Computer Vision for Visual Effects

CVFX 2015

Today's Plan

- Object Removal by Exemplar-Based Inpainting
 - > Criminisi *et al.*
 - › CVPR 2003
- > Online Dictionary Learning for Sparse Coding
 - > Mairal et al.
 - > ICML 2009

Inpainting



Photo Restoration



Object Removal





Automatic Digital Inpainting





[Bertalmio *et al.]*

Automatic Digital Inpainting



[Bertalmio *et al.]*





The Algorithm of Bertalmio *et al.*

- > Imitating professionals
- > Propagation of information
 - > Smoothness

isophotes: lines of equal gray values

$$\nabla$$
(Smoothness) $\cdot \nabla^{\perp} I = 0$
(Laplacian)



 $\frac{\partial I}{\partial t} = \nabla (fI) \cdot \nabla^{\perp} I \quad \text{introduces blur in large regions}$ $I^{n+1}(i,j) = I^n(i,j) + \Delta t I^n_t(i,j), \forall (i,j) \in \Omega$

Exemplar-Based Texture Synthesis

- > To replicate both texture and structure
 - > Special attention to linear structures
 - > Dependent on the order in which the filling proceeds
 - Propagation of confidence



Isophote-Driven Image Sampling

- > Find the best-match source patch
- > Isophote orientation is automatically preserved



Region-Filling Algorithm

- > Window size: 9x9 pixels
 - Greater than the largest texel

or the thickest structure



 Encouraging propagation of linear structure together with texture

Computing Patch Priorities

- > Best-first
 - Patches which are on the continuation of strong edges and which are surrounded by high-confidence pixels

$$P(\mathbf{p}) = C(\mathbf{p})D(\mathbf{p}) \quad \mathbf{p} \in \delta\Omega$$

priority = confidence term * data term



Confidence Term

$$C(\mathbf{p}) = \frac{\sum_{\mathbf{q} \in \Psi_{\mathbf{p}} \cap \bar{\Omega}} C(\mathbf{q})}{|\Psi_{\mathbf{p}}|}$$

amount of reliable information surrounding the pixel **p**

 $\Psi_{\mathbf{p}}$: patch

 $|\Psi_{\mathbf{p}}|$: area of $|\Psi_{\mathbf{p}}|$



Intuition

"Patches that include corners and thin tendrils of the target region will tend to be filled first, as they are surrounded by more pixels from the original image. These patches provide more reliable information against which to match. Conversely, patches at the tip of 'peninsulas' of filled pixels jutting into the target region will tend to be set aside until more of the surrounding pixels are filled in."



Data Term

$$D(\mathbf{p}) = \frac{|\boldsymbol{\nabla} I_{\mathbf{p}}^{\perp} \cdot \mathbf{n}_{\mathbf{p}}|}{\alpha} \qquad \begin{bmatrix} \mathsf{st} \\ \mathsf{h} \end{bmatrix}$$

strength of isophotes hitting the fror $\delta \Omega$

$\mathbf{n_{p}}$: unit vector orthogonal to the front $\delta\Omega$

 $\alpha = 255$



Balance between the Confidence and Data Terms

The data term tends to push isophotes rapidly inward, while the confidence term tends to suppress precisely this sort of incursion into the target region. As presented in the results section, this balance is handled gracefully via the mechanism of a single priority computation for all patches on the fill front."



Initialization

$C(\mathbf{p}) = 0 \quad \forall \mathbf{p} \in \Omega$ $C(\mathbf{p}) = 1 \quad \forall \mathbf{p} \in \mathcal{I} - \Omega$



Computing Patch Priorities

- > Best-first
 - Patches which are on the continuation of strong edges and which are surrounded by high-confidence pixels $P(\mathbf{p}) = C(\mathbf{p})D(\mathbf{p}) \quad \mathbf{p} \in \delta\Omega$

priority = confidence term * data term



Propagating Texture and Structure Information

> Search in the source region for the patch most similar to $\Psi_{\hat{\mathbf{p}}}$

$$\Psi_{\hat{\mathbf{q}}} = \arg\min_{\Psi_{\mathbf{q}}\in\Phi} d(\Psi_{\hat{\mathbf{p}}}, \Psi_{\mathbf{q}})$$

