

Lesson 04

KAZE, Non-linear diffusion filtering, ORB, MSER

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KAZE

ORB: an efficient alternative to SIFT and SURF

MSER - Maximally stable extremal regions



KAZE - “wind” in Japanese

- ▶ Classical Gaussian scale spaces used in SIFT et.al. have undesirable property of blurring the edges of images
- ▶ This lowers the localization precision of key-points
- ▶ KAZE introduces a new scheme for creating the scale-space using the **Nonlinear Diffusion Filtering**
- ▶ The NDF has a nice property of preserving the image edges
- ▶ “NDF describes the evolution of the luminance of an image through increasing scale levels as the divergence of a certain *flow* function that controls the diffusion process.” (WTF?!?)



- ▶ Diffusion is the net movement of molecules or atoms from a region of high concentration (or high chemical potential) to a region of low concentration (or low chemical potential).
- ▶ NDF is normally described by nonlinear partial differential equations

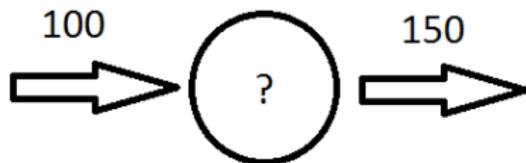
$$\frac{\partial L}{\partial t} = \text{div} (c(x, y, t) \cdot \nabla L) \quad (1)$$

- ▶ L is the luminance function (the image)
- ▶ div is the divergence operator
- ▶ $c(x, y, t)$ is a conductivity function



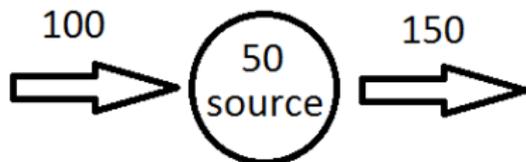
Divergence

- ▶ In vector calculus, divergence is a vector operator that produces a signed scalar field giving the quantity of a vector field's source at each point



Divergence

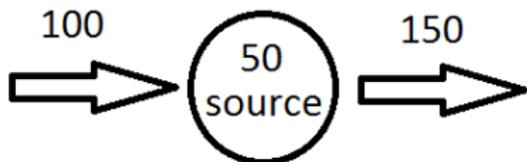
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$$\operatorname{div} \mathbf{F}(p) = \lim_{V \rightarrow \{p\}} \iint_{S(V)} \frac{\mathbf{F} \cdot \mathbf{n}}{|V|} dS \quad (2)$$

Divergence

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$$\operatorname{div} \mathbf{F}(p) = \nabla \cdot \mathbf{F} = \left(\frac{\partial}{\partial x}, \frac{\partial}{\partial y}, \frac{\partial}{\partial z} \right) \cdot (U, V, W) = \frac{\partial U}{\partial x} + \frac{\partial V}{\partial y} + \frac{\partial W}{\partial z} \quad (4)$$

Perona and Malik Diffusion Eq.

- ▶ Nonlinear diffusion filtering was introduced in 1990
- ▶ $\frac{\partial L}{\partial t} = \text{div} (c(x, y, t) \cdot \nabla L)$
- ▶ Perona and Malik proposed to make the conductivity function c dependent on the gradient magnitude
- ▶ $c(x, y, t) = g(\nabla L_\sigma(x, y, t))$
- ▶ σ is the blurring parameter - variance of Gaussian
- ▶ More functions have been proposed, KAZE uses:
- ▶ $g = \exp\left(-\frac{|\nabla L_\sigma|^2}{k^2}\right)$
- ▶ k is the contrast parameter – empirical or estimated



Additive Operator Splitting

- ▶ No analytical solution for PDEs - we need a numerical approximation = AOS
- ▶ Lets assume a 1-D case

$$\frac{\partial u}{\partial t} = \text{div} \left(g \left(\left| \frac{\partial u}{\partial x} \right| \right) \cdot \frac{\partial u}{\partial x} \right) = \frac{\partial \left(g \left(\left| \frac{\partial u}{\partial x} \right| \right) \cdot \frac{\partial u}{\partial x} \right)}{\partial x} \quad (5)$$

