PSyCo: Manifold Span Reduction for Super Resolution

Patch Symmetry Collapse

Eduardo Pérez-Pellitero [1,2], Jordi Salvador [2], Javier Ruiz-Hidalgo [3], Bodo Rosenhahn [1]

[1] Information Processing Institute, Leibniz Universität Hannover
[2] Technicolor R&I
[3] Image Processing Group, Universitat Politècnica de Catalunya

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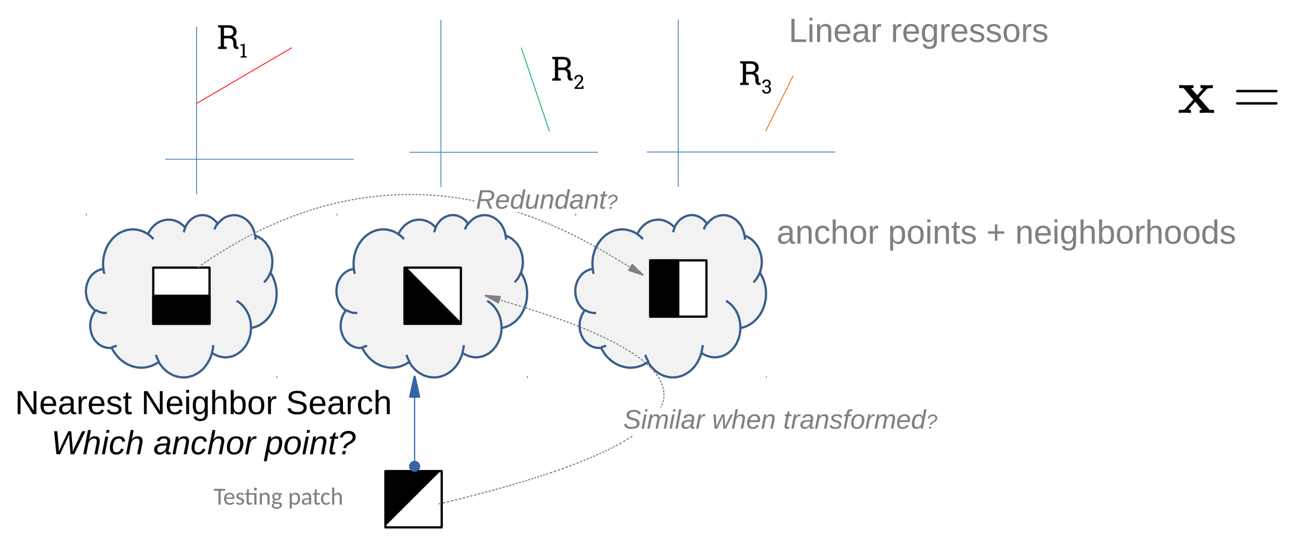
1. Regression-based SR

- Mapping between low-res and high-res patch manifolds is non-linear
  - Locally linear assumption
  - Ensemble of linear regressors to model non-linearity [1] (anchor points)



$$\mathbf{x} = \mathbf{c} + R^{*}\mathbf{y_F}$$

Some questions we asked ourselves :

- Is there redundancy among the regressors we learn?
- More generally, are the manifolds in which patches lie redundant?
- Can we obtain transformation models that describe that redundancy?
- Can we get rid of redundancy?