- Distance between two patches: sum of squared difference (SSD)
- > CIE Lab color space
- > Copy the value of each pixel-to-be-filled in $\Psi_{\hat{\mathbf{p}}} \cap \Omega$ from its corresponding position in $\Psi_{\hat{\mathbf{q}}}$
 - Patch-based, fast

Updating Confidence Values

$C(\mathbf{q}) = C(\hat{\mathbf{p}}) \quad \forall \mathbf{q} \in \Psi_{\hat{\mathbf{p}}} \cap \Omega$

- > As filling proceeds, confidence values decay
 - Less sure of the values of pixels near the center of the target region

Region Filling Algorithm

Extract the manually selected initial front $\delta \Omega^0$.

Repeat until done:

- **1a.** Identify the fill front $\delta \Omega^t$. If $\Omega^t = \emptyset$, exit.
- **1b.** Compute priorities $P(\mathbf{p}) \quad \forall \mathbf{p} \in \delta \Omega^t$.
- 2a. Find the patch $\Psi_{\hat{\mathbf{p}}}$ with the maximum priority, *i.e.*, $\Psi_{\hat{\mathbf{p}}} \mid \hat{\mathbf{p}} = \arg \max_{\mathbf{p} \in \delta \Omega^t} P(\mathbf{p})$
- **2b.** Find the exemplar $\Psi_{\hat{\mathbf{q}}} \in \Phi$ that minimizes $d(\Psi_{\hat{\mathbf{p}}}, \Psi_{\hat{\mathbf{q}}})$.
- **2c.** Copy image data from $\Psi_{\hat{\mathbf{q}}}$ to $\Psi_{\hat{\mathbf{p}}}$.
 - **3.** Update $C(\mathbf{p}) \ \forall \mathbf{p} \ | \mathbf{p} \in \Psi_{\hat{\mathbf{p}}} \cap \Omega$

Results











Results



Questions?

Summary

- A fast method to replicate both texture and structure
- Filling the region in a right ordering
 → linear structure preserved
- > Priority = confidence term * data term

Further Reading



Sparse Representation for Color Image Restoration

- > J. Mairal, M. Elad, and G. Sapiro.
 - > IEEE Transactions on Image Processing. volume 17, issue 1, January 2008, pages 53-69.
 - Online Dictionary Learning for Sparse Coding
 » J. Mairal, F. Bach, J. Ponce, and G. Sapiro
 » ICML 2009

Principal Component Analysis (PCA)

$$\min_{\mathsf{D}} \sum_{i} ||\mathbf{x}_{i} - \mathsf{D}\mathsf{D}^{\mathsf{T}}\mathbf{x}_{i}||_{2}^{2}$$

$$\mathsf{D}^\mathsf{T}\mathbf{x}_i = \boldsymbol{lpha}_i$$

 $\mathsf{D}^\mathsf{T}\mathsf{D} = \mathsf{I}$

Sparse Representation

> Dictionary learning

$$\begin{split} \min_{\substack{\boldsymbol{\alpha} \in \mathbb{R}^{p \times n} \\ \mathbf{D} \in \mathcal{C}}} \sum_{i=1}^{n} \frac{1}{2} ||\mathbf{x}_{i} - \mathbf{D}\boldsymbol{\alpha}_{i}||_{2}^{2} + \lambda ||\boldsymbol{\alpha}_{i}||_{1} \\ \mathcal{C} \stackrel{\Delta}{=} \{ \mathbf{D} \in \mathbb{R}^{m \times p} \text{ s.t. } \forall j = 1, \dots, p, ||\mathbf{d}_{j}||_{2} \leq 1 \}. \end{split}$$



L1 Norm? Sparse?



zero norm?

Higher Dimension



Online Dictionary Learning

Require: $\mathbf{D}_0 \in \mathbb{R}^{m \times p}$ (initial dictionary); $\lambda \in \mathbb{R}$

- 1: $\mathbf{A}_0 = 0$, $\mathbf{B}_0 = 0$.
- 2: for t=1,...,T do
- 3: Draw **x**_t
- 4: Sparse Coding

$$\boldsymbol{\alpha}_t \leftarrow \operatorname*{arg\,min}_{\boldsymbol{\alpha} \in \mathbb{R}^p} rac{1}{2} || \mathbf{x}_t - \mathbf{D}_{t-1} \boldsymbol{\alpha} ||_2^2 + \lambda || \boldsymbol{\alpha} ||_1,$$

