Image Error Concealment based on Joint Sparse Representation and Non-local Similarity

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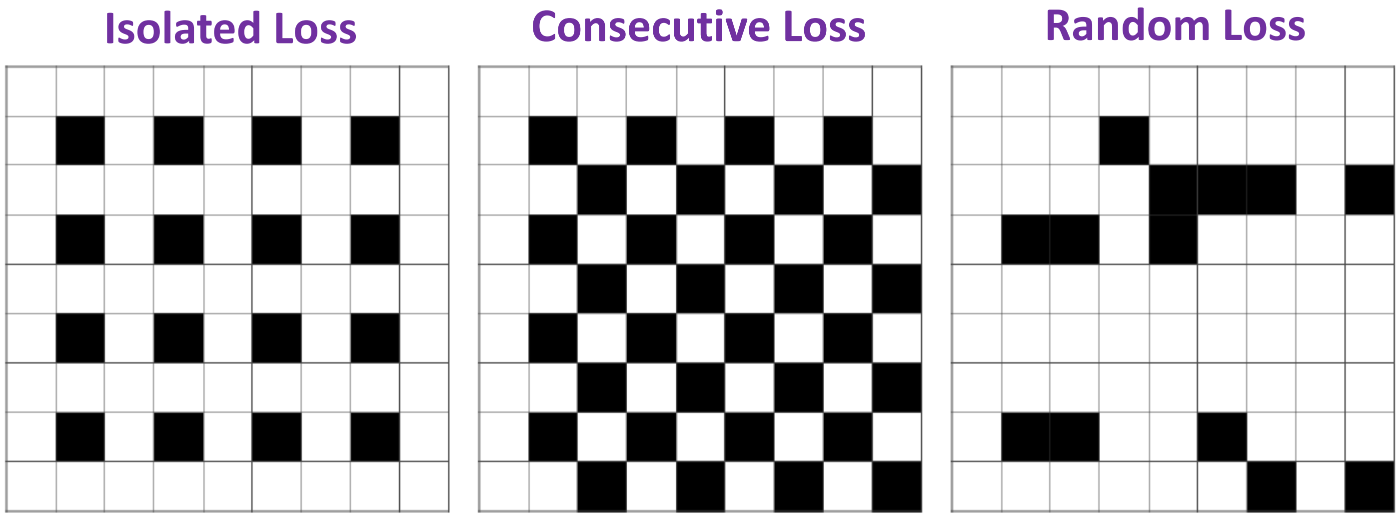
Motivation

Image and Video Transmission Systems

- ➢ Each frame is partitioned into non-overlapped blocks and each block is encoded/transmitted/packetized separately.

Typical Block Loss Pattern

- ➢ Transmission over an error-prone channel: undesired packet erasure leads to block loss.



Error Concealment (EC)

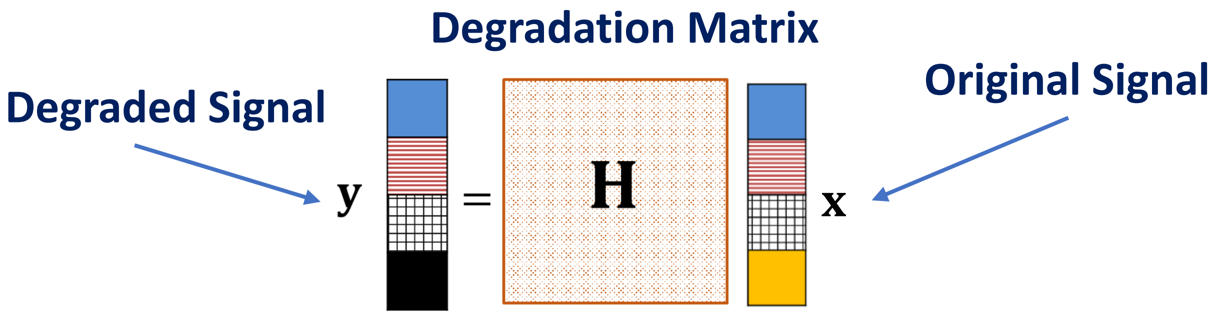
- ➢ Estimation of the lost blocks from the correctly received data.

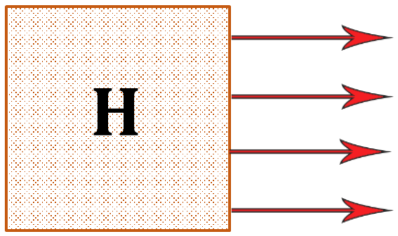
Motivation

Inverse Problem Regularization

- Reconstructing the original signal **x** from its degraded observed version **y**

$$y = Hx$$





Diagonal matrix, whose diagonal entries are either 0 or 1	Image Impainting or Error Concealment (EC)
Random measurement matrix of size $M \times N$ ($M < N$)	Compressed Sensing (CS)
Filtering operator:	Image Deblurring
Composite operator of blurring and downsampling	Interpolation or Super Resolution problem

Recovering x from y

$$\hat{x} = \underset{x}{\operatorname{argmin}} \underbrace{\|y - Hx\|_2^2}_{\text{Fidelity}} + \lambda \underbrace{S(x)}_{\text{Regularizer}}$$

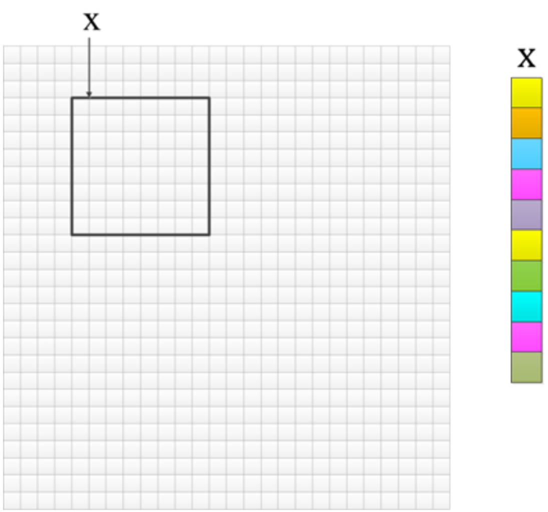
- **Our focus**: a new regularization term based on joint local sparsity and non-local redundancies existing in the natural images.

