Recent Image Search Techniques: Introduction

Sung-Eui Yoon

Course URL: http://sglab.kaist.ac.kr/~sungeui



Web-Scale Visual Data and Novel Applications

- Visual data are widely used for various communication and, and are more widely consumed at Web and mobile devices
 - YouTube, Facebook, Flickr, etc.
- Processing them requires scalable algorithms
- Web-scale visual data can enable new applications (e.g., photo tourism and scene completion)





Photo Tourism



Scene Completion





Image Collection

Pixels

Pixels + Semantics

Hays and Efros, SIGGRAPH 2007

Results



Image Search or Content-Based Image Retrieval (CBIR)

 Identify similar images given a userspecified image or other types of inputs



Image Search or Content-Based Image Retrieval (CBIR)

 Identify similar images given a userspecified image or other types of inputs







Find other sizes of this image: All sizes - Small - Medium - Large

Best guess for this image: eiffel tower





About 7 results (0.61 seconds)



Image size: 433 × 624 Find other sizes of this image: All sizes - Medium

Best guess for this image: landmark







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Best guess for this image: landmark

The Landmark, Los Angeles | Showtimes | Landmark Theatres https://www.landmarktheatres.com/los-angeles/the-landmark -

Discover the best in film at The Landmark, Los Angeles!

Movie Showtimes & Listings in Kanata, Ontario | Landmark Cin...

https://www.landmarkcinemas.com/kanata 🔻

Find out the latest movie showtimes and listings at your local Landmark Cinema in Kanata, Ontario.

Visually similar images

Report images







Applications

- Search
- Image stitching
- Object/scene/location recognitions
- Copyright detection
- Robot motion planning



Panorama Stitching



(a) Matier data set (7 images)



(b) Matier final stitch

[Brown, Szeliski, and Winder, 2005]

http://www.cs.ubc.ca/~mbrown/autostitch/autostitch.html



iPhone version available

Object Detection





Landmark or Location Detection





query

City-scale image DB



Possible Application Domains





Issues of Web-Scale Image Search

- Accuracy issues
- Memory issues
- Handling dynamic databases of images
- Novel applications?



About the Tutorial

• We focus on the following things:

- Broad understanding on image search
- In-depth study on recent large-scale image search



Tutorial Schedule

- 2:00pm, basic materials, S. Yoon
 - Introduction on image search
 - Compact representations of images
- 3:30pm, 15min break
- 3:45pm, recent techniques, Z. Lin
 - Indexing scheme for large-scale image search
 - Applications
- 5:15pm, the end





Other Related Tutorials

Compact Features for Visual Search

- Today, morning
- Rongrong Ji, Wei Liu, Yue Gao



Key Components of Image Search

- Image representations
- Indexing algorithms
- Matching methods
- Classification, Localization, etc.
 - Apply image search (or nearest neighbor search)
 - Data-driven approach



Image Representations

• SIFT, GIST, CNN, etc.

• Invariant to different transformations



David G. Lowe. "Distinctive image features from scale-invariant keypoints." IJCV 60 (2), pp. 91-110, 2004.



Image Retrieval

At pre-processing, build an database for efficient retrieval at runtime





Image Retrieval

• At pre-processing, build an database for efficient retrieval at runtime



Index schemes: vocabulary trees, hashing, and inverted files



Image Retrieval: Runtime Procedure





Image Retrieval: Runtime Procedure



Post-Processing



Image Retrieval with Spatially Constrained Similarity Measure



[Xiaohui Shen, Zhe Lin, Jon Brandt, Shai Avidan and Ying Wu, CVPR 2012]

Classification through Image Search

• Image search

Find images that have smaller distances to the query

Classification

- Find classes that have smaller distances to the query
- Utilize labels

Classification using image search

- Naïve Bayes Nearest Neighbor (NBNN) [Boiman et al., 08]
- Image classification and Retrieval are ONE [Xie et al., 15]



Resource

- Reference
 - Computer vision: algorithms and applications

Its file is available (<u>http://szeliski.org/Book/</u>)