- 5: Aggregate sufficient statistics $\mathbf{A}_t \leftarrow \mathbf{A}_{t-1} + \alpha_t \alpha_t^T$, $\mathbf{B}_t \leftarrow \mathbf{B}_{t-1} + \mathbf{x}_t \alpha_t^T$
- 6: Dictionary Update (block-coordinate descent)

$$\mathbf{D}_t \leftarrow \operatorname*{arg\,min}_{\mathbf{D}\in\mathcal{C}} \frac{1}{t} \sum_{i=1}^t \left(\frac{1}{2} ||\mathbf{x}_i - \mathbf{D}\alpha_i||_2^2 + \lambda ||\alpha_i||_1 \right).$$

7: end for $\underset{\mathbf{D}\in\mathcal{C}}{\arg\min}\frac{1}{t}\left(\frac{1}{2}\operatorname{Tr}(\mathbf{D}^{T}\mathbf{D}\mathbf{A}_{t})-\operatorname{Tr}(\mathbf{D}^{T}\mathbf{B}_{t})\right)$

[Mairal, Elad, and Sapiro., 2008]



[Mairal, Elad, and Sapiro., 2008]



THE SALINAS VALLEY IS IN NORTHERN California. It is a long narrow swale between two raligue 61 ms. The Salinus River winds and califis up the center until it fails at last into Monterey Bay.

r remember my shillheed names for grosses and searct flowers. I remember where a tood may live and what time the birds awaken in the symmer and what trees not seasons smelled like how people looked and walked and smelled exec. The memory of odors is very floh

I temember that the Gabian Mountains to the east of the valley were hight day industains full of our and leveliness and a kind of invitation, so that you wanted to climb into their warm featibilis almost as you want to chimb into the tap of a beloved mother. They were becknning mountains with a brown grass loss. The Saxta Lastas stead up against the sky to the west and keat the valley from the prior sea, and they were dark and prooding unfriendly and dangerous. I always found in myself a design of west and a love of east. Where I ever got such an idea I cannot say, unless it could be that the morning came over the peaks of the Gabilans and the might drifted back from the ridges of the Santa Lucias. It may be that the birth and death of the day had some part in my tealing about the two ranges of meantains.

From both sides of the valley little streams slipped out or one hill canyons and fell into the beau of the salinat River in the winter of wet years the streams ran full-freshet, and they swelled the river until sometimes it reged and boiled, bank full, and then it was a destroyer. The river tore the edges of the farm lands and washed whole acres down; it toppled barns and houses into itself, to go floating and bobbing away. It trapped cows and pigs and sheep and drowned though its mudiciles and water and carried them to the sea. Then when the late spring came, the river drew of from 10 angles and the sand barks appeared. And is one summar the river didn't run at all oppose ground. Some pools would be left in the deep swift places under a high bank. The fulles and graves grow back, and with we straightened op with the flood denses in their upper branches. The Salinas was only point time river. The dense we dense will have been allowed by was the oppy one we find and in we beened about it how dangerous it wat in a well water and new dry it was the dry summer. You we boast about anything in it's all you have. Maybe the less you have, the more you are required to heast.

The floor of the Salinas Valley, between the ranges and below the foothills, is revel because this valley used to be the beccom of a hundred only fillet from the sea. The layer mouth at Moss Landing was centuries ago the entrance to this long inland water once, fifty miles down the valley, my father burget a well. The drift rame up first with top on and then with a ovel and then with white sea sand top of shells and even pl.







Conclusion

- > Sparse coding, sparse representation
 - ICCV tutorial on sparse coding and dictionary learning for image processing http://lear.inrialpes.fr/people/mairal/tutorial_iccv09/
 - › Compressive sensing <u>http://dsp.rice.edu/cs</u>

Goal of This Course

- > Literature survey
 - > How to solve interesting image problems
 - > Learn mathematical modeling techniques
 - > Come up with new ideas and find new applications
- Hands-on experience
 - > 10+ Assignments
- > Doing research
 - > Term project

Related Topics

> Optimization

- Maximizing joint/conditional probabilities
- Minimizing cost/error functions
- Image representations
 - Markov random fields
 - Vector fields
- Math
 - > Linear algebra, numerical methods, probability