Efficient Interest Point Detectors & Features

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16-623 - Designing Computer Vision Apps



Today

- Review.
- Efficient Interest Point Detectors.
- Efficient Descriptors.

Review

- In classical Structure from Motion (SfM) computer vision pipeline there are four steps,
 - 1. Locate interest points.



Review - Harris Corner Detector



Make decision based on image structure tensor

$$\mathbf{H} = \sum_{i \in \mathcal{N}} \frac{\partial I(\mathbf{x}_i)}{\partial \mathbf{x}} \frac{\partial I(\mathbf{x}_i)}{\partial \mathbf{x}}^T$$

Scalar Measures of "Cornerness"

- A popular measure for measuring a corner $\,\lambda_1+\lambda_2\,$,

$$tr[\mathbf{H}_{(x,y)}] = ||\nabla_x * I(x,y)||_2^2 + ||\nabla_y * I(x,y)||_2^2$$
$$\approx ||L * I(x,y)||_2^2$$



"Laplacian (L)"

"Difference of Gaussians (DOG)"

Example - DoGs in SIFT



Review

- In classical Structure from Motion (SfM) computer vision pipeline there are four steps,
 - 1. Locate interest points.
 - 2. Generate descriptors.





Review - SIFT Descriptor





1. Compute image gradients

- 2. Pool into local histograms
- 3. Concatenate histograms
- 4. Normalize histograms

HOGGles



Review

- In classical Structure from Motion (SfM) computer vision pipeline there are four steps,
 - 1. Locate interest points.
 - 2. Generate descriptors.
 - 3. Matching descriptors.

Matching Descriptors



View 1





See BFMatcher class in OpenCV!!!

Matching Descriptors



View 1

View 2

$$\zeta(i) = \arg\min_{j} ||\psi\{\mathbf{x}_{i}^{(1)}\} - \psi\{\mathbf{x}_{j}^{(2)}\}||_{2}^{2}$$

Variants other than nearest neighbor are possible!!!

Review

- In classical Structure from Motion (SfM) computer vision pipeline there are four steps,
 - 1. Locate interest points.
 - 2. Generate descriptors.
 - 3. Matching descriptors.
 - 4. Robust fit.

$$\arg\min_{\mathbf{\Phi}} \eta\{\mathbf{x}_i^{(1)} - \mathbf{hom}[\mathbf{x}_{\zeta(i)}^{(2)}; \mathbf{\Phi}]\}$$

Review - RANSAC



Original images

Initial matches

Inliers from RANSAC







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Efficient Interest Point Detection

 Most classical interest point detectors require the employment of oriented edges.



Problem - Gaussian Filtering is Slow

 Naively, filtering with Gaussians is relatively slow on most modern architectures.



- Does not lend itself well to parallelization as the variance of the Gaussian filter increases (even with FFT).
- Computational cost increases dramatically as a function of the size of the filter.

Gaussian Filter is Separable

In MATLAB,

>> h1D = fspecial('gaussian',[25,1],3);



>> h2D = kron(h1D, h1D');



Gaussian Filter is Separable



In MATLAB,

>> mesh(i)



>> h2D = imfilter(i, h1D);
>> h2D = imfilter(h2d, h1D');
>> mesh(h2D)

More Problems - Scale

 However, even slower when you have to process things across multiple scales.



Solution - Box Filters

- One strategy has been to approximate oriented filters with box filters.
- Most notably the SURF (Speed Up Robust Feature) descriptor of Bay et al. ECCV 2006.



Integral Image Trick

 We need to compute the box filter values many, many times and we must do it very fast!

$$II(x,y) = \sum_{x' \le x, y' \le y} I(x',y') \qquad (x,y)$$

• Computing sum of pixels in a rectangular area:

f(A) =



• Computing sum of pixels in a rectangular area:

f(A) = II(A)



• Computing sum of pixels in a rectangular area:

f(A) = II(A) - II(B)



• Computing sum of pixels in a rectangular area:

f(A) = II(A) - II(B) - II(C)



(Black)

• Computing sum of pixels in a rectangular area:

f(A) = II(A) - II(B)- II(C) + II(D)



• A 3 box filter array

takes only 8 lookups.