Other Resources

Technical papers

- CVPR, ICCV, ECCV, ACM MM, SIGGRAPH, etc.
- Computer vision resource (<u>http://www.cvpapers.com/</u>)

Course homepages

- http://sglab.kaist.ac.kr/~sungeui/IR/
- My own ongoing write-up



Recent Image Search Techniques: Bag-of-Words (BoW) and Inverted File

Sung-Eui Yoon

Course URL: <u>http://sglab.kaist.ac.kr/~sungeui</u>



Review and Outline

Introduction on image search

- Bag-of-visual-Word (BoW) model
- Inverted index
- Compact representations of images


Bag-of-visual-Words (BoW)

• Inspired by text based search





Ack: Fei-Fie Li



Bag-of-visual-Words (BoW)

Inspired by text based search



China is forecasting a trade surplus of \$90bn (£51bn) to \$100bn this year, a threefold increase on 2004's \$32bn. The Commerce Ministry said the surplus would be created by a predicted 30% \$750bn. compared y China, trade, \$660bn. J annov t surplus, commerce China exports, imports, US, delibe agrees /uan, bank, domestic yuan is foreign, increase, aoverno trade, value also need demand so country. China yuan against the do permitted it to trade within a narrow but the US wants the yuan to be allowed e freely. However, Beijing has made it cl it will take its time and tread carefully be allowing the yuan to rise further in value.

Ack: Fei-Fie Li

definition of "BoW"

Independent features



Ack: Fei-Fie Li

definition of "BoW"

- Independent features
- histogram representation





1.Feature detection and representation





Ack: Fei-Fie Li

1.Feature detection and representation



Detect patches [Mikojaczyk and Schmid '02] [Mata, Chum, Urban & Pajdla, '02] [Sivic & Zisserman, '03]

Slide credit: Josef Sivic

1.Feature detection and representation





Region Proposals

Adopted commonly by many recognition approaches



Identify different regions as candidates of objects Selective Search, Uijlings et al.



Representation

- Building blocks: Sampling strategies



Interest operators



Dense, uniformly



Multiple interest operators



Randomly

Convolutional Neural Network (CNN)

• Features from some layers of CNNs



System from Krizhevsky et al., NIPS 2012



2. Codewords dictionary formation



Ack: Fei-Fie Li



K-Means Clustering

• Minimizing the within-cluster sum of squares (WCSS) \mathbf{I}_{2}

$$\underset{\mathbf{S}}{\operatorname{arg\,min}} \sum_{i=1}^{n} \sum_{\mathbf{x}_j \in S_i} \|\mathbf{x}_j - \boldsymbol{\mu}_i\|^2$$

Demonstration of the standard algorithm



1) k initial "means" (in this case k=3) are randomly selected from the data set (shown in color).



2) k clusters are created by associating every observation with the nearest mean. The partitions here represent the Voronoi diagram generated by the means.



3) The centroid of each of the k clusters becomes the new means.



4) Steps 2 and 3 are repeated until convergence has been reached.

Codewords Dictionary Formation





Image Patch Examples of Codewords

18

| Sivic et al. 2005 |
|-------------------|

Issues of Visual Vocabulary

Related to quantization

- Too many words: quantization artifacts
- Too small words: not representative
- K-means also takes long computation times

Alternatives

- Faster performance: vocabulary tree, Nister et al.
- Low quantization artifacts: soft quantization, Philbin et al.





3. Bag of word representation



Ack: Fei-Fie Li

3. Bag of word representation





Learning and Recognition



Similarity and Distance Functions

- L1 or Euclidean distance $L1(h_1, h_2) = \sum_i |h_1^i - h_2^i|$
- χ^2 distance

$$D(h_1, h_2) = \sum_{i=1}^{N} \frac{(h_1(i) - h_2(i))^2}{h_1(i) + h_2(i)}$$

• Quadratic distance (cross-bin)

$$D(h_1, h_2) = \sum_{i,j} A_{ij} (h_1(i) - h_2(j))^2$$

Jan Puzicha, Yossi Rubner, Carlo Tomasi, Joachim M. Buhmann: <u>Empirical Evaluation of</u> <u>Dissimilarity Measures for Color and Texture</u>. ICCV 1999



Programming Assignment (PA2)

- Understand and implement a basic image retrieval system
- Use the original UKBenchmark
- Measure its accuracy







Problems of BoW Model

- No spatial relationship between words
- How can we perform segmentation and localization?