Outline

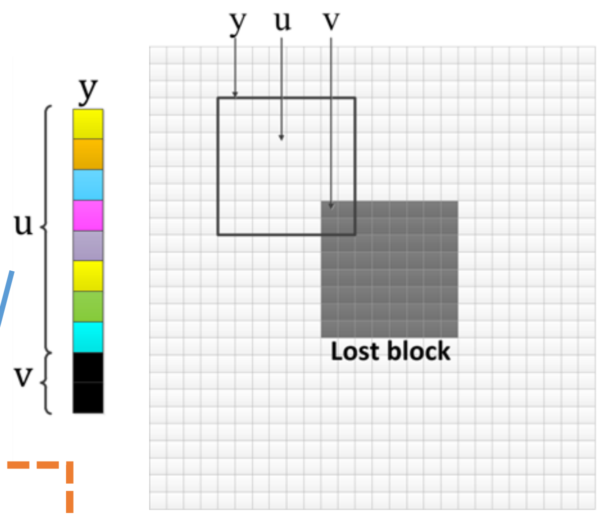
1. Joint Sparse Representation Modeling
2. Error Concealment based on self-similarity property of natural images and joint sparse representation
3. Conclusion

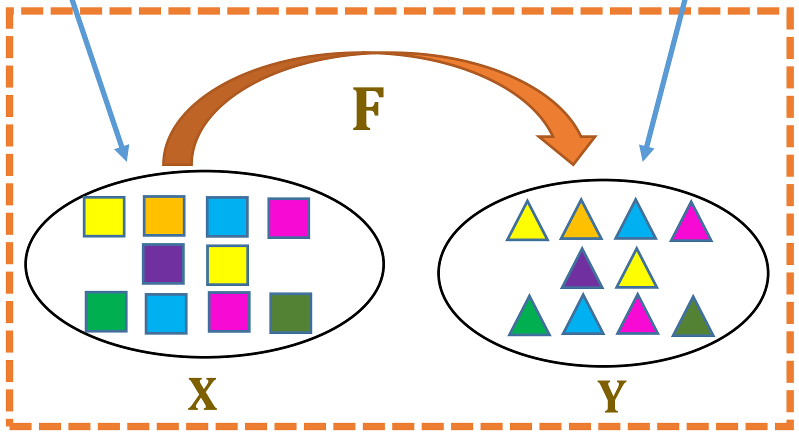
Basic Idea

Original Image



Corrupted Image



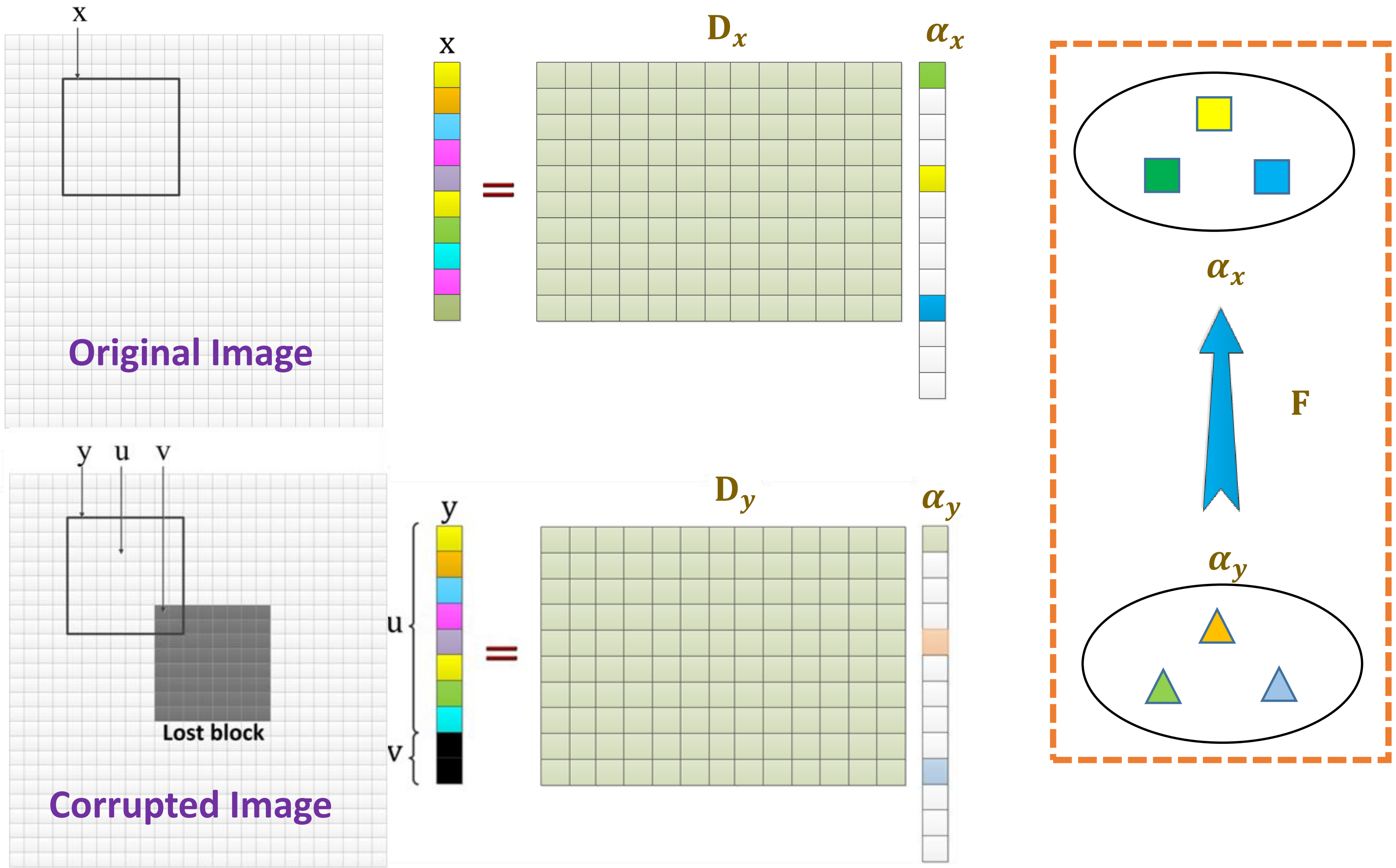


There is a relationship, denoted by F, between these subspaces.

