Lecture 16:

Image Processing Algorithm Grab Bag

Visual Computing Systems
CMU 15-869, Fall 2013

Today

- Grab bag of image processing techniques relevant to computational photography
- High level description of algorithms to help you build intuition (just scratching the surface of concepts and results from field of image processing)
- At the end of class:
  - We'll discuss how we might design an efficient image processor for these types of workloads

Review: 2D convolution with 5x5 filter

```
int WIDTH = 1024;
int HEIGHT = 1024;
uint8 input[(WIDTH+2) * (HEIGHT+2)];
uint8 output[WIDTH * HEIGHT];
uint8 weights[] = {1, 1, 1, 1, 1,
                   2, 2, 2, 2, 2,
                   3, 3, 3, 3, 3,
                   2, 2, 2, 2, 2,
                   1, 1, 1, 1, 1};

for (int j=0; j<HEIGHT; j++) {
  for (int i=0; i<WIDTH; i++) {
    int tmp = 0.f;
    for (int jj=0; jj<5; jj++)
      for (int ii=0; ii<5; ii++)
         tmp += (int)input[(j+jj)*(WIDTH+2) + (i+ii)] * weights[jj*5 + ii];
    output[j*WIDTH + i] = uint8(tmp / 25);
  }
}
```

Recall:

Total work = 25 x WIDTH x HEIGHT

For NxN filter: N^2 x WIDTH x HEIGHT

2D convolution with 5x5 filter

```
int WIDTH = 1024;
int HEIGHT = 1024;
uint8 input[(WIDTH+2) * (HEIGHT+2)];
uint8 output[WIDTH * HEIGHT];
uint8 weights[] = {1, 1, 1, 1, 1,
                   2, 2, 2, 2, 2,
                   3, 3, 3, 3, 3,
                   2, 2, 2, 2, 2,
                   1, 1, 1, 1, 1};

for (int j=0; j<HEIGHT; j++) {
  int tmp = 0;
  for (int jj=0; jj<5; jj++)
    for (int ii=0; ii<5; ii++)
      tmp += (int)input[(j+jj)*(WIDTH+2) + ii] * weights[jj*5 + ii];
  output[j*WIDTH] = uint8(tmp);

  for (int i=1; i<WIDTH; i++) {
    int tmp1=0, tmp2=0;
    for (int jj=0; jj<5; jj++) {
      tmp1 = (int)input[(j+jj)*(WIDTH+2) + i+4] * weights[jj*5 + 4];
      tmp2 = (int)input[(j+jj)*(WIDTH+2) + i] * weights[jj*5 + 0];
    }
    output[j*WIDTH + i] = output[j*WIDTH + i - 1] + uint8(tmp1-tmp2);
  }
}
```

Incremental computation:
~ Total work = 2*N x WIDTH x HEIGHT

Filter is separable, so same work complexity as two-pass approach, but using only one pass over the data.

At what cost?

5x5 median filter

- Noise reduction filter
  - Unlike gaussian, one bright pixel doesn't drag up the average for entire region
- Not linear, not separable
  - Filter weights are 1 or 0 (depending on image content)
- Naive algorithm for width N square kernel support region:
  - Sort N^2 elements in support region, pick median: $O(N^2 \log(N^2))$ work per pixel

```
int WIDTH = 1024;
int HEIGHT = 1024;
uint8 input[(WIDTH+2) * (HEIGHT+2)];
uint8 output[WIDTH * HEIGHT];

for (int j=0; j<HEIGHT; j++) {
  for (int i=0; i<WIDTH; i++) {
    output[j*WIDTH + i] = // median of pixels in surrounding 5x5 pixel window
  }
}
```

5x5 median filter

- $O(N^2)$ work-per-pixel solution: radix sort algorithm for 8 bit-integer data
  - Bin elements in support region. Scan histogram to find median

```
int WIDTH = 1024;
int HEIGHT = 1024;
uint8 input[(WIDTH+2) * (HEIGHT+2)];
uint8 output[WIDTH * HEIGHT];
int histogram[256];

for (int j=0; j<HEIGHT; j++) {
  for (int i=0; i<WIDTH; i++) {
    for (int ii=0; ii<256; ii++)
      histogram[ii] = 0;
    for (int jj=0; jj<5; jj++)
      for (int ii=0; ii<5; ii++)
         histogram[input[(j+jj)*(WIDTH+2) + (i+ii)]]++;
    int count = 0;
    for (int ii=0; ii<256; i++) {
       if (count + histogram[i] >= 13)    // median of 25 elements is bin containing 13th value
         output[j*WIDTH + i] = uint8(i);
       count += histogram[i];
    }
  }
}
```

Can you design a O(N) work-per-pixel median filter?

