From Example-Based to Local Gaussian Priors. Applications to Inpainting, HDR & Challenges Ahead

Andrés Almansa

Workshop on New Trends in Optimization for Imaging
Sanya, January 19th 2015
Outline

• Overview
  – Example-based image inpainting
  – From example-based to model-based regularization
  – Local Gaussian Models vs GMM

• Local Gaussian Models in HDR Imaging

• Challenges ahead

Input: Visible part of the image $u|_{O^c}$
Output: reconstruction of the occluded part $u|_{O}$ via

$$\min_{u|_{O}} \sum_{m \in O} \|p_m(u) - p_{\varphi(m)}(u)\|^2$$

where

$$\varphi(m) = \arg \min_{n \in O^c} \|p_m(u) - p_n(u)\|^2$$

is the nearest neighbour of $p_m(u)$:

patches in Images and videos:
Example-based image inpainting [Arias-Caselles-Facciolo 2012]

Input: Visible part of the image $u|_{O^c}$
Output: reconstruction of the occluded part $u|_{O}$ via

$$\min_{w, u|_{O}} \sum_{m \in O, n \in O^c} w(m, n) \|p_m(u) - p_n(u)\|^2 - T \sum_m H(w(m, \cdot))$$

under the constraint $\sum_n w(m, n) = 1, \forall m \in O$

where $H(f) = -\sum_n f(n) \log(f(n))$ is the entropy of the probability density distribution $f$. 
Example-based image inpainting [Arias-Caselles-Facciolo 2012]

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where $H(f) = -\sum_n f(n) \log(f(n))$ is the entropy of the probability density distribution $f$.

Non-convex problem
Alternated minimisation of convex problems

- **w-minimization** *(Learn local distribution)*

  $$w(m, n) = \frac{1}{Z} e^{-\frac{1}{\tau} \|p_m(u) - p_n(u)\|^2}$$

- **u-min** *(a posteriori expectation)*

  $$\hat{p}_m = E[p \mid p_m(u)] = \sum_n w(m, n) p_n$$

- Aggregation: $u(m) = \sum_n \hat{p}_n[n - m]$
Example-based image inpainting [Arias-Caselles-Facciolo 2012]

Input: Visible part of the image $u|_{O^c}$
Output: reconstruction of the occluded part $u|_{O}$ via

$$
\min_{w, u|_{O}} \sum_{m \in O, n \in O^c} w(m, n) ||p_m(u) - p_n(u)||^2 - T \sum_m H(w(m, \cdot))
$$

under the constraint $\sum_n w(m, n) = 1, \forall m \in O$

where $H(f) = -\sum_n f(n) \log(f(n))$ is the entropy of the probability density distribution $f$.

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  $$w(m, n) = \frac{1}{Z} e^{-\frac{1}{T} ||p_m(u) - p_n(u)||^2}$$

- **$u$-min: (a posteriori expectation)**
  $$\hat{p}_m = E[p | p_m(u)] = \sum_n w(m, n)p_n$$

- Aggregation: $u(m) = \sum_n \hat{p}_n[n-m]$

Challenges
- Computation of $w$ truncated and approximated by Patch Match [Barnes 2009] Other alternatives? non-structured data?
- Non-convexity: Multi-scale
- Patch similarity: $\ell^2$ is ambiguous for fine textures
Video Inpainting – original video
Video Inpainting [Newson-Almansa-Fradet-Gousseau-Perez 2014]

## Example-based vs. Model-based Image Inpainting

### Example-based

- **$w$-minimization** *(Learn local distribution)*
  
  $$w(m, n) = \frac{1}{Z} e^{-\frac{1}{T} \| p_m(u) - p_n(u) \|^2}$$

- **$u$-min: (a posteriori expectation)**
  
  $$\hat{p}_m = E[p | p_m(u)] = \sum_n w(m, n) p_n$$

- **Aggregation:** $u(m) = \sum_n \hat{p}_n[n - m]$  

### Model-based

- **$w$-minimization** *(Learn local model)*

  $$w(m, \cdot) \sim N(\mu_m, \Sigma_m)$$ that fits \( \{ p_n(u) : \| p_m(u) - p_n(u) \|^2 < T \} \)