Ack.: Fei-Fei Li



Post-Processing or Reranking



Post-Processing

Geometric verification
RANSAC



Matching w/o spatial matching

(Ack: Edward Johns et al.)

Query expansion





Geometric Verification using RANSAC for Affine Transform

Repeat N times:

- Randomly choose 3 matching pairs
- Estimate transformation

- Predict remaining points and count "inliers"



Query Expansion [Chum et al. 07]



Efficient Search: Inverted File

 For each word, list images containing the word



Scalability

• Issues with billions of images?

- Too much memory
- Still low accuracy



Recent Image Search Techniques: Hashing Techniques

Sung-Eui Yoon

Associate Professor KAIST

http://sglab.kaist.ac.kr



Image Retrieval

Finding visually similar images













Image Descriptor

High dimensional point



Image Descriptor

High dimensional point Nearest neighbor search (NNS) in high dimensional space



Challenge

| | BoW | GIST |
|------------|-------|----------------|
| Dimensions | 1000+ | 300+ |
| 1 image | 4 KB+ | 1.2 KB+ |
| 1B images | 3 TB+ | 1 TB+ |

 $\frac{144 \text{ GB memory}}{1 \text{ billion images}} \approx \frac{128 \text{ bits}}{1 \text{ image}}$



Binary Code


Binary Code



* Benefits

- Compression
- Very fast distance computation (Hamming Distance, XOR)



Hyper-Plane based Binary Coding





Hyper-Plane based Binary Coding



Distance between Two Points

- Measured by bit differences, known as Hamming distance
- Efficiently computed by XOR bit operations

$$d_{hd}(b_i, b_j) =$$

$$|b_i\oplus b_j|$$





Good and Bad Hyper-Planes



Previous work focused on how to determine good hyper-planes

Components of Spherical Hashing

- Spherical hashing
- Hyper-sphere setting strategy
- Spherical Hamming distance



Components of Spherical Hashing

- Spherical hashing
- Hyper-sphere setting strategy
- Spherical Hamming distance



Spherical Hashing [Heo et al., CVPR 12]





Spherical Hashing [Heo et al., CVPR 12]





Hyper-Sphere vs Hyper-Plane



Average of maximum distances within a partition: - Hyper-spheres gives tighter bound!



Components of Spherical Hashing

- Spherical hashing
- Hyper-sphere setting strategy
- Spherical Hamming distance



Good Binary Coding [Yeiss 2008, He 2011]









Intuition of Hyper-Sphere Setting

1. Balance

2. Independence







Hyper-Sphere Setting Process

- 1. Balance
- by controlling radius for $n(S) = \frac{N}{2}$



2. Independence - by moving two hyperspheres for $n(S_1 \cap S_2) = \frac{N}{4}$

Iteratively repeat step 1, 2 until convergence.



Components of Spherical Hashing

- Spherical hashing
- Hyper-sphere setting strategy
- Spherical Hamming distance



Max Distance and Common '1'





Max Distance and Common '1'





Max Distance and Common '1'



Average of maximum distances between two partitions: decreases as number of common '1'



Spherical Hamming Distance (SHD)

$$d_{shd}(b_i, b_j) = \frac{|b_i \oplus b_j|}{|b_i \wedge b_j|}$$

SHD: Hamming Distance divided by the number of common '1's.



Results



384 dimensional 1 million GIST descriptors Source codes are available



Results



960 dimensional 1 million GIST descriptors



Results



384 dimensional 75 million GIST descriptors



Summary



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