See Weiss [SIGGRAPH 2006] for O(lg N) work-per-pixel median filter

Bilateral filter

$$BF[I](p) = \sum_{q \in S} f(|I_p - I_q|) G_\sigma(\|p - q\|) I(q)$$

Output pixel *p* is the weighted sum of all pixels in the support region *S* of a truncated gaussian kernel (width σ)

But weight is combination of <u>spatial distance</u> and <u>input image pixel intensity</u> difference.
(like median filter, filter weights depend on image content)

- **Non-linear filter**
- **An "edge preserving" filter: down weight contribution of pixels on the other side of strong edges.** $f(x)$ **defines what "strong edge means"**
- **Spatial distance weight term** $f(x)$ **could be a gaussian**
  - **Or very simple:** $f(x) = 0$ *if* $x >$ *threshold, 1 otherwise*

Bilateral filter

- **Non-linear, edge preserving, smoothing filter**

Pixels with significantly different intensity contribute little to filtered result

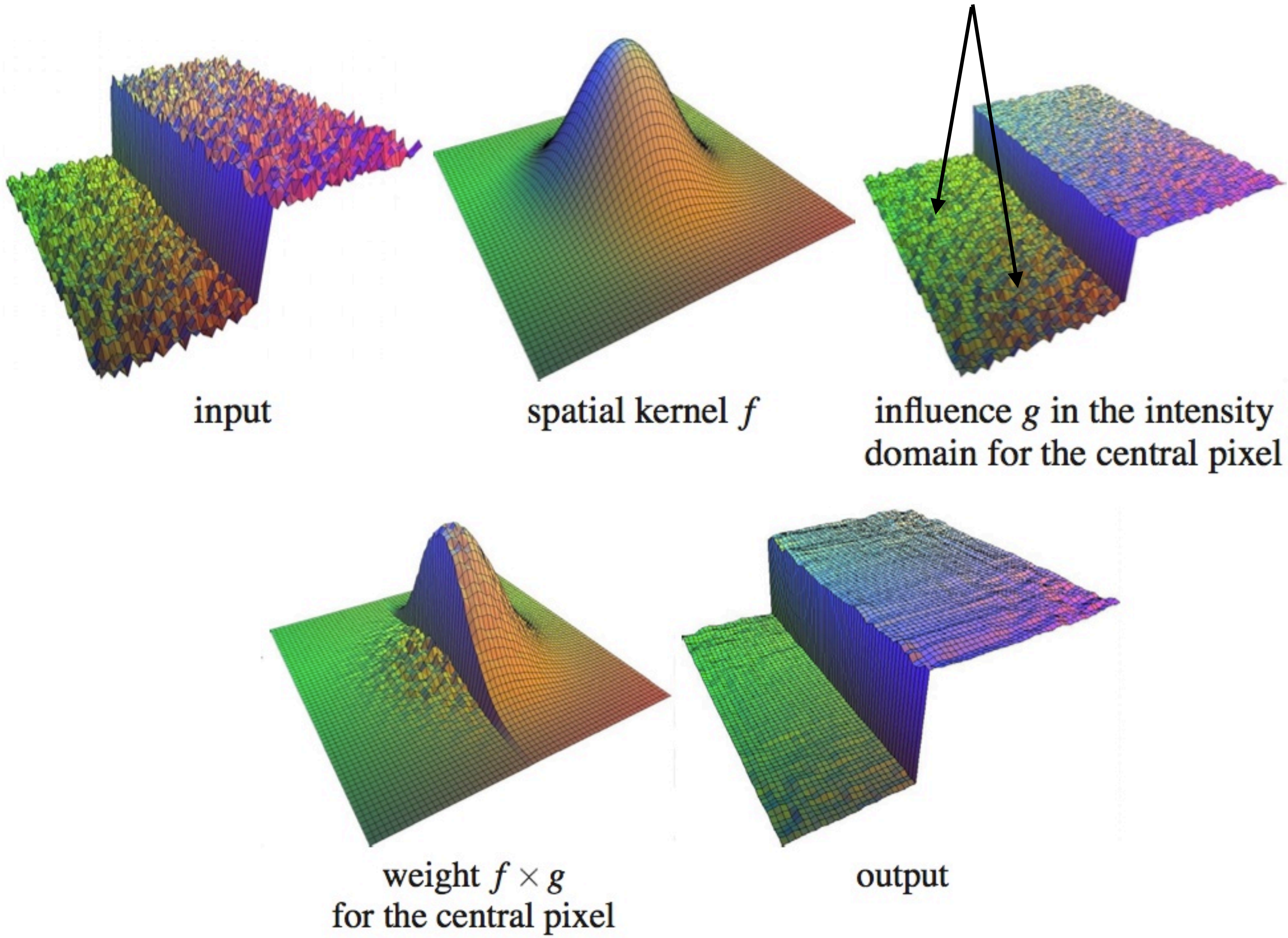
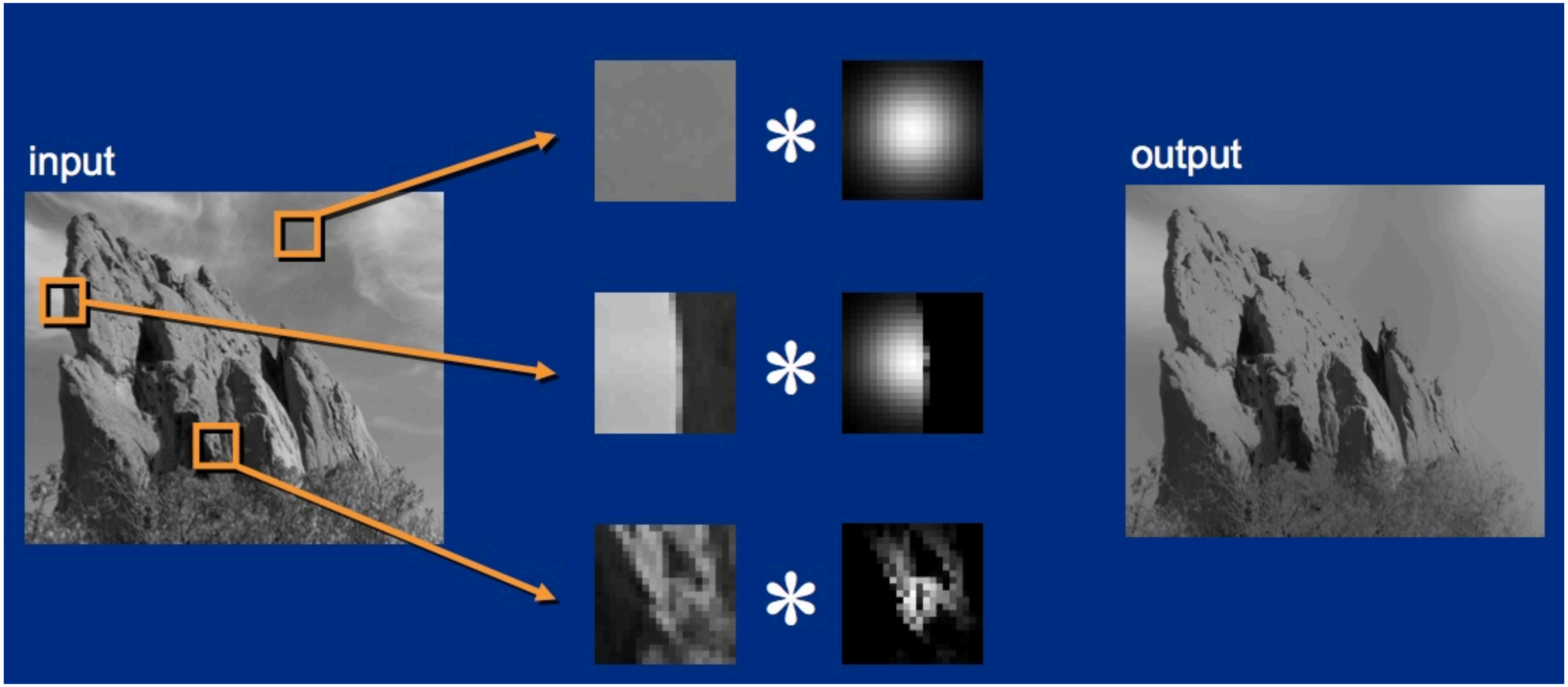


Figure credit: Durand and Dorsey, "Fast Bilateral Filtering for the Display of High-Dynamic-Range Images", SIGGRAPH 2002

Bilateral filter: kernel depends on image content



See Paris et al. [ECCV 2006] for a fast approximation to the bilateral filter

Question: describe a type of edges the bilateral filter will not respect (it will blur across).