- **$u$-minimization:** estimate $\hat{p}_n$ by:
  
  - EAP (blurry), or...
  - MAP, or...
  - Random synthesis near $p_m(u)$ based on $N(\mu_m, \Sigma_m)$

- **Aggregation:** $u(m) = \sum_n \hat{p}_n[n - m]$  

### Fast Algorithms on Unstructured Data (CovTree)

- Synthesize vs. Copy
Model-based image inpainting [Raad-Desolneux-Morel 2014]

Synthesized (example-based)  Synthesized (model-based)
Non-Local Means denoising [Buades-Coll-Morel 2005]

Input: Noisy image $\tilde{u} = u + n$ where $n \sim N(0, \sigma^2 \text{Id})$.
Output: Estimated clean image $\hat{u}$ via

$$\max_u \sum_{m,n} w(m,n) \| p_m(u) - p_n(\tilde{u}) \|^2 - T \sum_m H(w(m, \cdot))$$

under the constraint $\sum_n w(m,n) = 1$, $\forall m \in O$

Example based

- $w$-minimization (Learn local distribution)

  $$w(m, n) = \frac{1}{\mathcal{Z}} e^{-\frac{\| p_m(u) - p_n(\tilde{u}) \|^2}{T}}$$

- $u$-minimization: (a posteriori expectation)

  $$\hat{p}_m = \sum_n w(m, n) p_n$$

- Aggregation: $\hat{u}(m) = \sum_n \hat{p}_n[n - m]$
Non-Local Bayes denoising [Lebrun-Buades-Morel 2013]

Input: Noisy image \( \tilde{u} = u + n \) where \( n \sim N(0, \sigma^2 I_d) \).
Output: Estimated clean image \( \hat{u} \) via

\[
\max_u \Pr [p_m(u) \mid p_n(\tilde{u}), N(\mu_m, \Sigma_m)]
\]

s.t. \( N(\mu_m, \Sigma_m) \) fits \( \{p_n(u) : \|p_n(u) - p_m(u)\| < \delta\} \)

Model based

- \( w \)-minimization (Learn Local Gaussian Model)
  \[
  \mu_m = \frac{1}{Z} \sum_n e^{-\frac{\|p_m(u) - p_n(\tilde{u})\|^2}{\sigma^2}} p_n(\tilde{u})
  \]

  \[
  \Sigma_m = \frac{1}{Z} \sum_n e^{-\frac{\|p_m(u) - p_n(\tilde{u})\|^2}{\sigma^2}} \tilde{p}_n(\tilde{u}) \tilde{p}_n(\tilde{u})^T - \sigma^2 I_d
  \]

- \( u \)-minimization: (MAP)
  \[
  \hat{p}_m = \arg\min_q \frac{1}{\sigma^2} \|q - p_m(\tilde{u})\|^2 + (q - \mu_m)^T \Sigma_m^{-1} (q - \mu_m)
  \]

- Aggregation: \( \hat{u}(m) = \sum_n \hat{p}_n [n - m] \)
Input: Perturbed image $\tilde{u} = Au + n$ where $n \sim N(0, \sigma^2 I_d)$.
Output: Restored image $\hat{u}$ via

$$
\max_{u(m), k(m)} \Pr \left[ p_m(u) \mid p_n(\tilde{u}), N(\mu_k(m), \Sigma_k(m)) \right]
$$

with $k = 1, \ldots, 20$

s.t. $N(\mu_k(m), \Sigma_k(m))$ fits $\{p_n(u) : k(m) = k(n)\}$

Model based

- **initialization**: $\hat{u}^0, (\mu_k^0, \Sigma_k^0), k(m)$
- Relearn Gaussian Models $(\mu_k^i, \Sigma_k^i)$ to fit $\{p_m(u) : k(m) = k\}$
- Signal estimation ($\hat{p}_m$) and model selection ($k(m)$)

$$
(\hat{p}_m, k(m)) = \arg \max_{q,k} \Pr [q \mid p_m(\tilde{u}), N(\mu_k, \Sigma_k)]
$$