Finding F between the patches in the spatial domain is difficult.

Joint Sparse Representation Modeling

Image patches are sparse with respect to certain dictionaries.
Mapping function F is found more accurately in the sparse representation domain.



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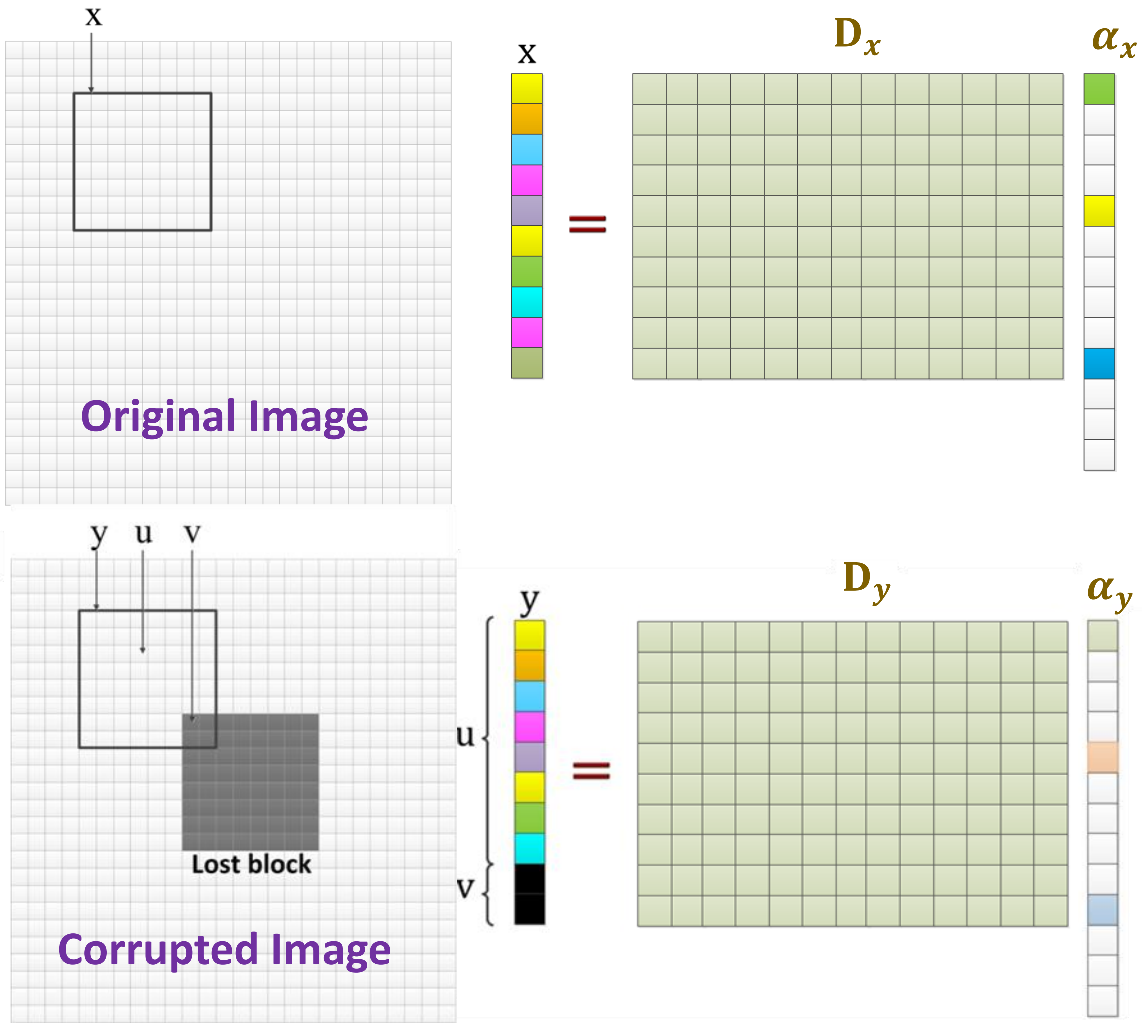
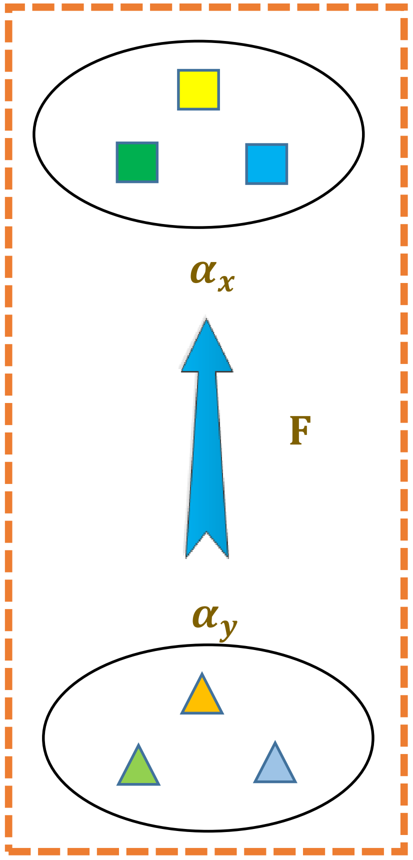
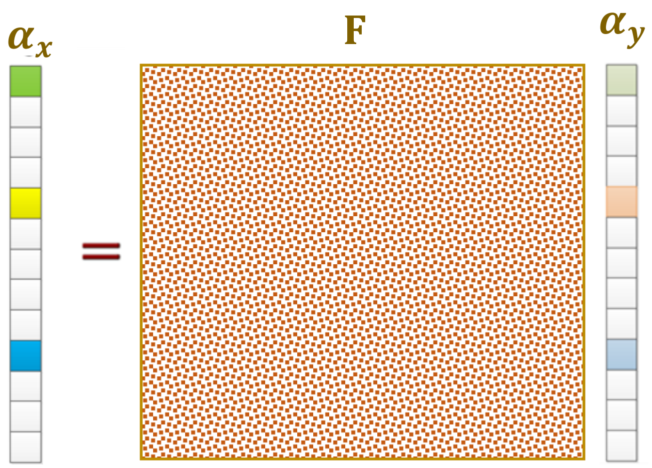