- ▶ The simplest approximation is

$$\frac{u_i^{k+1} - u_i^k}{\tau} = \sum_{j \in N(i)} \frac{g_j^k + g_i^k}{2h^2} (u_j^k - u_i^k) \quad (6)$$

- ▶ Where u is the image, i, j are the locations, τ is the time difference, h is the grid size, k is the time, $N(i)$ is the neighbourhood of location i



- ▶ Gradient is approximated by central differences

$$g_i^k = g \left(\frac{1}{2} \sum_{p,q \in \mathcal{N}(i)} \left(\frac{u_p^k - u_q^k}{2h} \right)^2 \right) \quad (7)$$

- ▶ The matrix notation: $\frac{u^{k+1} - u^k}{\tau} = A(u^k)u^k$
- ▶ And matrix A has entries:

$$a_{ij}(u^k) := \begin{cases} \frac{g_i^k + g_j^k}{2h^2} & (j \in \mathcal{N}(i)), \\ - \sum_{n \in \mathcal{N}(i)} \frac{g_i^k + g_n^k}{2h^2} & (j = i), \\ 0 & (\text{else}). \end{cases}$$

- ▶ This yields a set of linear equations which can be solved

- ▶ By arranging the expression we obtain
- ▶ $u^{k+1} = (I + \tau A(u^k)) u^k$
- ▶ This is the explicit scheme (restrictions on step size \Rightarrow slow)
- ▶ KAZE uses so-called semi-explicit scheme which is
- ▶ $\frac{u_i^{k+1} - u_i^k}{\tau} = A(u^k) u^{k+1}$
- ▶ $(I - \tau A(u^k)) u^{k+1} = u^k$ which has no explicit solution
- ▶ We have to solve as:

$$u^{k+1} = (I - \tau A(u^k))^{-1} u^k \quad (8)$$

- ▶ In the KAZE paper notation: $L^{i+1} = (I - \tau \sum_{l=1}^m A_l(L^i))^{-1} L^i$
- ▶ This sum in the expression reflects that there are more directions in an image



KAZE scale space, detector, descriptor

- ▶ Contrast parameter k : 70% percentile of the gradient histogram of a smoothed version of the original image
- ▶ Scale σ : has octaves and sub-levels as SIFT
- ▶ $\sigma_i(o, s) = \sigma_0 2^{o+s/2}$
- ▶ Time step t : is a mapping from scale
- ▶ $t_i = \frac{1}{2} \sigma_i^2$
- ▶ Detector as in SIFT
- ▶ Descriptor as in SURF