- Aggregation: $\hat{u}^i(m) = \sum_n \hat{p}_n[n - m]$
Learning-based restoration [Zoran-Weiss 2011]

Offline learning

**Input:** a huge database of *natural image patches* $p_i \in P$.

**Output:** Gaussian Mixture Model $\{N(\mu_k, \Sigma_k) : k = 1, \ldots, 250\}$ fitting the data (several days worth of computation)

Restoration

**Input:** *Perturbed image* $\tilde{u} = Au + n$ where $n \sim N(0, \sigma^2 I_d)$.

- Gaussian Mixture Model $\{N(\mu_k, \Sigma_k) : k = 1, \ldots, 250\}$ (representing the manifold of natural image patches)

**Output:** *Restored image* $\hat{u}$ via

$$\max_{u(m), k(m)} \Pr[p_m(u) \mid p_n(\tilde{u}), N(\mu_{k(m)}, \Sigma_{k(m)})]$$
### Learning

**Input:** a huge database of *data points* \( p_i \in \mathcal{P} \).

**Output:** pre-computed Local Gaussian Models at several *scales* and *locations*.

### Query

**Input:** a query point \( q \) and a scale \( \sigma \).

**Output:** accurate approximation of \( N(\mu_q, \Sigma_q) \) fitting \( \mathcal{P} |_{B(q, \sigma)} \).

### Bayesian Restoration
Covariance Trees [Guillemot-Almansa-Boubekeur 2014]
Learning-based denoising

Bruité | NLB | CovTree NLB | CovTree + Dictionary
--- | --- | --- | ---
PSNR : 22.4 dB | PSNR : 30.2 dB | PSNR : 30.0 dB | PSNR : 31.1 dB
Covariance Trees [Guillemot-Almansa-Boubekeur 2014]

Challenges
- Time-dependent data
- Non-gaussian noise
- Incomplete patches
Single-Shot High Dynamic Range Imaging using Local Gaussian Models

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High Dynamic Range Imaging (HDR)

Capture a scene containing a large range of intensity levels...

Limited dynamic range of the camera → loss of details in bright and/or dark areas.
High Dynamic Range Imaging (HDR)

... using a standard digital camera.

Limited dynamic range of the camera → loss of details in bright and/or dark areas.
High Dynamic Range Imaging (HDR)

... using a standard digital camera.

Limited dynamic range of the camera $\rightarrow$ loss of details in bright and/or dark areas.
HDR imaging - Multi-image approach

HDR generation

Irradiance Map
(number of photons reaching each pixel per unit time)
Challenges of Multi-image HDR Imaging

moving objects

noise

camera motion
Challenges of Multi-image HDR Imaging

Input frames: camera + object motion

Result: ghosting artifacts
Alternative: Single-image HDR

Spatially Varying pixel Exposures (SVE) [Nayar and Mitsunaga, 2000]
Alternative: Single-image HDR

1 image = N exposures
SVE Single-image HDR

✓ No need for image alignment.
✓ No need for motion detection.
✓ No ghosting problems.
✓ No large saturated regions to fill.

✗ Unknown pixels to be restored (over and under exposed pixels).
✗ Noise.
✗ Need to modify the standard camera.
  ● Alternative without camera modification [Hirakawa and Simon, 2011].
SVE: Regular or Random?

Random pattern to avoid aliasing [Schöberl et al., 2012]
Single-image HDR - Problem to solve
Single-image HDR - Problem to solve
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Single-image HDR - Problem to solve
Our approach

Extension of Piecewise Linear Estimators (PLE) [Yu et al., 2012]
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Patch-based method
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Patch-based method

Gaussian prior to restore missing information

$(\mu, \Sigma)$
Our approach

Extension of Piecewise Linear Estimators (PLE) [Yu et al., 2012]

Patch-based method

Gaussian prior to restore missing information

$(\mu, \Sigma)$
PLE Patch Model

Observed patch

\[ y = U f + n \]
PLE Patch Model

\[
y = U f + n
\]