(Black)

Fast Gaussian Filtering

 Iterative box filters can also be applied to obtain extremely efficient Gaussian filtering,



In MATLAB,

>> mesh(b)



>> mesh(imfilter(imfilter(b,b),b))

SURF - Efficient Computation

- Positives:-
 - Filters can be efficiently applied irrespective of size.
 - Integral images well suited in particular to SIMD.
 - Can take advantage of fixed integer arithmetic.
- Negatives:-
 - Due to recursive nature cannot be easily parallelized.
 - All pixels in local region need to be touched.
 - Outputs floating/integer point metric of interest.

FAST

- Features from Accelerated Segment Test (FAST) basis for most modern day computationally efficient interest point detectors.
- Proposed by Rosten et al. PAMI 2010.
- Operates by considering a circle of sixteen pixels around the corner candidate.



Why is it FAST?

• FAST relies heavily upon simple binary test,

$$I(\mathbf{x}_p) - t > I(\mathbf{x}_n)$$

- Does not have to touch all pixels before making a decision.
- Again, lends itself strongly to the employment of SIMD.
- Does not rely on integral images.
- Very good at finding possible corner candidates.
- Can still fire on edges, (can use Harris to remove false positives).
- Is NOT multi-scale.

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- Efficient Descriptors.

SURF Descriptor

 SURF also proposed a more efficient descriptor extraction strategy using box filters,



• Rest of the descriptor quite similar to SIFT.

Reminder - SIFT Descriptor





1. Compute image gradients

- 2. Pool into local histograms
- 3. Concatenate histograms
- 4. Normalize histograms

BRIEF Descriptor

- Proposed by Calonder et al. ECCV 2010.
- Borrows idea that binary comparison is very fast on modern chipset architectures,

$$\psi_{I}(\mathbf{x}, \Delta_{1}, \Delta_{2}) = \begin{cases} 1 : I(\mathbf{x} + \Delta_{1}) > I(\mathbf{x} + \Delta_{2}) \\ 0 : \text{otherwise} \end{cases}$$

• Combine features together compactly,

$$\psi_I(\mathbf{x}) = \sum_i 2^{i-1} \psi_I(\mathbf{x}, \Delta_1^{(i)}, \Delta_2^{(i)})$$

Why do Binary Features Work?

- Success of binary features says something about perception itself.
- Absolute values of pixels do not matter.
- Makes sense as variable lighting source will effect the gain and bias of pixels, but the local ordering should remain relatively constant.



BRIEF Descriptor

- Do not need to "touch" all pixels, can choose $\{\Delta_1, \Delta_2\}$ pairs randomly and sparsely,



BRIEF Descriptor

• Measuring distance between descriptors,

$$d(\psi{\mathbf{x}_i}, \psi{\mathbf{x}_j}) = \text{Hamming distance}$$

• e.g.,



Why not use Euclidean distance?

Binary Descriptor Variants

- At the same time that BRIEF was proposed similar variants were also proposed and have gained some popularity.
 - BRISK Binary Robust Invariant Scalable Keypoints Leutenegger 2011.
 - FREAK Fast REtinA Keypoints Alahi et al. 2012.
- Both use AGAST for keypoint detection an extension of FAST proposed by Mair et al. 2010.



ORB

- Rublee et al. ICCV 2011 proposed Oriented FAST and Rotated BRIEF (ORB).
- Essentially combines FAST with BRIEF.
- Demonstrated that ORB is 2 <u>orders</u> of magnitude faster than SIFT.
- Very useful for mobile devices.



ORB

• ORB is patent free and available in OpenCV,

Detector	ORB	SURF	SIFT
Time per frame (ms)	15.3	217.3	5228.7

These times were averaged over 24 640x480 images from the Pascal dataset [9]. ORB is an order of magnitude faster than SURF, and over two orders faster than SIFT.