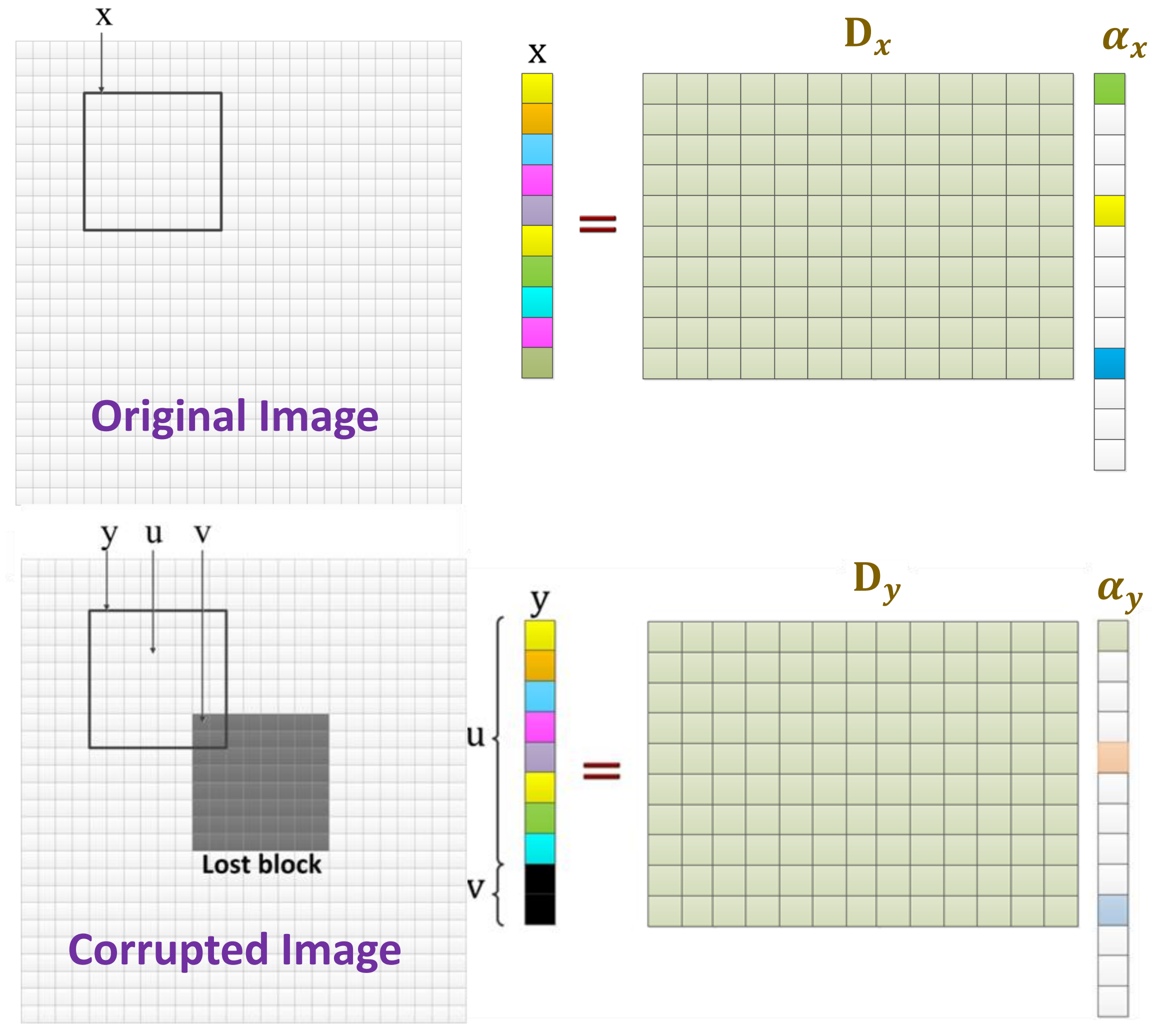
It is assumed that the sparse representations are related to each other via a linear mapping.