Observed patch
Patch we seek to estimate

Gaussian prior for patches
PLE Patch Model

\[ y = U f + n \]

- Observed patch
- Patch we seek to estimate
- Known degradation operator
- Gaussian prior for patches
PLE Patch Model

\[ y = Uf + n \]

- **Observed patch**
- **Patch we seek to estimate**
- **Gaussian noise**
  - constant variance \( \mathcal{N}(0, \sigma^2 I_d) \)

- Known degradation operator
- Gaussian prior for patches
Patch Model for Raw Data

RAW data:

\[ y = U x f + n \]
Patch Model for Raw Data

RAW data:

\[ y = U f + n \]

Masking due to saturation
Patch Model for Raw Data

RAW data:

\[ y = U f + n \]

Masking due to saturation

Gaussian noise constant variance \( \mathcal{N}(0, \sigma^2 I_d) \)

Gaussian noise variable variance dependent on \( f \)
Patch Model for Raw Data

**RAW data:**

\[ y_j \sim \mathcal{N}(f_j, \sigma^2(f_j)) \]

- \( f_j \): irradiance
- \( \tau \): exposure time
- \( g \): camera gain
- \( o \): SVE optical gain
- \( \alpha \): photo-response non-uniformity factor
- \( \mu_r, \sigma_R^2 \): readout noise mean and variance

Gaussian noise variable variance dependent on \( f \)

Main noise sources:
- ✔ Shot noise
- ✔ Readout noise

\[
\sigma^2(f_j) = \frac{g^2 o \alpha \tau f_j + \sigma_R^2}{(g^2 o \alpha \tau)^2}
\]
Patch Model for Raw Data

\[
y = U f + n
\]

\[
\mathcal{N}(\mu, U \Sigma U^T + \Sigma_n(f)) \quad \mathcal{N}(\mu, \Sigma) \quad \mathcal{N}(0, \Sigma_n(f))
\]

Gaussian prior for patches
Patch Reconstruction

\[ y = Uf + n \]

\[ \mathcal{N}(\mu, U\Sigma U^T + \Sigma_n(f)) \] \hspace{1cm} \[ \mathcal{N}(\mu, \Sigma) \] \hspace{1cm} \[ \mathcal{N}(0, \Sigma_n(f)) \]

Minimize mean squared error:

\[ W = \arg \min_W E[(Wy - f)^2] \]
Patch Reconstruction

\[
y = U f + n
\]

\[
\mathcal{N}(\mu, U\Sigma U^T + \Sigma_n(f)) \quad \mathcal{N}(\mu, \Sigma) \quad \mathcal{N}(0, \Sigma_n(f))
\]

Minimize mean squared error:

\[
W = \arg \min_W \mathbb{E}[(Wy - f)^2]
\]

Wiener filter:

\[
W = \Sigma U^T (U\Sigma U^T + \Sigma_n(f))^{-1}
\]

How to set Gaussian prior \(\mu\) and \(\Sigma\)?
Patch Reconstruction

\[
y \quad = \quad U x + n
\]

\[
\mathcal{N}(\mu, U\Sigma U^T + \Sigma_n(f)) \quad \mathcal{N}(\mu, \Sigma) \quad \mathcal{N}(0, \Sigma_n(f))
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\]

Patch reconstruction:

\[
\hat{f} = W(y - U\mu) + \mu
\]

How to set Gaussian prior \(\mu\) and \(\Sigma\)?
Patch Reconstruction

\[ y = Uf + n \]

\[ \mathcal{N}(\mu, U\Sigma U^T + \Sigma_n(f)) \]

\[ \mathcal{N}(\mu, \Sigma) \quad \mathcal{N}(0, \Sigma_n(f)) \]

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Patch reconstruction:

\[ \hat{f} = W(y - U\mu) + \mu \]

How to set Gaussian prior \( \mu \) and \( \Sigma \)?
Gaussian models for image patches
Gaussian models for image patches
Gaussian models for image patches