ORB SLAM



ORB SLAM

ORB-SLAM

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More to read...

BRIEF: Binary Robust Independent Elementary Features^a

chard Calonder, Vincent Lepetit, Christoph Stevilas, and Pascal Fuz CVLab, 19971, Lauranne, Switzenland e-mult 19972ana - Sarranatolog71 - 0.

Abstract. We prepare to use binary strings as an efficient herizer guide domainton, which we call BHERT. We show that it is high discrimination errors where using relatively law bits and one to computed using single intensity effluences bein. Furthermore, the disconfusion intensity can be conducted using the Hamming dataway, which is very efficient to comgues, instead of the La corons as it would show. We compare its against KMFF is very how both to build and to match. We compare it against KMFF and U-EAUE meaning dataway, while running is a flucture of the true required by vertex.

Introduction

Future point descriptors are now at the core of many Computer Vision-technologies, ends as object recognition, 3D reconstruction, image relatived, and converse backatories. Since applications of them technologies have to handle ever more data or to run on mobile devices with limited computational sessaries, there is a graving seed for level developtors that are that to compute, but to match, and armony efficient.

One way to speed up matrixing and reduce memory commutation is to ward with dust developtions. They can be relation by speedping dimensionality softwtion, such as PCA [3] or 120A [3], to an original descriptor such as NBT [3] or MNBP [4]. For example, it was shown in $\beta \geq 1$ dust fluctuation of the descriptor works could be quantized using wey free bins provide without has d neurophytical professions. As even more dustic dimensionality reduction can be descriptor works, and the fluctuation of the dust of the stars and only and startered by using hash functions that soften SBT complex to binary arrings, as done in [6]. These strings supresent binary descriptors whose similarity can be measured by the Hamming distance.

In measured by the Hamming distance. While offsetive, these approaches to dimensionality reduction respire fact mapping the bill discretying before hatber processing can take place. In this paper, we show that this which computations can be shortwit by discreting room ping, hinary othergo from image pathets. The individual bits are evidented by comparing the interactive of pairs of points along the same lines as in [9] but with our requiring a toximing plane. We robe to the resulting descriptor an BEREF. ¹Thm work has been supported in part by the first National Sissens Foundation.

- E. Rublee et al. "<u>ORB: an efficient alternative to SIFT or</u> <u>SURF</u>", ICCV 2011.
- Calonder et al. "<u>BRIEF: Binary Robust Independent</u> <u>Elementary Features</u>", ECCV 2010.
- E. Rosten et al. "Faster and better: A machine learning approach to corner detection" IEEE Trans. PAMI 2010.
- P. Kovesi "Fast Almost Gaussian Filtering" DICTA 2010.

ORB: an efficient alternative to SIFT or SURF Ethan Rubies Vincent Rabard Kutt Konolige Gary Bradski Wiley Garge, Neel Pet, Californi (weatless)(weatless)(heatlass)(heatlass)(heatlass)(heatlass))	Faster and better: a machine learning approach	2000 Digital Image Computing: Techniques and Applications Fast Almost-Gaussian Filtering Pater Kareai Comic for Exploration Tecpring Biologi Biologi Biologi Distribution Communic Distribution With 4000 Distribution With 4000 Distribution With 4000 Distribution With 4000
Ahrrad Therefore, the architecture of the law of manage compared in the first particular structure of the law of the	to corner detection	Advisort-fange zeranging can be performed very efficiently indig advice superdite moving energy tilters at ity sing emands they are equivalent to a sum of large range tilters at ity sing emands they are equipted to a sum of large range tilters at ity sing emands they are equipted to a sum of large range tilters at the sing emands they are equipted to a sum of large range tilters at the sing of the sing of the approximations to transmiss filtering and the sing of the sing of the sing of the sing of the sing of the sing. The sing of the sing
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	Tom Drummond is with Cambridge University, Cambridge University Engineering Department, Trumpington Street, Cam- bridge, UK, CP2 107 Envil- tou-Difference on the	104 AM 4/1 AM 6/1 M 104