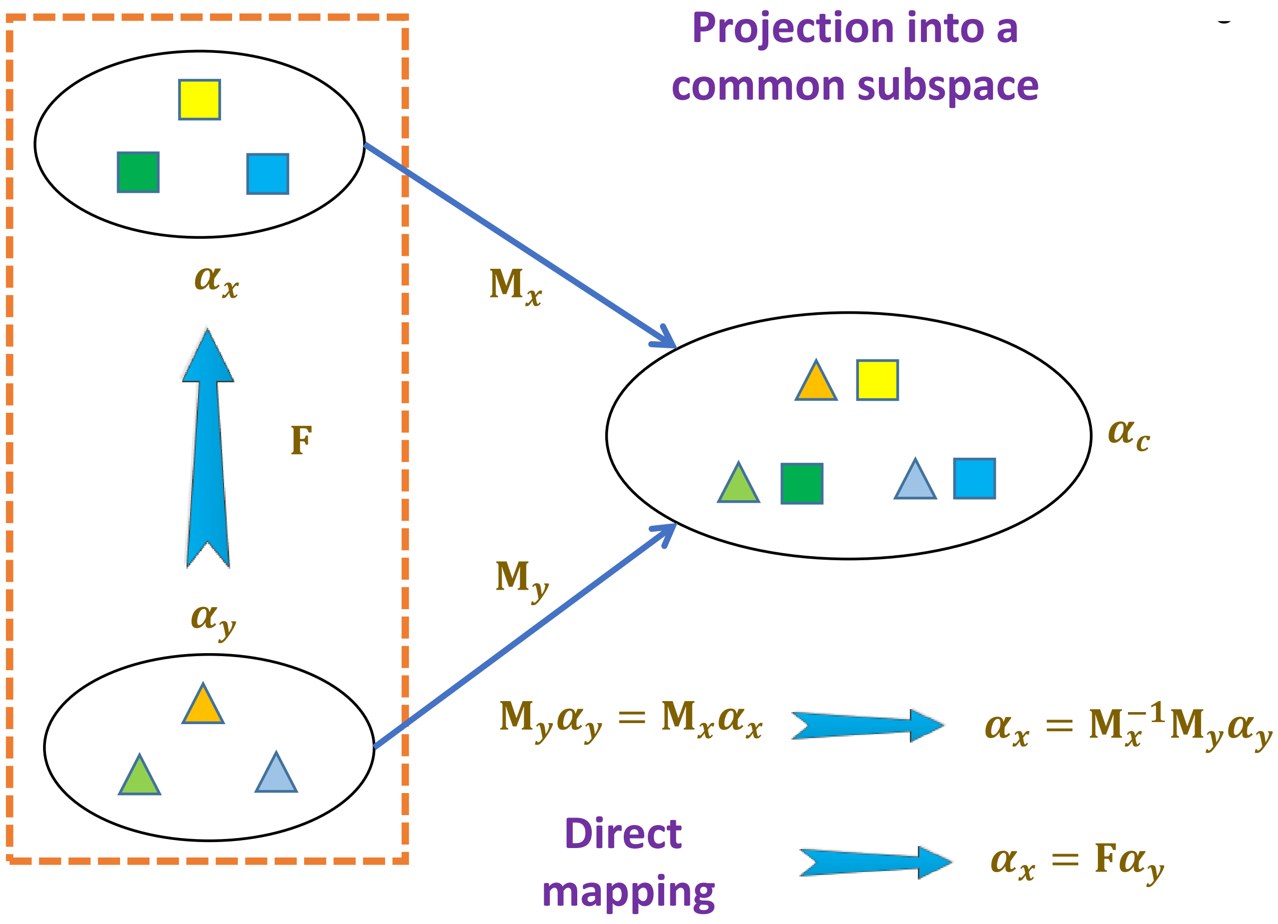


$$\alpha_x = \mathbf{F}\alpha_y$$

Joint Sparse Representation Modeling using a Common Space

More efficient relationship is found by projection into a common space:

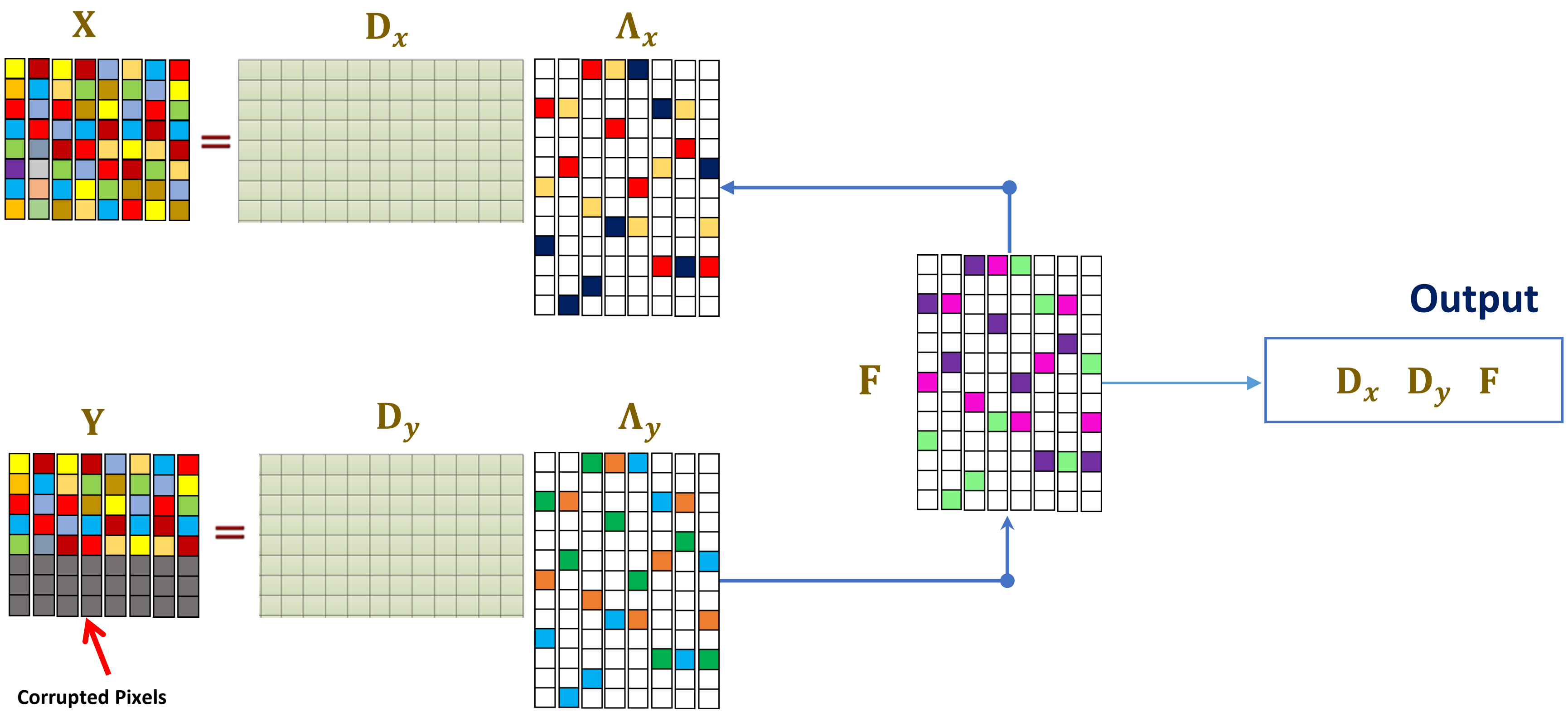




A. Akbari, M. Trocan, S. Sanei, and B. Granado, "Joint sparse learning with nonlocal and local image priors for image error concealment," Submitted to IEEE Transactions on Circuits and Systems for Video Technology.

Joint-Domain Dictionary Learning

One of the most flexible ways to discover the projection matrices is learning from training data:

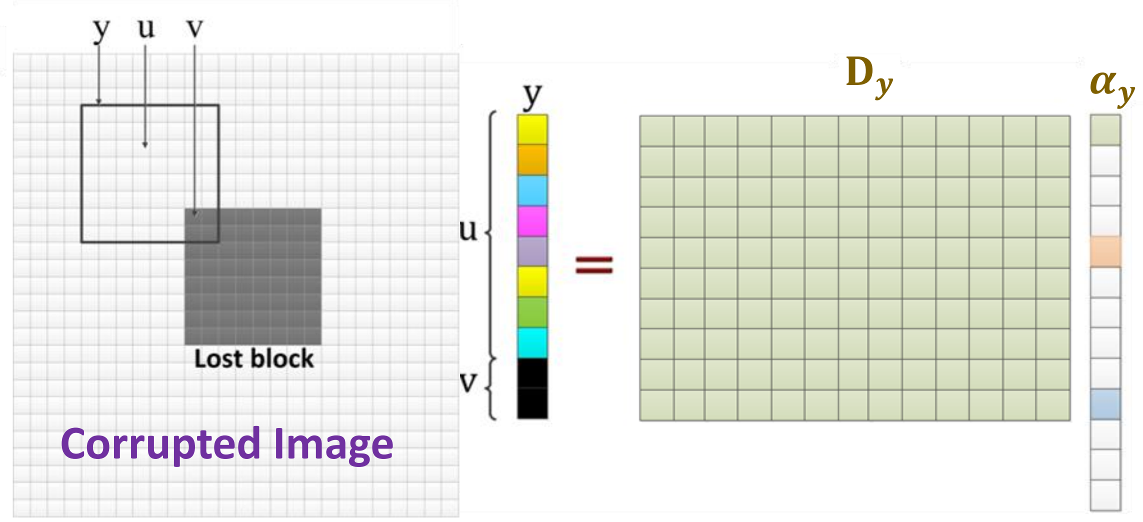


$$\underset{\mathbf{D}_x,\,\mathbf{D}_y,\,\boldsymbol{\Lambda}_x,\,\boldsymbol{\Lambda}_y,\,\mathbf{F}}{\operatorname{argmin}} \underbrace{\|\mathbf{X}-\mathbf{D}_x\boldsymbol{\Lambda}_x\|_2^2+\|\mathbf{Y}-\mathbf{D}_y\boldsymbol{\Lambda}_y\|_2^2}_{\text{Fidelity terms}}+\underbrace{\gamma\|\boldsymbol{\Lambda}_x-\mathbf{F}\boldsymbol{\Lambda}_y\|_2^2}_{\text{Mapping fidelity term}}+\underbrace{\lambda\|\boldsymbol{\Lambda}_x\|_1+\lambda\|\boldsymbol{\Lambda}_y\|_1+\lambda_f\|\mathbf{F}\|_2^2}_{\text{Regularizer}}$$

D. A. Huang and Y. C. F. Wang, "Coupled dictionary and feature space learning with applications to cross-domain image synthesis and recognition," in Proceeding of IEEE Conference on Computer Vision, Dec 2013, pp. 2496–2503.