$k = 1$

$k = 2$

$k = 3$

$k = 4$

$k = K$ classes
Gaussian models for image patches
Class parameters estimation

For each class:

\[ k = 1, \ldots, K \]

\[
\begin{align*}
\tilde{\mu}_k &= \frac{1}{|C_k|} \sum_{i \in C_k} \hat{f}_i \\
\tilde{\Sigma}_k &= \frac{1}{|C_k|} \sum_{i \in C_k} (\hat{f}_i - \tilde{\mu}_k) (\hat{f}_i - \tilde{\mu}_k)^T
\end{align*}
\]
How to choose the best class?

$$\hat{k} = \arg \max_k \text{(posterior probability } p(f|y, \mu_k, \Sigma_k))$$
Summary: iterative procedure

Estimation Step:
1. Patches assigned to classes
2. Patches restored with chosen class \((\mu_k, \Sigma_k)\)
\[
\hat{f} = W(y - U\mu_k) + \mu_k
\]

Class Update Step:
\[
\begin{align*}
\tilde{\mu}_k &= \frac{1}{|C_k|} \sum_{i \in C_k} \hat{f}_i \\
\tilde{\Sigma}_k &= \frac{1}{|C_k|} \sum_{i \in C_k} (\hat{f}_i - \tilde{\mu}_k)(\hat{f}_i - \tilde{\mu}_k)^T
\end{align*}
\]

2 to 3 iterations
Applied in sub-regions of size 128 x 128
Initialization

$K$ classes to set
Initialization

**K** classes to set

(K - 1) classes

edges with different orientations

\[
\begin{align*}
\tilde{\mu}_k &= 0 \\
\tilde{\Sigma}_k &= \frac{1}{|C_k|} \sum_{i \in C_k} (\hat{f}_i - \tilde{\mu}_k)(\hat{f}_i - \tilde{\mu}_k)^T
\end{align*}
\]

\[
\theta_k = \frac{\pi k}{K - 1}
\]

\(\forall k = 1, \ldots, K - 1\)
Initialization

K classes to set

(K - 1) classes

$\theta_k = \frac{\pi k}{K - 1}$

$\forall k = 1, \ldots, K - 1$

edges with different orientations

$\tilde{\mu}_k = 0$

$\tilde{\Sigma}_k = \frac{1}{|C_k|} \sum_{i \in C_k} (\hat{f}_i - \tilde{\mu}_k)(\hat{f}_i - \tilde{\mu}_k)^T$

K = 20
patch size = 8x8

DCT
for isotropic patterns
Results synthetic data
Results synthetic data

<table>
<thead>
<tr>
<th>Ground-truth</th>
<th>PLEV</th>
<th>Schöberl et al.</th>
<th>Nayar-Mits.</th>
<th>Mask</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>29.1 dB</td>
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<td>18.5 dB</td>
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<td>31.3 dB</td>
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Improvement: Patch-based Bayesian restoration method (on-going work)

- Inspired from:
  - **Piecewise Linear Estimators (PLE)** [Yu et al., 2012] High performance in interpolation of missing pixels.

- General restoration method.
Patch Reconstruction

\[ y = Uf + n \]

\[ N(\mu, U\Sigma U^T + \Sigma_n(f)) \]
\[ N(\mu, \Sigma) \quad N(0, \Sigma_n(f)) \]

Patch reconstruction:
\[ \hat{f} = W(y - U\mu) + \mu \]

Wiener filter:
\[ W = \Sigma U^T(U\Sigma U^T + \Sigma_n(f))^{-1} \]

How to set Gaussian prior $\mu$ and $\Sigma$?
Patch Reconstruction

\[
y = Uf + n
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Patch reconstruction:

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\hat{f} = W(y - U\mu) + \mu
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W = \Sigma U^T (U\Sigma U^T + \Sigma_n(f))^{-1}
\]

How to set Gaussian prior \( \mu \) and \( \Sigma \)?
How to set Gaussian prior parameters $\mu$ and $\Sigma$?

Inspired by NLB denoising power:

- Estimate Gaussian parameters $(\mu, \Sigma)$ **locally** from similar patches.