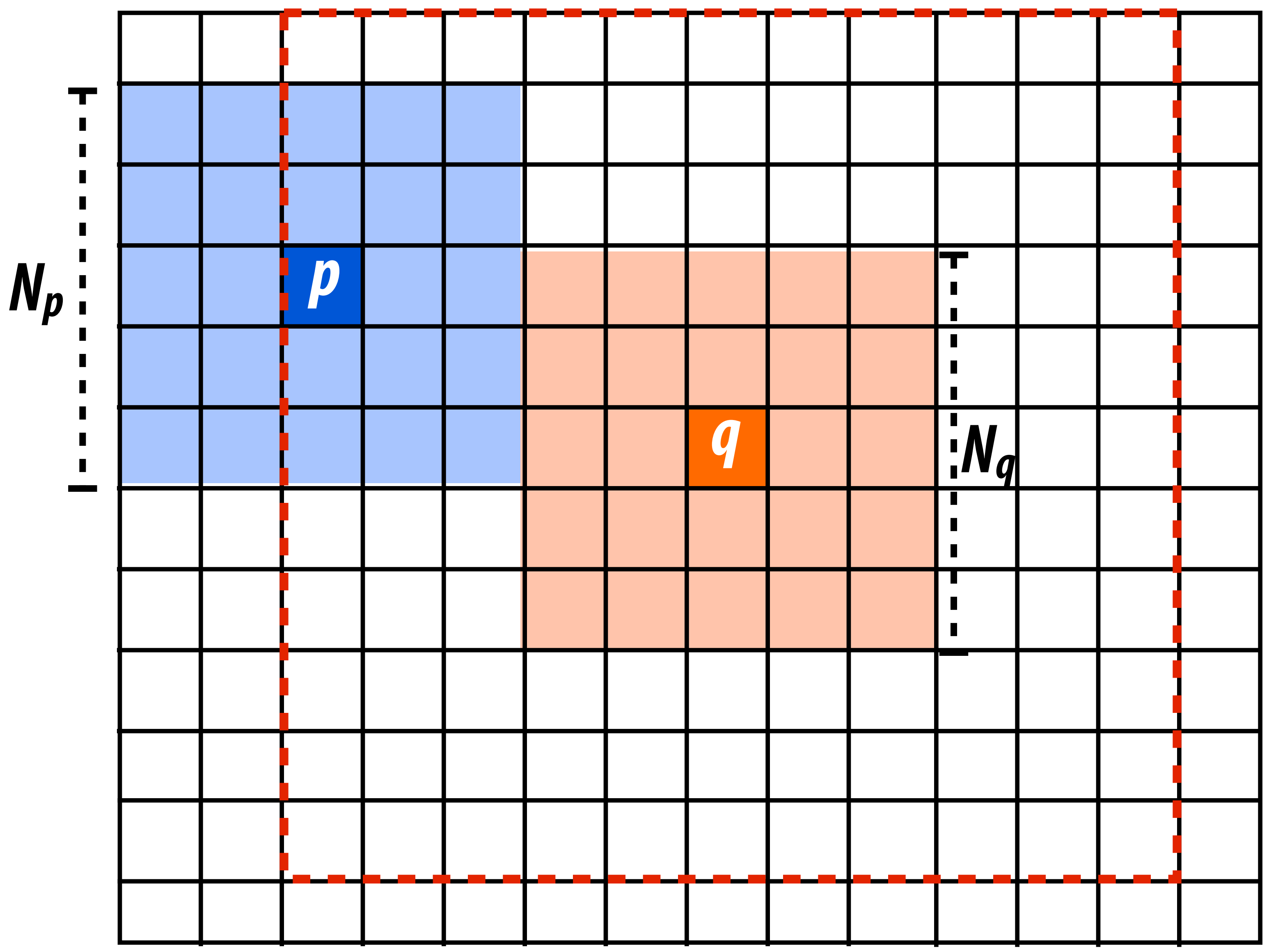
Figure credit: SIGGRAPH 2008 Course: "A Gentle Introduction to Bilateral Filtering and its Applications" Paris et al.

Denoising using non-local means

- **Main idea: replace pixel with average value of nearby pixels that <u>have a similar surrounding region</u>.**
  - **Prior: images have repeating texture**

$$NL[I](p) = \sum_{q \in S} w(p,q) I(q)$$

$$w(p,q) = \frac{1}{C_p} e^{\frac{-\|N_p - N_q\|_2^2}{h^2}}$$



N_p and P_q are vectors of pixel values in square window around pixels *p* and *q*.