Simple Error Concealment Algorithm based on Joint Sparse Representation

Step 1: Find the sparse representation of the corrupted patch with respect to the dictionary $\mathbf{D}_y$



$$\alpha_y = \underset{\alpha}{\mathbf{argmin}} \|\mathbf{y} - \mathbf{D}_y \alpha\|_2^2 + \lambda \|\alpha\|_0$$

Step 2: Find the sparse representation of the original patch by projection into common subspace

$$\alpha_x = \mathbf{F}\, \alpha_y$$

Step 3: Obtain the concealed patch $\mathbf{x} = \mathbf{D}_x \alpha_{\mathrm{x}}$

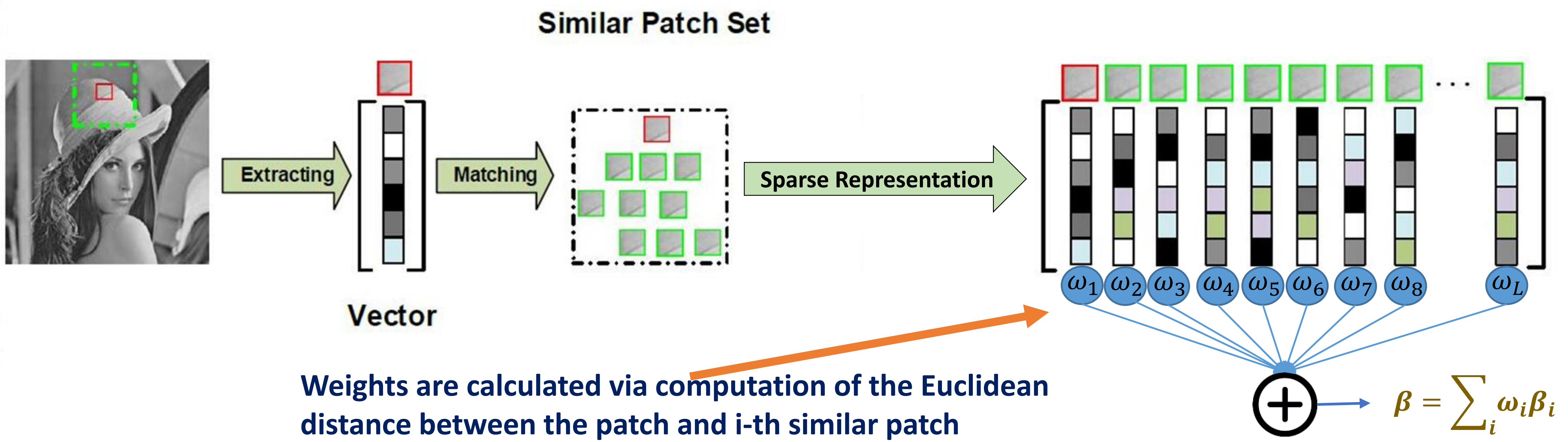
Enhanced Error Concealment Algorithm based on Joint Sparse Representation and Self-similarity property of Natural Images

An additional regularization term is added to find more accurate sparse representation.

$$\alpha_y = \underset{\alpha}{\operatorname{argmin}} \|y - D_y\alpha\|_2^2 + \lambda\|\alpha\|_0 \quad \longrightarrow \quad \alpha_y = \underset{\alpha}{\operatorname{argmin}} \|y - D_y\alpha\|_2^2 + \lambda\|\alpha\|_0 + \boxed{\delta\|F\alpha - \beta\|_1}$$

This difference should be small.

- **β is the true sparse representation of the patch.**
- **Since β is unknown, it is estimated by linear combination of the sparse representation vectors of similar patches in the image.**



Weights are calculated via computation of the Euclidean distance between the patch and i-th similar patch

Enhanced Error Concealment Algorithm based on Joint Sparse Representation and Self-similarity property of Natural Images

Recovery Algorithm

Step 1: **Initialization**

$$\boldsymbol{\alpha}_y^{[0]} = \underset{\alpha}{\mathbf{argmin}} \left\| \mathbf{y} - \mathbf{D}_y \boldsymbol{\alpha} \right\|_2^2 + \lambda \|\alpha\|_0$$

$$\mathbf{x}^{[0]} \longrightarrow \boldsymbol{\beta}^{[0]}$$

Step 1: **Iterative shrinkage algorithm**

$$\boldsymbol{\nu}^{[0]} = \boldsymbol{\alpha}_y^{[0]} + \mathbf{D}_y^T \left(\mathbf{y} - \mathbf{D}_y \boldsymbol{\alpha}_y^{[0]} \right) \longrightarrow \boldsymbol{\alpha}_y^{[1]} = \mathbf{Threshold}\ (\boldsymbol{\nu}^{[0]} - \mathbf{F}^{-1}\, \boldsymbol{\beta}^{[0]}) + \mathbf{F}^{-1}\, \boldsymbol{\beta}^{[0]}$$