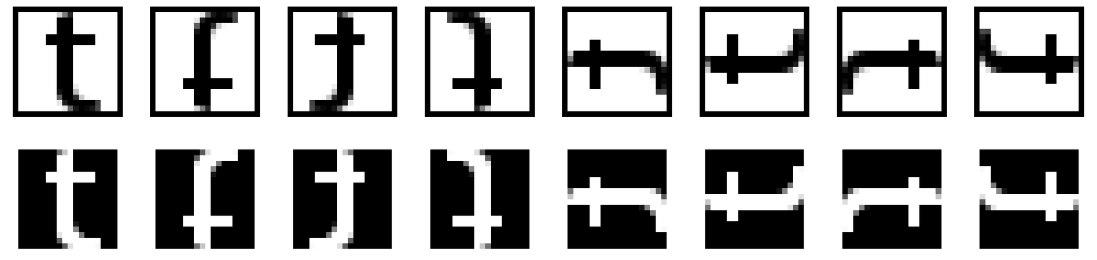
2. Extending the Search Space

- Extending the NN search space with transformation models solves partially the problem:
  - Rotation
  - Antipodal Points [2]
  - Homography [3]
  - Reflection
  - Cross-scale [3]
- More search candidates increase the search cost
- Problem: Redundancy persists within dictionary atoms
- **Proposed Alternative**: variability collapse

3. Dihedral Group as Symmetries

- Dihedral group (i.e. rotations and reflections)
  - Exist a lossless inverse transform
  - Finite group, can be composed by three operators g_x, g_y and g_T
  - Defines a set of 8 high-dimensional points for a given point in the manifold (with 8 additional antipodal points)

$$g_x = \begin{pmatrix} -1 & 0 \\ 0 & 1 \end{pmatrix},\ g_y = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix},\ g_T = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$$

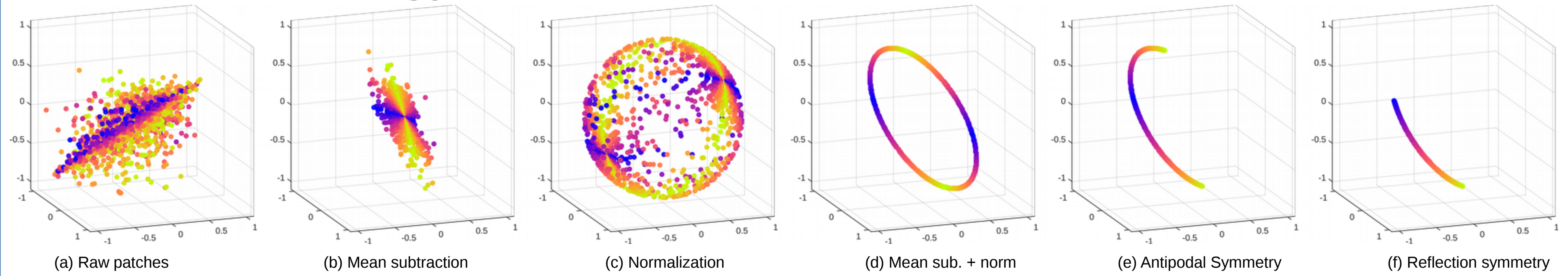


Dihedral and antipodal group of transforms

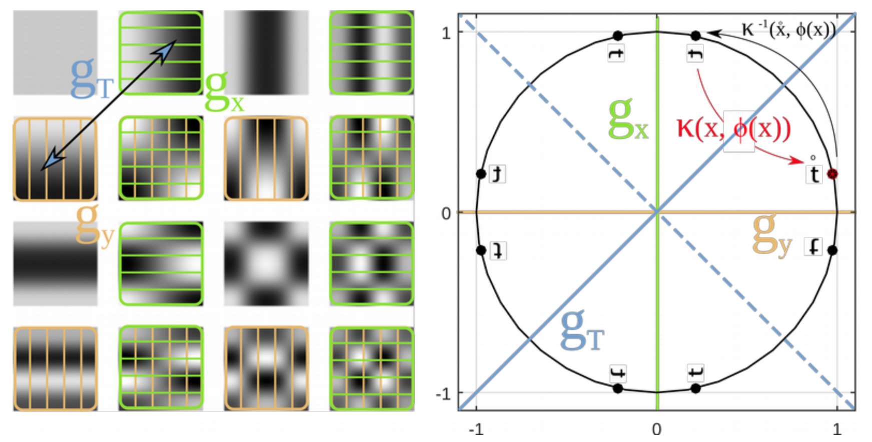
- Symmetry is defined as non-trivial group of action that defines isomorphism

4. Patch Symmetry Collapse

- Similar strategy as normalization or mean subtraction:



- Dihedral group of transforms in the DCT: sign change and transpose
  - Low-dimensional representation enables to find symmetry axes.
  - Collapse transform K based on the Symmetric Distance of [4]



$$\mathring{c} = \kappa(c, \varphi(c))$$
$$g_j = \varphi(c)$$
$$c = \kappa^{-1}(\mathring{c}, g_j)$$

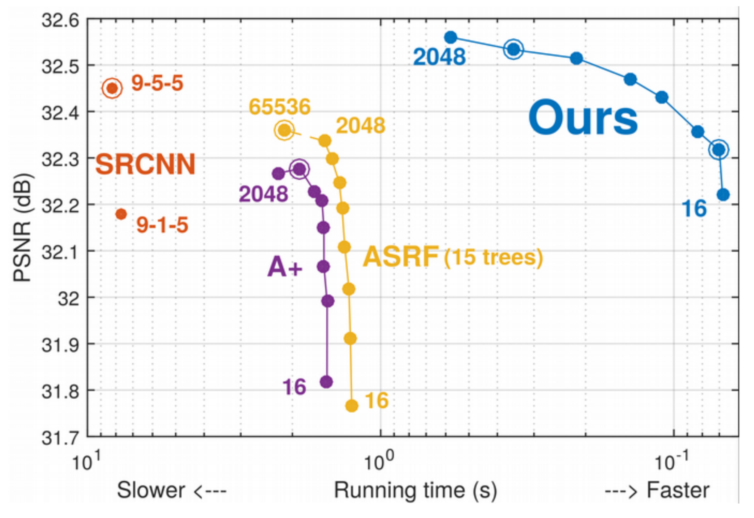
$$R_i = (1+\lambda)(\mathring{\mathbf{X}}_i - \mathring{\mathbf{C}}_i)\overline{\mathring{\mathbf{C}}}_i^{\intercal}(\overline{\mathring{\mathbf{C}}}_i\,\overline{\mathring{\mathbf{C}}}_i^{\intercal} + \lambda\mathbf{I})^{-1}$$
$$\tilde{\mathbf{x}} = \mathbf{c} + \kappa^{-1}(R^{*}\,\overline{\mathring{\mathbf{c}}}, \varphi(\overline{\mathbf{c}})),$$

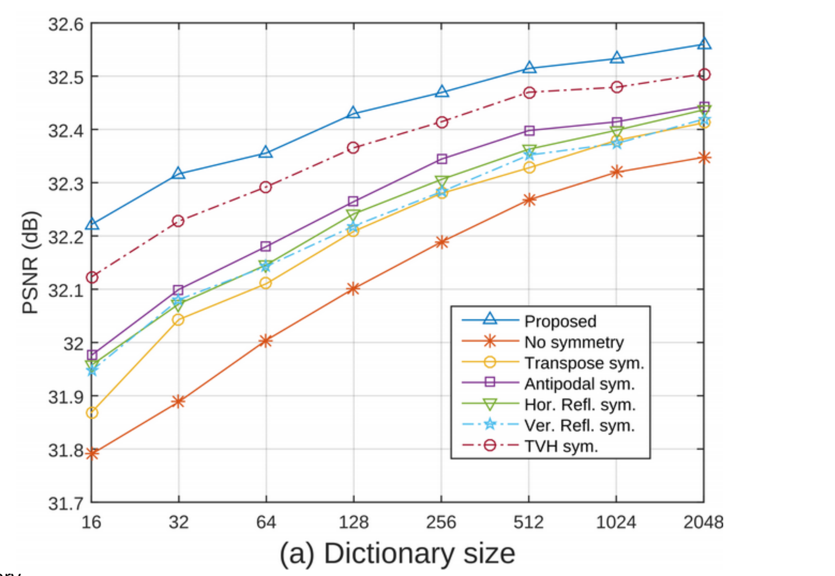
5. Conclusions and Results

- Avoid dihedral and antipodal redundancy in the dictionary and nearest neighbor search
- Reduce manifold span to be learnt, thus improving regressor specialization
- Cover the whole space by the exploitation of symmetries
- Effectively obtain dictionaries 16 to 32 times smaller (faster search, less memory usage)
- Avoid brute force solutions
- Applicable to any patch-based regression:

Input patches → K → Patch-based Regression → K^{-1} →

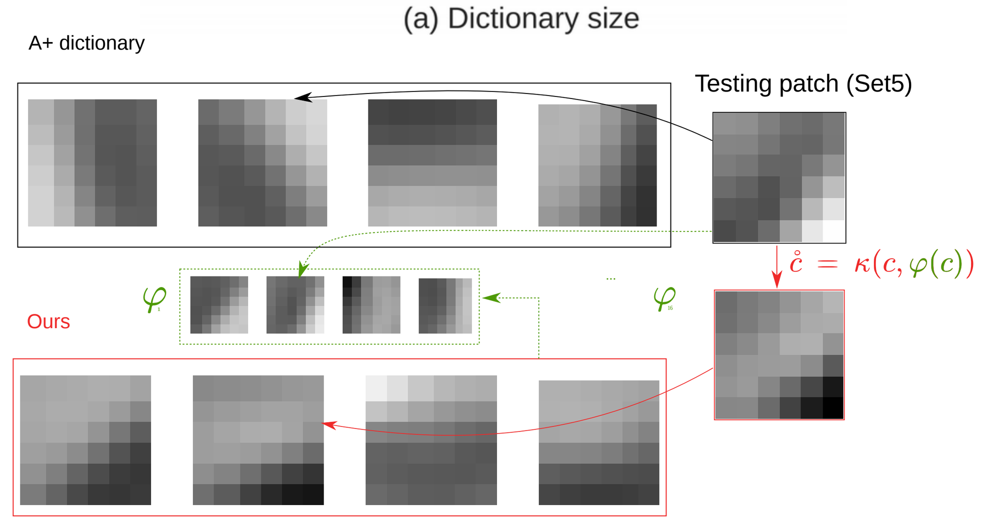
- Improve SR state of the art performance up to 0.2dB and 0.25 (IFC), fastest method by an order of magnitude

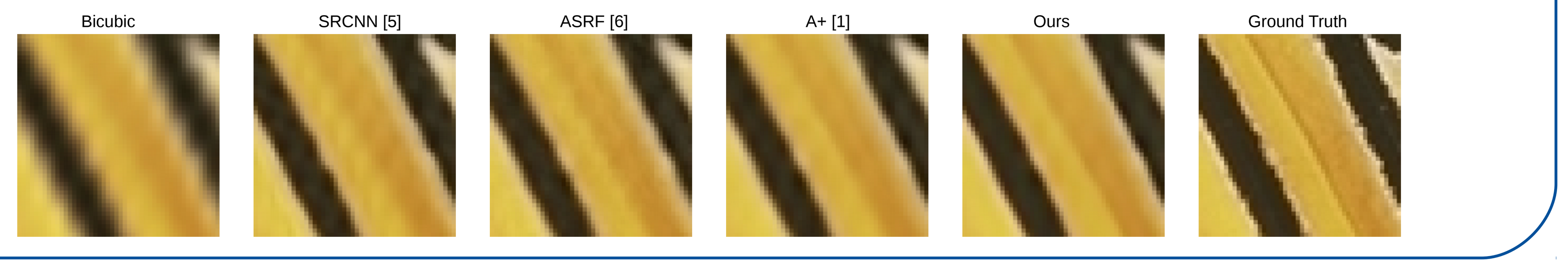




(a) Dictionary size

Experimental setup
- Datasets: Set5, Set14, Urban100, Kodak.
- MF: x2, x3, x4
- Measured PSNR, IFC, time.
- Compared with SRCNN, TselfEx, ASRF, A+





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