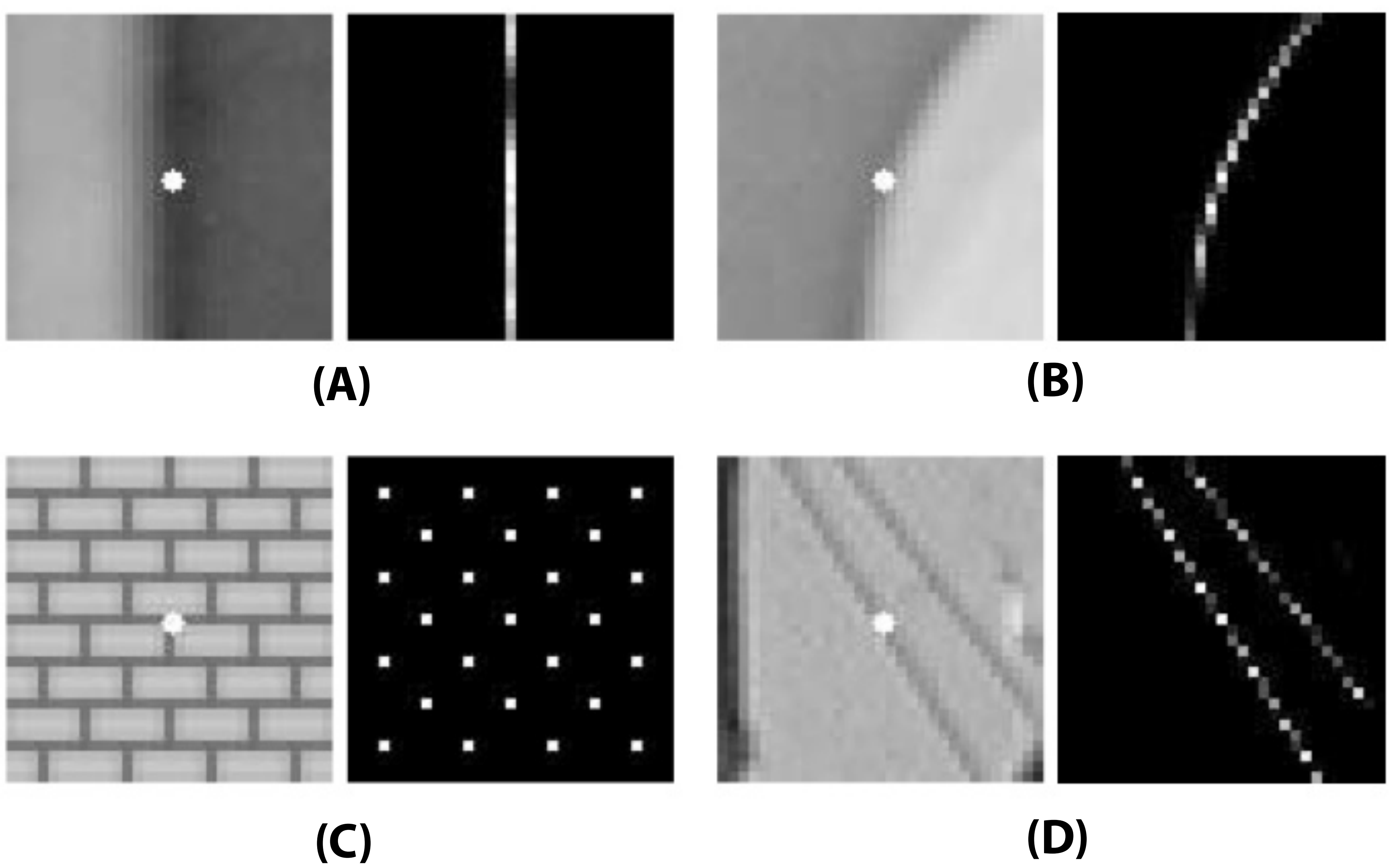
(Difference of these vectors = "similarity" of surrounding regions)

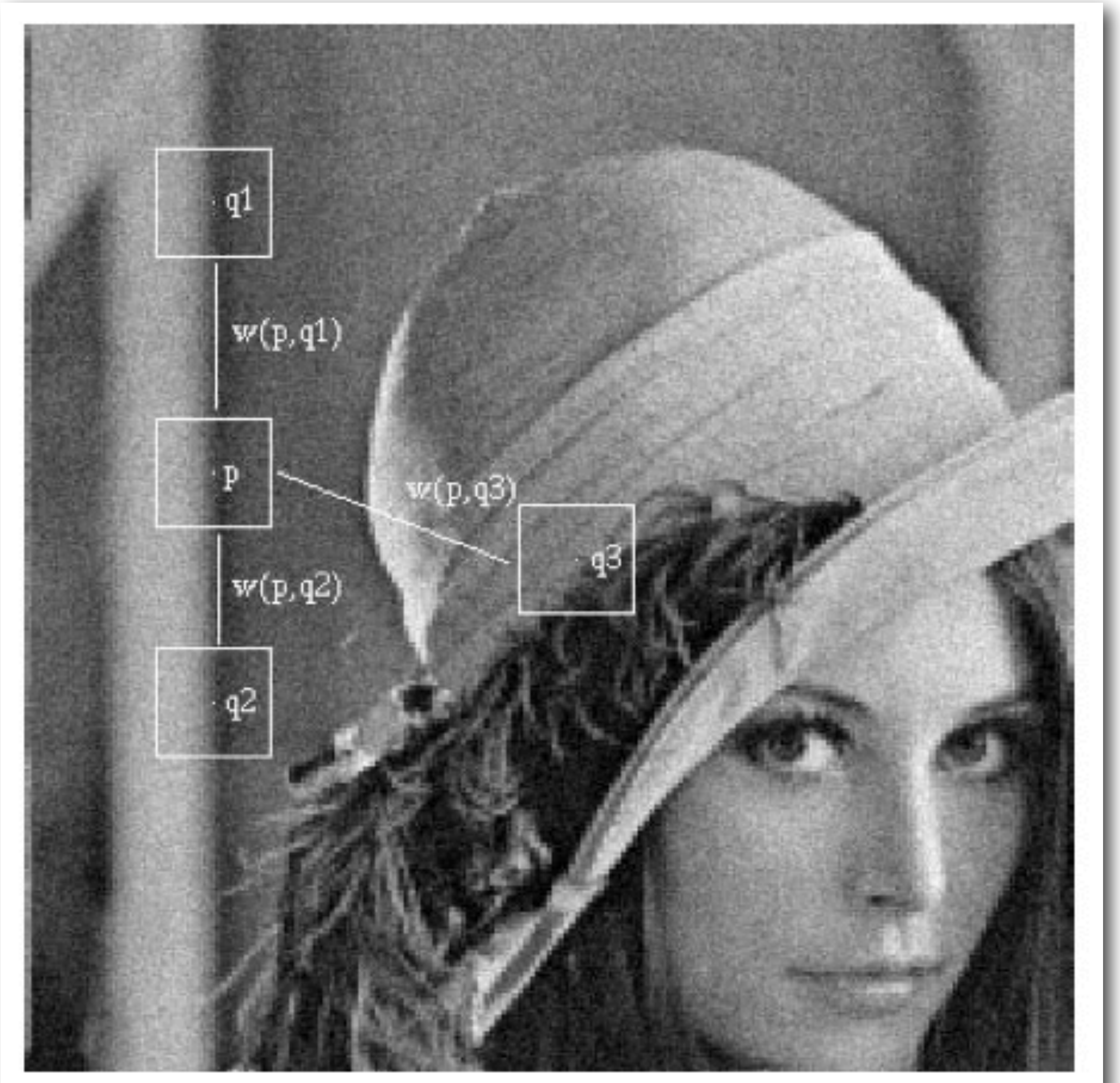
C*p* is just a normalization constant to ensure weights sum to one for pixel *p*.

Non-local means

- **Large weight for pixels that have similar neighborhood**
  - "Take the average of pixels "like" this one"
  - In example below-right: *q1* and *q2* have high weight, *q3* has low weight

In each pair below:
- Image at left shows pixel to denoise.
- Image at right shows weights of pixels in 21x21-pixel kernel support window.