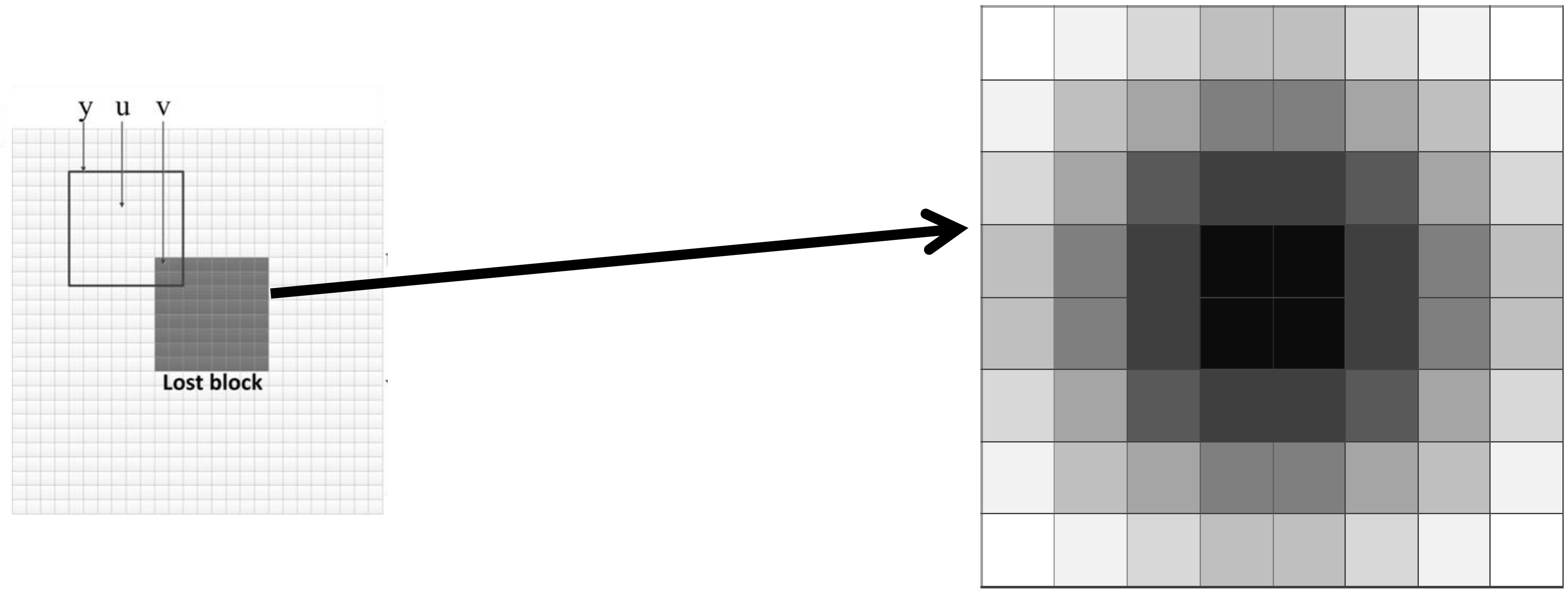
$$\mathbf{x}^{[1]} \longrightarrow \boldsymbol{\beta}^{[1]}$$

I. Daubechies, M. Defrise, and C. De Mol, "An iterative thresholding algorithm for linear inverse problems with a sparsity constraint," Comm. Pure Appl. Math., vol. 57, no. 11, pp. 1413-1457, 2004.

Sequential Error Concealment

Sequential Error Concealment

- The lost block is sequentially recovered.
- The reconstruction order depends on the available pixels in the neighbourhood of the lost block



Experimental Results

Objective Comparison by Different EC Techniques for 30% Random Block Loss

- Image Size: 512 × 512 pixels
- Patch Size: 5 × 5 pixels
- Lost Block Size: 8 × 8 pixesls
- Dictionary size: 25 × 256

Loss Pattern		AVC	POCS	CAD	VC	MRF	MKDE	SLP	LSR	ALP	JSR	JSR+NL
							EC Technique					
							Lena					
Isolated	PSNR	32.04	29.15	33.97	34.58	34.38	34.55	33.72	34.45	35.69	35.08	**35.78**
	MSSIM	0.976	0.950	0.982	0.986	0.985	0.985	0.983	0.983	0.989	0.987	**0.989**
Consecutive	PSNR	28.84	26.21	27.43	22.83	31.09	30.57	29.48	30.13	32.14	31.80	**32.56**
	MSSIM	0.950	0.898	0.945	0.781	0.969	0.964	0.959	0.952	0.975	0.973	**0.976**
Random	PSNR	28.92	26.94	26.45	18.18	31.55	31.45	30.62	31.35	**32.61**	31.91	32.38
	MSSIM	0.945	0.921	0.915	0.576	0.971	0.970	0.966	0.963	**0.977**	0.973	0.975

Reconstruction Time (Second) by Different EC Techniques for 30% Random Block Loss

Loss Pattern	AVC	POCS	CAD	VC	MRF	MKDE	SLP	LSR	ALP	JSR	JSR+NL
						EC Technique					
Isolated	0.09	6.07	4.10	559	9.23	236	82	64	158	22	39
Consecutive	0.20	8.70	5.22	1079	16.73	363	126	126	281	41	58
Random	0.15	5.83	3.90	586	10.34	253	85	75	171	25	42

Experimental Results

Visual comparison for Lena by different EC techniques for 30% random block loss

Conclusions

- The error concealment problem is modelled in the form of invers problems.
- Two image priors are used to regularize the solution space:
  - One prior is based on learning a mapping between the original image and corrupted patches from training data sets
  - Second prior is based on the self-similarities between image patches that existing in the natural images.

Experimental Results

Effect of mapping approach on the EC performance (PSNR) for THE IMAGE Lena at Different PLRs

	PLR (%)				
Mapping	**10**	**20**	**30**	**40**	**50**
JSR-C	38.41	34.96	32.31	30.13	27.28
JSR-D	38.31	34.87	32.23	30.05	27.26
JSR-I	37.35	33.88	31.16	29.24	27.24

Basic Idea

One of the most flexible ways to discover F is learning from training data: