Single Image Interpolation via Adaptive Non-Local Sparsity-Based Modeling

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Motivation and Goals

Adaptive sparse representation modeling is a promising image prior, which has been shown to be powerful in filling-in missing pixels in an image. Processing groups of related patches together (based on the self-similarity assumption) exploits their correspondence and leading often times to improved results.

The Interpolation Problem

- Given a Low-Resolution (LR) image \( y = U_L x \), where \( x \) is the High-Resolution (HR) image and \( U_L \) decimates the image by a factor of \( L \) along the horizontal and vertical dimensions, our goal is to recover \( x \) from \( y \).

The Proposed Algorithm

- We suggest training a dictionary using the LR image itself and restore each decimated patch by a sparse composition over the dictionary using a weighted version of the Simultaneous OMP.
- The restored image is obtained by averaging the HR patches, followed by a simple projection of the known pixels in \( x \) on the outcome.

The Core Idea

- A common patch-based image restoration scheme:
- Zero-filled Image
- Initial Dictionary
- Interpolated each patch
- Dictionary Update
- Notations:
  - \( W_{ij} \) sets a high weight for known pixels and a low one for the unknown ones, multiples by \( \exp(-\|r_i - s_j\|/\omega) \).
  - \( |A_i|^p \) counts the non-zero elements rows in the matrix \( [c_i, A_i]^p \).
  - \( A_i^p \) is the representation of the non-weighted version of the reference patch (stabilizer).
  - \( A_i \) is the representation of the weighted versions of the reference patch and its K – Nearest Neighbors.
  - \( R_i \) is an operator that extracts the \( i \)-th patch from the image.
- The proposed two-stage algorithm:
  - **First stage:** Joint sparse-coding using the K-nearest “strong” patches and reconstructing the image using the “strongest” patches.
  - **Second stage:** Use all the patches (“strong” and “weak”), both in the sparse-coding and the reconstruction steps.

A Basic Observation

- The more known pixels within a patch, the better the restoration.
- The number of known pixels depends on its location ("strong" and "weak" patches).
- We suggest "increasing" the number of known pixels based on the self-similarity assumption (e.g., the bright patches are the K-Nearest Neighbors of each dark patch).

Visual Results

- Interpolation by a factor of 2 (75% missing pixels)
- Interpolation by a factor of 3 (~89% missing pixels)

Results

- State-of-the-art Performance
  - Average PSNR over 18 well-known images:
    - \( \text{Method} \) \hspace{1cm} \text{Cubic} \hspace{1cm} \text{SAI} \hspace{1cm} \text{SME} \hspace{1cm} \text{PLE} \hspace{1cm} \text{NARM} \hspace{1cm} \text{Ours} \hspace{1cm} \text{Cubic} \hspace{1cm} \text{SAI} \hspace{1cm} \text{SME} \hspace{1cm} \text{PLE} \hspace{1cm} \text{NARM} \hspace{1cm} \text{Ours}
    - \text{PSNR} \hspace{1cm} 28.98 \hspace{1cm} 29.51 \hspace{1cm} 29.62 \hspace{1cm} 29.62 \hspace{1cm} 29.98 \hspace{1cm} 30.09 \hspace{1cm} 25.52 \hspace{1cm} 25.83 \hspace{1cm} 25.95 \hspace{1cm} 26.08 \hspace{1cm} 26.21 \hspace{1cm} 26.44
  - Peak Signal to Noise Ratio (PSNR) (dB) = 20 \log_{10} (255/\text{MSE}), Higher is better.

References


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