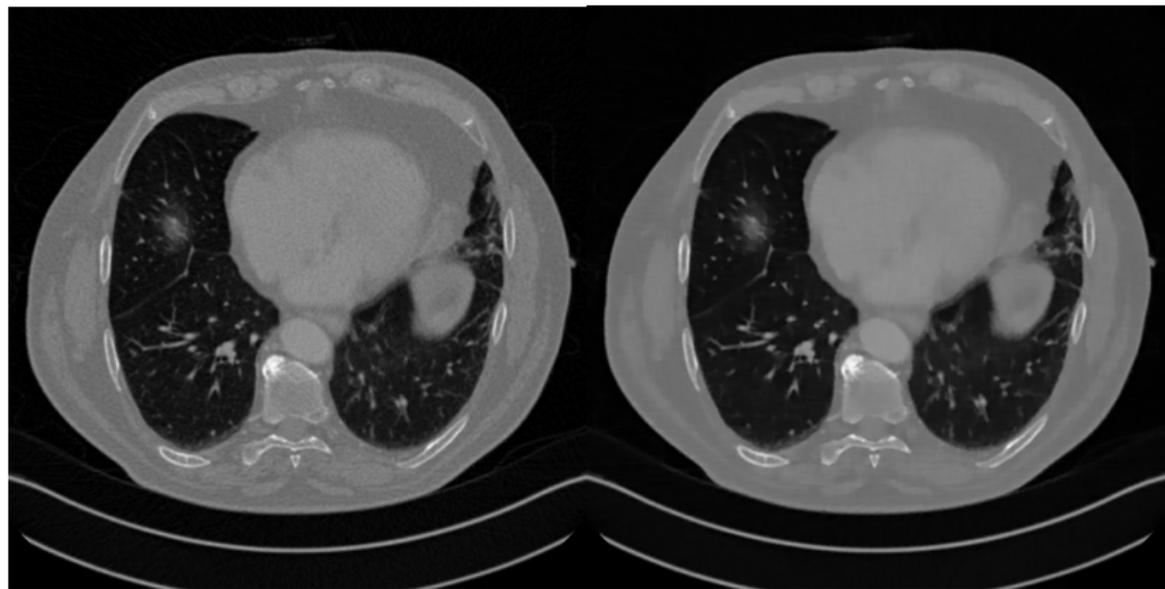
Comparison of scale-spaces



Comparison of scale-spaces



Example of filtered image

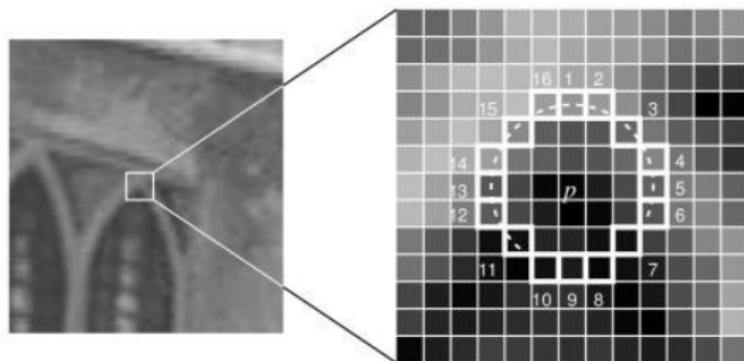


ORB: an efficient alternative to SIFT and SURF

- ▶ SIFT and SURF - impose large computational burden (speed and energy)
- ▶ ORB - Oriented FAST and Rotated BRIEF
- ▶ FAST - Features from Accelerated Segment Test - paper “Machine learning for high-speed corner detection” in 2006, revisited in 2010
- ▶ BRIEF - Binary Robust Independent Elementary Features - paper “BRIEF: Binary Robust Independent Elementary Features” in 2010



- ▶ Algorithm for keypoint detection:
- ▶ Select a pixel p with intensity I_p
- ▶ Select appropriate threshold t
- ▶ Consider a circle of 16 pixels around the pixel under test



- ▶ A point p is an interest point (in this case a corner) if there are n contiguous pixels brighter than $I_p + t$ or darker than $I_p - t$
- ▶ High-speed test - check only 4 pixels (1, 9, 5, 13), if at least 3 are brighter/darker

- ▶ It is a binary descriptor of interest points
- ▶ It selects pairs of pixels of a smoothed image around an interest point and compares them binary
- ▶ If $I(p) < I(q)$ then the result is 1, else it is 0
- ▶ The selection of the pixel pairs will be explained later (details also in the paper)
- ▶ Based on the number of pixel pairs an n -dimensional binary feature vector is obtained which serves as the descriptor of the interest point
- ▶ Distance of the descriptors is calculated as a Hamming distance (which is a XOR operator and bit count)



Oriented FAST

- ▶ The location of keypoints is detected using FAST-9 algorithm (circular radius of 9 px)
- ▶ Since FAST has large response on edges the oFAST computes a Harris corner measure for each keypoint
- ▶ The keypoints are ordered according to this measure of cornerness
- ▶ Furthermore a pyramid of the image is built and thus multi-scale FAST keypoints are detected
- ▶ N best keypoints are considered (N is defined by the user)



Oriented FAST - Orientation computation

- ▶ Orientation is computed as *intensity centroid*

$$m_{pq} = \sum_{x,y} x^p y^q I(x,y) \quad (9)$$

$$C = \left(\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}} \right) \quad (10)$$