Buades et al. CVPR 2005

Optical flow

- **Goal: determine 2D screen-space velocity of visible objects in image**

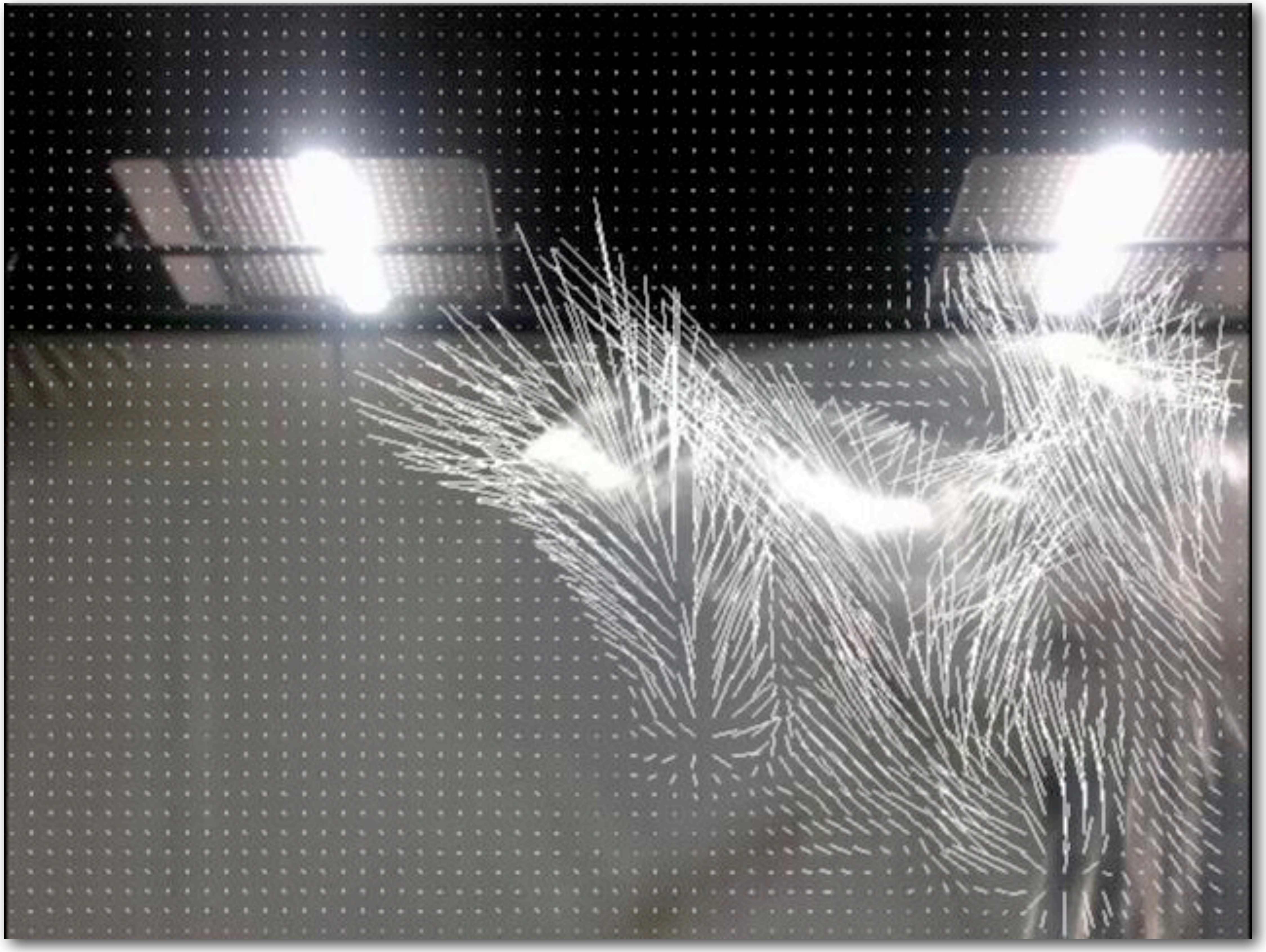


Image source: https://vimeo.com/28395792

Optical flow

- Given image A (at time *t*) and image B (at time $t + \Delta t$) compute optical flow between the two images
- Major assumption 1: brightness constancy
  - The appearance of point in image A is same as same point in image B

$$I(x + \Delta x, y + \Delta y, t + \Delta t) = I(x, y, t)$$

← The point observed at (*x*,*y*) at time *t* moves to ($x+\Delta$, $y+\Delta$) at $t+\Delta t$

Tailor expansion

$$I(x + \Delta x, y + \Delta y, t + \Delta t) = I(x, y, t) + I_x(x, y, t)\Delta x + I_y(x, y, t)\Delta y + I_t(x, y, t)\Delta t + \text{higher order terms}$$

So...

$$I(x, y, t) \approx I(x, y, t) + I_x(x, y, t)\Delta x + I_y(x, y, t)\Delta y + I_t(x, y, t)\Delta t$$

$$\boxed{I_x(x, y, t)\Delta x + I_y(x, y, t)\Delta y} + \boxed{I_t(x, y, t)\Delta t} = 0$$

← The observed change in pixel (x,y)

Is due to object motion at point by (Δx, Δy)

Problem: underconstrained

Gradient-constraint equation is insufficient to solve for motion

One equation, two unknowns: (Δx, Δy)

$$I_x(x, y, t)\Delta x + I_y(x, y, t)\Delta y + I_t(x, y, t)\Delta t = 0$$

Known: observed change in pixel (x,y)

