Distribution Fields

A Unifying Representation for Low-Level Vision Problems Erik Learned-Miller with Laura Sevilla Lara, Manju Narayana, Ben Mears

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Basin of attraction studies





Basin of attraction results



Question

 How can we get the benefits of congealing without lots of images, and without a massive computational burden?

How do we line up a new image? *Funneling*...

Sequence of successively "sharper" models



Take one gradient step with respect to each model.

How to align a new image after congealing?

- More efficient to save sequence of distribution fields from congealing
 - High entropy to low entropy sequence → "Image Funnel"
- Funneling: increase likelihood of new image at each iteration according to corresponding distribution field



Aligning two images using the funneling concept

- Given image I and image J
- Generate many perturbed versions of image I, including the original image.
- Generate image funnel for set of I images.

Perturbed versions of an image



As an image stack.



Summing the perturbed stack.



Distribution of perturbed stack.



- Is there a simpler way to generate the idea of the distributions in a perturbed stack than to randomly make the images and then compute the distributions?
- Yes, distribution fields.

Exploding an image



Spatial Blur: 3d convolution with 2d Gaussian



Spatial Blur: 3d convolution with 2d Gaussian



KEY PROPERTY: doesn't destroy information through averaging

Feature space blur



How to compare?



How to compare?



- L1 distance?
- L2 distance?
- KL divergence?

The likelihood match

- Recall image I and patch J.
- Make a distribution field out of I and evaluate the likelihood of J under the field.

Image I



Patch J



The likelihood match

Given distribution field $D = D(I; \sigma)$ and image J.

$$Prob(J) = \prod_{i=1}^{N} p_{x,y}(J_{x,y})$$

Sharpening match

$$\max_{\sigma} Prob(J;\sigma) = \prod_{i=1}^{N} p_{x,y}^{\sigma}(J_{x,y})$$

. .

Understanding the sharpening match



What standard deviation maximizes the likelihood of a given point under a zero-mean Gaussian?

Intuition behind sharpening match

 Increase standard deviation until it matches "average distance" to matching points.



Properties of the sharpening match

- A patch has probability of 1.0 under its own distribution field.
- Probability of an image patch degrades gracefully as it is translated away from best position.
- Optimum "sigma" value gives a very intuitive notion of the quality of the image match.

Tracking results

- State of the art results on tracking with standard sequences
 - Very simple code
 - Trivial motion model
 - Simple memory model



It's not perfect...



Closely Related work

- Mixture of Gaussian backgrounding (Stauffer...)
- Shape contexts (Belongie and Malik)
- Congealing (me)
- Bilateral filter
- SIFT (Lowe), HOG (Dalal and Triggs)
- Geometric Blur (Berg)
- Rectified flow techniques (Efros, Mori)
- Mean-shift tracking
- Kernel tracking
- and many others...

Lots more applications

- Backgrounding
- Image matching
- Pixel unmixing
- Superresolution

Motivations

• A distance between images:

- Many metrics "broken" by slight misalignments.
 - Measure of distance or similarity should degrade gracefully with transformation.
- "Invariant metrics" throw away a lot of information.
 - Integrating over regions
 - "max pooling"
 - Averaging over regions
 - Lose fine-grained spatial info:
 - Face recognition

Spatial Blur: Compare to regular image blur

