)

Image	Bicubic	Glasner	Freedman	SCDL	BPJDL	Proposed
lena	30.0986	30.3197	30.6928	31.6493	31.6755	**31.7536**
zebra	23.6214	25.7724	26.8935	27.2387	27.5010	**27.7907**
cameraman	25.1935	25.9155	25.5409	26.2110	26.2032	**26.2221**
oldman	29.4678	28.9615	30.2424	30.5824	30.6059	**30.6666**
child	29.3479	29.4468	29.7914	30.9166	30.9433	**30.9467**

Reference and Code

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