Known: image gradients in image A

Major assumption 2: nearby pixels have similar motion (Lucas-Kanade)

$$I_x(x_0, y_0, t)\Delta x + I_y(x_0, y_0, t)\Delta y + I_t(x_0, y_0, t)\Delta t = 0$$

$$I_x(x_1, y_1, t)\Delta x + I_y(x_1, y_1, t)\Delta y + I_t(x_1, y_1, t)\Delta t = 0$$

$$I_x(x_2, y_2, t)\Delta x + I_y(x_2, y_2, t)\Delta y + I_t(x_2, y_2, t)\Delta t = 0$$

$$\vdots$$

Now overconstrained system, compute least squares solution

Least-squares solution

$$I_x(x_0, y_0, t)\Delta x + I_y(x_0, y_0, t)\Delta y + I_t(x_0, y_0, t)\Delta t = 0$$

$$I_x(x_1, y_1, t)\Delta x + I_y(x_1, y_1, t)\Delta y + I_t(x_1, y_1, t)\Delta t = 0$$

$$I_x(x_2, y_2, t)\Delta x + I_y(x_2, y_2, t)\Delta y + I_t(x_2, y_2, t)\Delta t = 0$$

$$\vdots$$

Now overconstrained system, compute least squares solution by minimizing:

(x_i, y_i) are pixels in region around (x,y).

Weighting function *w*() weights error contribution based on distance between (x_i, y_i) and (x, y). e.g., Gaussian fall-off.

$$E(\Delta x, \Delta y) = \sum_{x_i, y_i} w(x_i, y_i, x, y)\left[I_x(x_i, y_i, t)\Delta x + I_y(x_i, y_i, t)\Delta y + I_t(x_i, y_i, t)\Delta t \right]^2$$

Solving for motion

E (Δx, Δy) minimized when derivatives are zero:

$$\frac{dE(\Delta x,\Delta y)}{d(\Delta x)} = \sum_{x_i, y_i} w(x_i, y_i, x, y)\left[I_x^2 \Delta x + I_x I_y \Delta y + I_x I_t\right] = 0$$

$$\frac{dE(\Delta x,\Delta y)}{d(\Delta y)} = \sum_{x_i, y_i} w(x_i, y_i, x, y)\left[I_y^2 \Delta y + I_x I_y \Delta x + I_y I_t\right] = 0$$

Rewrite, now solve the following linear system for Δx, Δy:

$$\Delta x \underbrace{\sum_{x_i, y_i} w(x_i, y_i, x, y) I_x^2}_{A0} + \Delta y \underbrace{\sum_{x_i, y_i} w(x_i, y_i, x, y) I_x I_y}_{B0} + \underbrace{\sum_{x_i, y_i} w(x_i, y_i, x, y) I_x I_t}_{C0} = 0$$

$$\Delta x \underbrace{\sum_{x_i, y_i} w(x_i, y_i, x, y) I_x I_y}_{A1} + \Delta y \underbrace{\sum_{x_i, y_i} w(x_i, y_i, x, y) I_y^2}_{B1} + \underbrace{\sum_{x_i, y_i} w(x_i, y_i, x, y) I_y I_t}_{C1} = 0$$

- **Precompute partial derivatives I_x, I_y, I_t from original images A and B**
- **For each pixel (*x*,*y*): evaluate A0, B0, C0, A1, B1, C1, then solve for (*Δx, Δy*) at (*x*,*y*)**

Optical flow, implemented in practice

Gradient-constraint equation makes a linear motion assumption

$$I(x, y, t) \approx I(x, y, t) + I_x(x, y, t)\Delta x + I_y(x, y, t)\Delta y + I_t(x, y, t)\Delta t$$

$$\boxed{I_x(x, y, t)\Delta x + I_y(x, y, t)\Delta y} + \boxed{I_t(x, y, t)\Delta t} = 0$$

The observed change in pixel (x,y)

Is due to object motion at point by (Δx, Δy)

- **Improvement: iterative techniques use this original flow field to compute higher order residuals (non-linear motion)**

- **Question: Why is it important for optical flow implementation to be very efficient?**
  - **Hint: consider linear-motion assumption, consider aliasing**

Class discussion

- **Imagine the your final project is to architect a processor to handle image processing tasks for the widely anticipated kPhone. (like the iPhone, but better)**
- **How would you characterize image processing workloads?**
  - Parallelism?
  - Data-access patterns?
  - Predictability? (of data access, of instruction stream)
- **What are good characteristics of a processor for image processing tasks?**
  - Programmable, or fixed-function?
    - If programmable, do we need: branch-prediction? out-of-order execution?
    - If fixed-function, in what ways can it be configured?
  - What forms of parallelism? (SIMD, multi-core)
  - Support for multi-threading, prefetching?
  - Data caches or on-chip buffers/scratchpads?

Readings

- **Adams et al. *The Frankencamera: An Experimental Platform for Computational Photography*. SIGGRAPH 2010**