- ▶ A vector from corner's center O to the intensity centroid C is computed
- ▶ the orientation is simply:

$$\theta = \text{atan2}(m_{01}, m_{10}) \quad (11)$$

- ▶ To obtain better results the C is computed only from pixels in a circular region with radius r



Classical BRIEF - details

- ▶ A test is defined over a smoothed image patch p of size $S \times S$ as:

$$\tau(p; x, y) = \begin{cases} 1 & : p(x) < p(y) \\ 0 & : p(x) \geq p(y) \end{cases} \quad (12)$$

- ▶ Binary feature vector (descriptor) is constructed as

$$f_n(p) = \sum_{1 \leq i \leq n} 2^{i-1} \tau(p; x_i, y_i) \quad (13)$$

- ▶ How to choose the pairs of pixel for the test τ ?
- ▶ The pixels x and y are sampled independently from a Gaussian distribution centered on the analyzed patch center with a variance of $\frac{1}{25} S^2$
- ▶ The smoothing is achieved using an integral image, where each test point is a 5×5 sub-window of a 31×31 pixel patch



Steered BRIEF

- ▶ Steered BRIEF respect the found orientation θ
- ▶ We define a matrix S to represent the binary tests

$$S = \begin{pmatrix} x_1, \dots, x_n \\ y_1, \dots, y_n \end{pmatrix} \quad (14)$$

- ▶ Using the patch orientation θ we construct a rotation matrix R_θ

$$R_\theta = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \quad (15)$$

- ▶ New test locations are computed as

$$S_\theta = R_\theta S \quad (16)$$

- ▶ In praxis the test locations are pre-generated
- ▶ Orientations are discretized into 12 degree regions
- ▶ The pre-generated test locations are pre-computed into the $360/12 = 30$ different orientations and stored into a look-up-table



rBRIEF - rotation aware BRIEF

- ▶ Experiments show that Steered BRIEF generate descriptors that are highly correlated (unwanted!)
- ▶ To recover from this an algorithm which yields rBRIEF is presented:
- ▶ Enumerate all possible binary tests (in their case it's 205590 tests)
- ▶ Take a lot of images, detect keypoints and run each test against all training patches
- ▶ Order the tests by their distance from a mean of 0.5, forming a vector T
- ▶ Greedy search:
 - ▶ Put the first test into the result vector R and remove it from T
 - ▶ Take the next test from T and compare it against all tests in R . If its absolute correlation is greater than a threshold, discard it; else add it to R
 - ▶ Repeat the previous step until there are 256 tests in R . If there are fewer than 256, raise the threshold and try again



MSER - Maximally stable extremal regions

- ▶ Image I is a mapping $I : D \subset \mathbb{Z}^2 \rightarrow S$. External region can be defined if:
 1. S is fully ordered
 2. adjacency exists $A \subset D \times D$
- ▶ Region Q is a connected subset from D - for every $p, q \in Q$ there exists a sequence $p, a_1, a_2, \dots, a_n, q$ which fulfils $pAa_1, a_1Aa_2, \dots, a_nAq$
- ▶ (Outer) boundary of a region is defined $\partial Q = \{q \in D \setminus Q : \exists p \in Q : qAp\}$
- ▶ Extremal region $Q \subset D$ is a region which fulfills that for every $p \in Q, q \in \partial Q : I(p) > I(q)$ or $I(p) < I(q)$
- ▶ **Maximally stable extremal region (MSER)**. Let $Q_1, \dots, Q_{i-1}, Q_i, \dots$ be a sequence of nested extremal regions (ie. $Q_i \subset Q_{i+1}$). Extremal region Q_{i^*} is maximally stable if:
 - ▶ $q(i) = \frac{|Q_{i+\Delta} \setminus Q_{i-\Delta}|}{|Q_i|}$ has a local minimum in i^* ($|\cdot|$ means cardinality). $\Delta \in S$ is the parameter of the method.