- Classical MLE formulas:

$$
\tilde{\mu} = \frac{1}{M} \sum_{i=1}^{M} \tilde{f}_i \\
\tilde{\Sigma} = \frac{1}{M} \sum_{i=1}^{M} (\tilde{f}_i - \tilde{\mu})(\tilde{f}_i - \tilde{\mu})^T
$$

$M$ similar patches
How to set Gaussian prior parameters $\mu$ and $\Sigma$?

Inspired by NLB denoising power:
- Estimate Gaussian parameters $(\mu, \Sigma)$ locally from similar patches.

$M$ similar patches

Classical MLE formulas:

$\tilde{\mu} = \frac{1}{M} \sum_{i=1}^{M} \tilde{f}_i$  
$\tilde{\Sigma} = \frac{1}{M} \sum_{i=1}^{M} (\tilde{f}_i - \tilde{\mu})(\tilde{f}_i - \tilde{\mu})^T$

MLE cannot be used due to missing pixels!
How to set Gaussian prior parameters $\mu$ and $\Sigma$?

Inspired by NLB denoising power:
- Estimate Gaussian parameters $(\mu, \Sigma)$ locally from similar patches.

- Classical MLE formulas:

\[
\tilde{\mu} = \frac{1}{M} \sum_{i=1}^{M} \tilde{f}_i \\
\tilde{\Sigma} = \frac{1}{M} \sum_{i=1}^{M} (\tilde{f}_i - \tilde{\mu})(\tilde{f}_i - \tilde{\mu})^T
\]

MLE cannot be used due to missing pixels!

Proposed solution: Maximum a posteriori (MAP) with a prior on $(\mu, \Sigma)$
MAP to compute Gaussian parameters $\mu$ and $\Sigma$

- Hyperprior on $(\mu, \Sigma)$: Normal - Wishart distribution
- MAP:
  
  $$(\hat{\mu}, \hat{\Sigma}) = \arg \max_{\mu, \Sigma} p(\mu, \Sigma|y_1, \ldots, y_M)$$

  $\arg \max_{\mu, \Sigma} \prod_{j=1}^{M} \mathcal{N}(U\mu, \Sigma^*|y=y_j) \mathcal{N}(\mu|\mu_0, \Sigma/\kappa) \mathcal{W}(\Sigma|(\nu\Sigma_0)^{-1}, \nu)$$

  $\{M$ similar patches$\}$ $\{\text{Hyperprior on model parameters}\}$

  $\rightarrow$ Inclusion of hyperprior information compensates for missing pixels.
Iterative approach

Model parameters estimation Step:

- M similar patches
- Hyperprior on \((\mu, \Sigma)\)

MAP \rightarrow (\hat{\mu}, \hat{\Sigma})

Restoration Step:

\[
\hat{f} = W(y - U\mu) + \mu
\]

\[
W = \Sigma U^T(U\Sigma U^T + \Sigma_n(f))^{-1}
\]

3 to 4 iterations
Initialization

From PLE [Yu et al., 2012]:

K predefined models: (K-1) edges with different orientations + DCT for isotropic patterns
Results HDR - Synthetic data
### Results HDR - Synthetic data

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#### Input

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#### PSNR:

<table>
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<tr>
<th>PSNR:</th>
<th>33.1dB</th>
<th>29.7dB</th>
<th>30.4dB</th>
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**HDR** (High Dynamic Range) images are used in photography and video to capture a greater range of brightness values than standard definition images. These images can capture very bright and very dark details within the same scene, making them useful in various applications, such as digital cinematography and video games.
Results HDR - Synthetic data

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</table>
Results on other applications

70% missing pixels + additive Gaussian noise variance 5%
Results on other applications

Ground-truth

HPNLB

PLE

Input

Differences to ground-truth

**PSNR:**

- HPNLB: 30.5 dB
- PLE: 28.6 dB
Conclusions

- Exemplar-based patch regularization: early self-similarity model
- GMM, PLE: Extension to more inverse problems
- Local Gaussian Models: finer details, continuous classification

Challenges ahead for local Gaussian models

- Invert non-diagonal operators
- Robust neighbors in ill-posed problems
- Formal framework needed
- More flexible learning/indexing over large databases
Thanks. Questions?