Deep Learning for Computer Vision

Feature Matching

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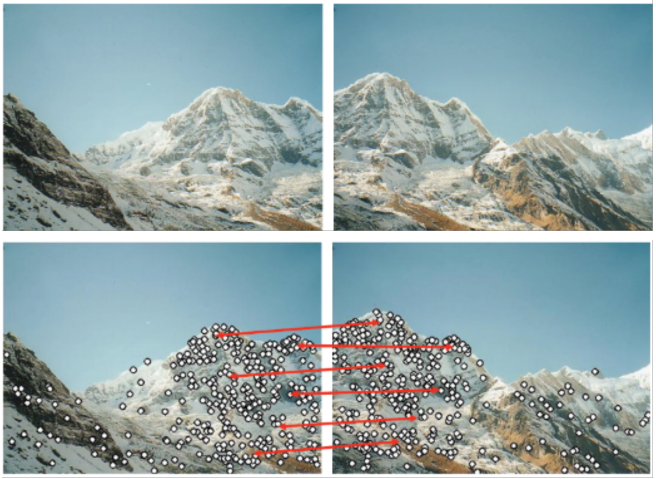
Acknowledgements

- Most of this lecture's slides are based on lectures of **Deep Learning for Vision** course taught by Prof Yannis Avrithis at Inria Rennes-Bretagne Atlantique

Review



How to match?

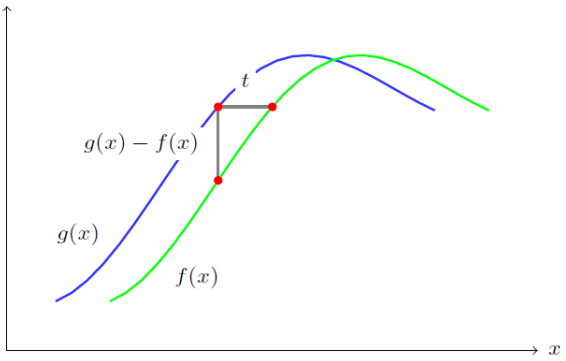
Dense Registration through Optical Flow[1]

- For each location in an image, find a displacement with respect to another reference image
- Appropriate for small displacements, e.g. stereopsis or optical flow

[1] Lucas and Kanade IJCAI 1981. An Iterative Image Registration Technique With an Application to Stereo Vision.

Dense Registration through Optical Flow[2]

- One dimension:



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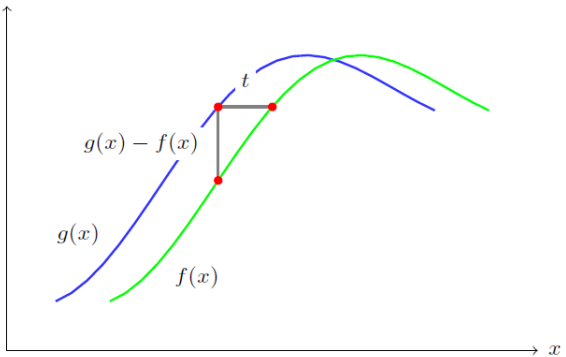

Assuming $g(x) = f(x + t)$ and t is small,

$$\frac{df}{dx}(x) \approx \frac{f(x+t) - f(x)}{t} = \frac{g(x) - f(x)}{t}$$

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Dense Registration through Optical Flow[2]

- Error given by:

$$E(t) = \sum_x w(x)\Big(f(x+t) - g(x)\Big)^2 \approx \sum_x w(x)\Big(f(x) + t^T \Delta f(x) - g(x)\Big)^2$$

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- Error minimized when gradient vanishes

$$\frac{\partial E}{\partial t} = \sum_x w(x) 2\Delta f(x)\Big(f(x) + t^T \Delta f(x) - g(x)\Big) = 0$$

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- Least-squares solution *(ignoring summation and arguments for simplicity)*:

$$w\Delta f(\Delta f)^T t = w\Delta f(g - f)$$

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- 2-D equivalent: Assume an image patch defined by window w; what is the error between patch shifted by t in reference image f and patch at origin in shifted image g?

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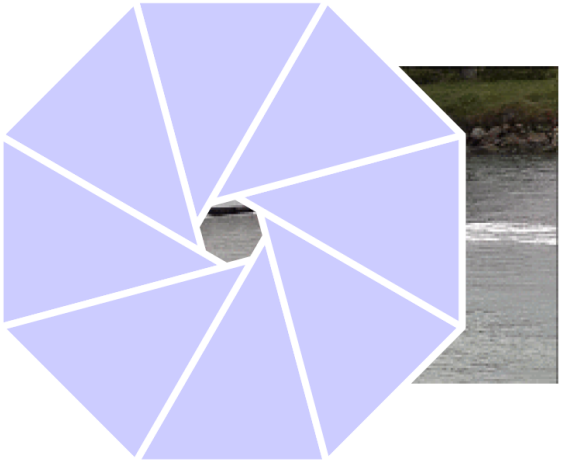

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Wide Baseline Spatial Matching

- In dense registration, we started from a local "template matching" process and found an efficient solution based on a Taylor approximation
- Both make sense for small displacements
- In wide-baseline matching, every part of one image may appear anywhere in the other
- We start by pairwise matching of local descriptors without any order, and then attempt to enforce some geometric consistency according to a rigid motion model

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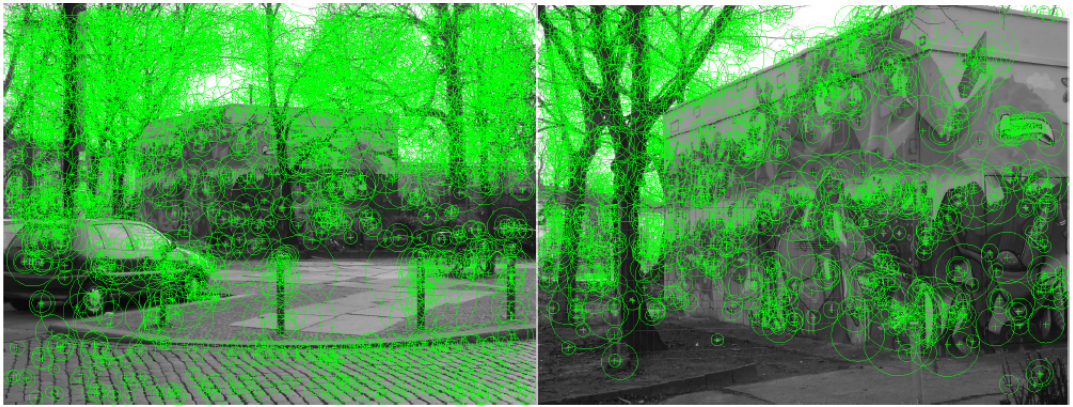
Wide Baseline Spatial Matching

A region in one image may appear anywhere in the other

Credit: Yannis Avrithis, Inria Rennes-Bretagne Atlantique

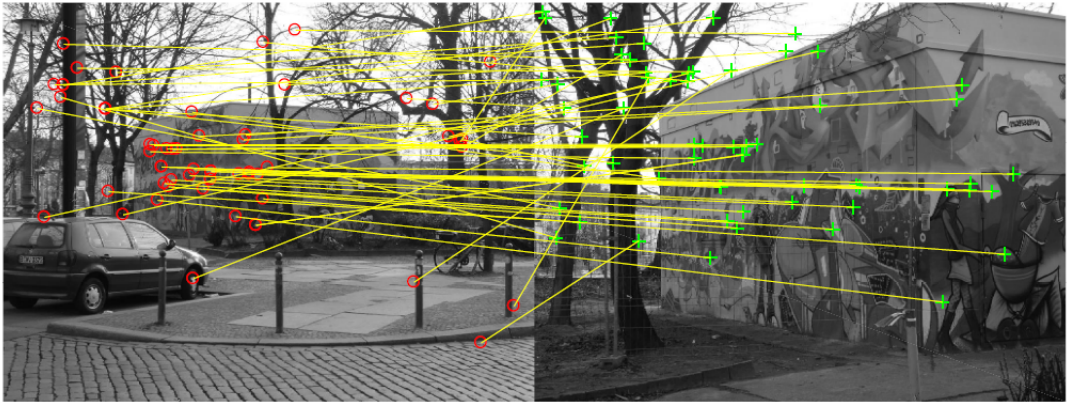
Wide Baseline Spatial Matching



Features detected independently in each image

Credit: Yannis Avrithis, Inria Rennes-Bretagne Atlantique

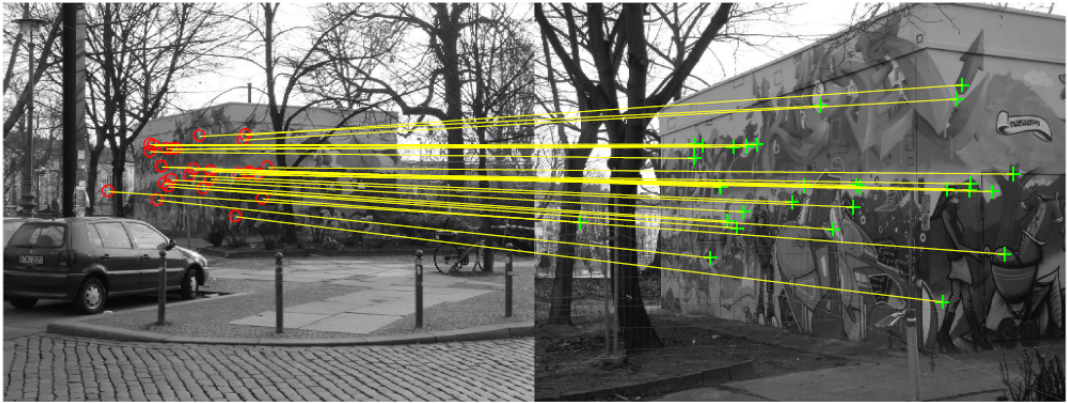
Wide Baseline Spatial Matching



Tentative correspondences by pairwise descriptor matching

Credit: Yannis Avrithis, Inria Rennes-Bretagne Atlantique

Wide Baseline Spatial Matching



Subset of correspondences that are 'inlier' to a rigid transformation

Credit: Yannis Avrithis, Inria Rennes-Bretagne Atlantique

Wide Baseline Spatial Matching

Descriptor Extraction:

For each detected feature in each image:

- Construct a local histogram of gradient orientations (HoG)
- Find one or more dominant orientations corresponding to peaks in histogram
- Resample local patch at given location, scale, and orientation
- Extract one descriptor for each dominant orientation

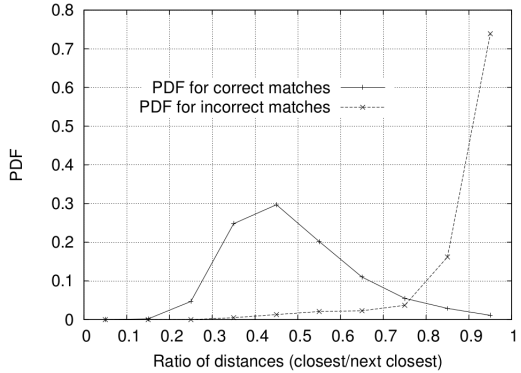
Wide Baseline Spatial Matching

Descriptor Matching:

- For each descriptor in one image, find its two nearest neighbors in the other
- If ratio of distance of first to distance of second is small, make a correspondence
- This yields a list of tentative correspondences

Wide Baseline Spatial Matching

Ratio Test:



Ratio of first to second nearest neighbour distance can determine the probability of a true correspondence

Credit: Yannis Avrithis, Inria Rennes-Bretagne Atlantique

Wide Baseline Spatial Matching

Why is it difficult?

- Should allow for a geometric transformation
- Fitting the model to data (correspondences) is sensitive to outliers: should find a subset of inliers first
- Finding inliers to a transformation requires finding the transformation in the first place
- Correspondences can have gross error
- Inliers are typically less than 50%

Geometric Transformations

- Two images I, I' are equal at points $\mathbf{x}, \mathbf{x}'$

$$I(\mathbf{x}) = I'(\mathbf{x}')$$

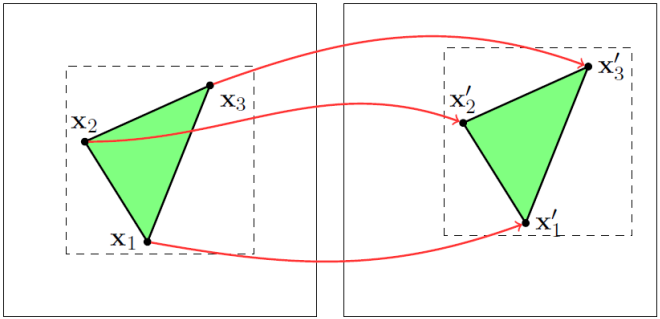
- $\mathbf{x}$ is mapped to $\mathbf{x}'$

$$\mathbf{x}' = T(\mathbf{x})$$

- T is a bijection of $\mathbb{R}^2$ to itself:

$$T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$$

Geometric Transformations

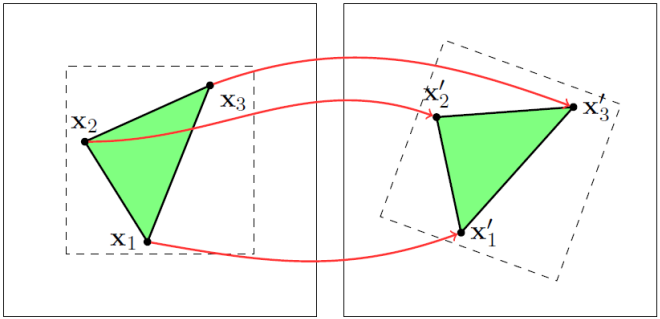


- Translation: 2 degrees of freedom

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$$

Credit: Yannis Avrithis, Inria Rennes-Bretagne Atlantique

Geometric Transformations



- Rotation: 1 degree of freedom

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$$

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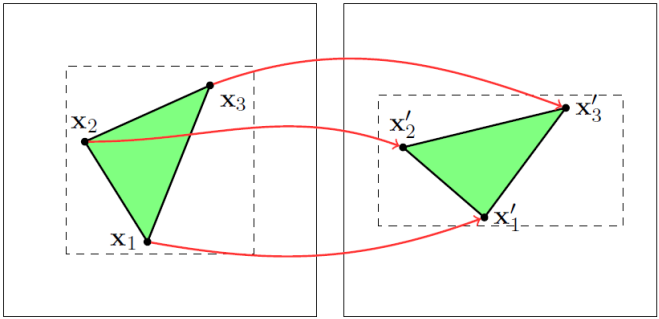
Geometric Transformations



- Similarity: 4 degrees of freedom

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} r\cos\theta & -r\sin\theta & t_x \\ r\sin\theta & r\cos\theta & t_y \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$$

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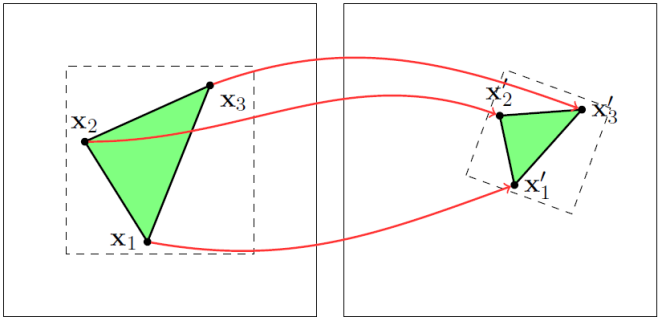

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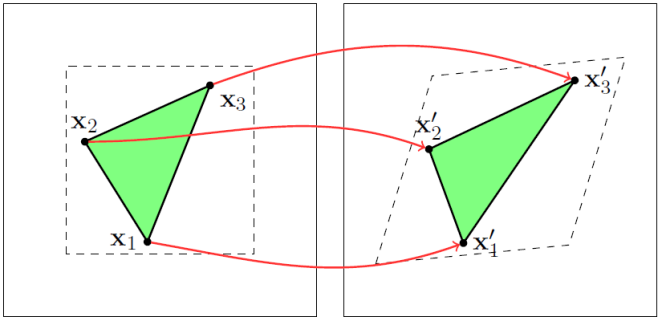

- Shear: 2 degrees of freedom

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} 1 & b_x & 0 \\ b_y & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$$

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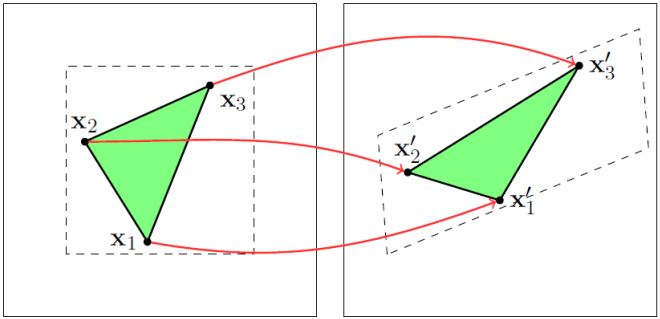

- Affine: 6 degrees of freedom

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$$

Credit: Yannis Avrithis, Inria Rennes-Bretagne Atlantique

Correspondence and Least Squares

- In all cases, the problem is transformed to a linear system (why?)

$$A\mathbf{x} = \mathbf{b}$$

where $\mathbf{x}$, $\mathbf{b}$ contain coordinates of known point correspondences from images I, I' respectively, and A contains our model parameters

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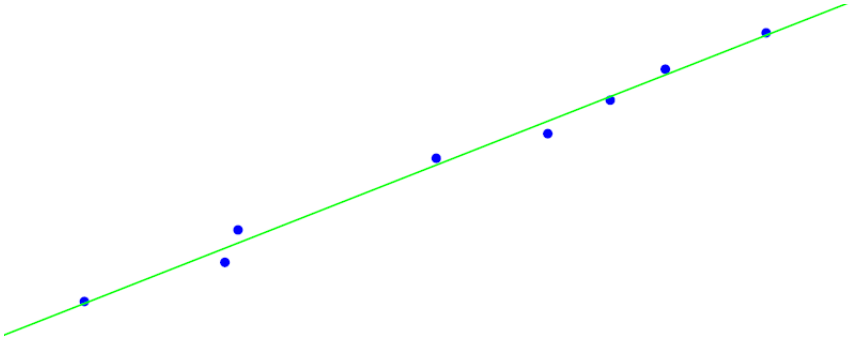
- Let's take the simplest model as an example: fit a line to two points

Correspondence and Least Squares



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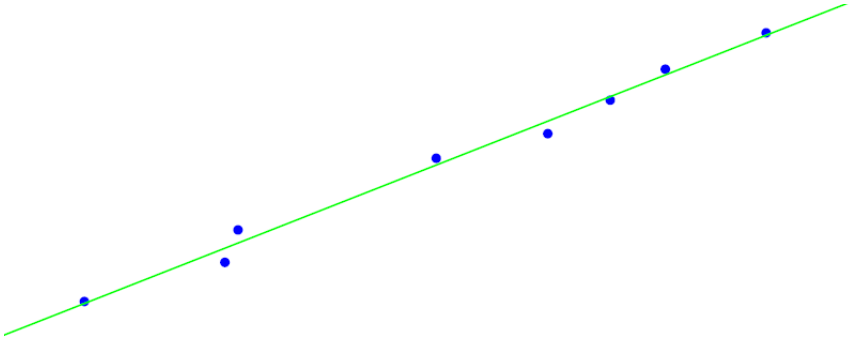

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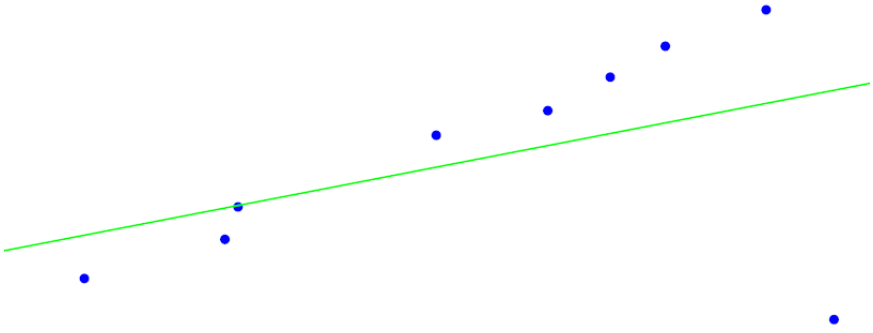

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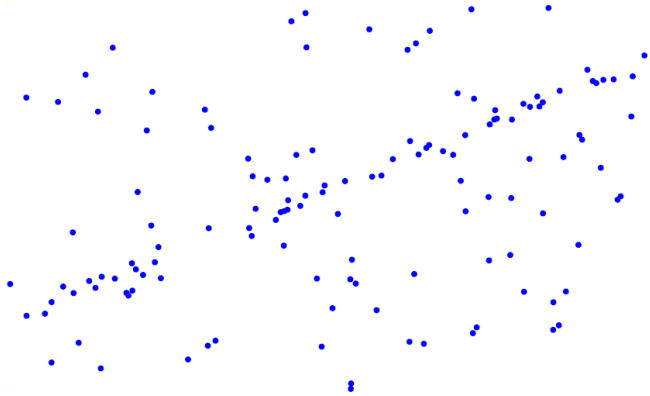
RANSAC (**RAN**dom **SA**mple **C**onsensus)[3]



- data with outliers - pick two points at random - draw line through them - set margin on either side - count inlier points

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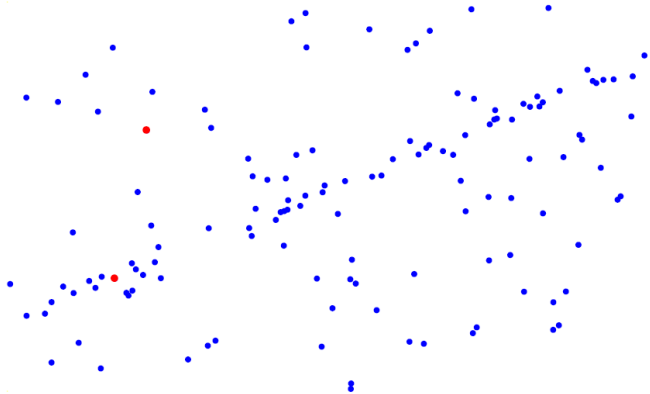

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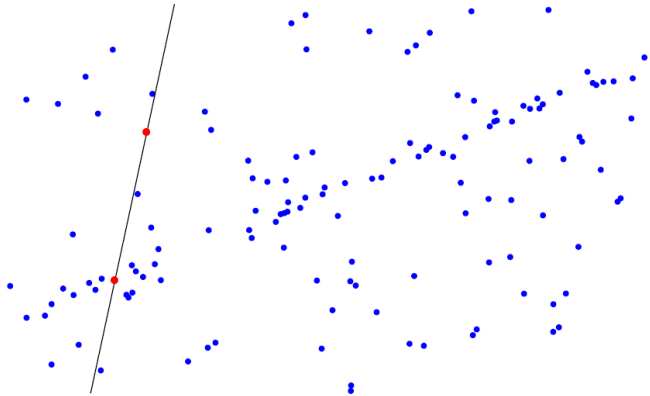

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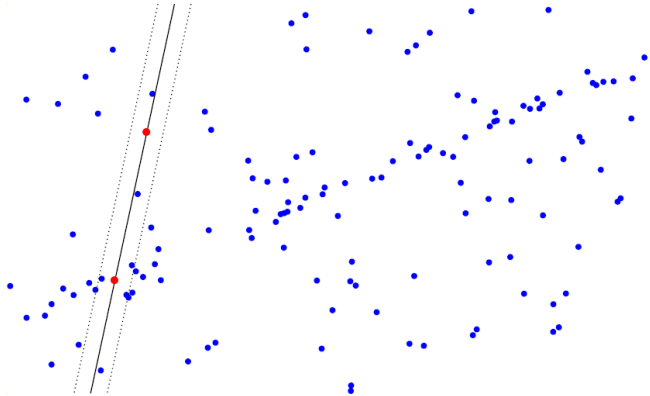

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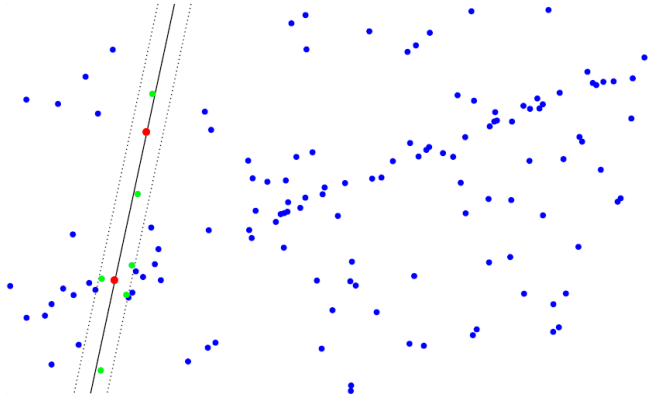

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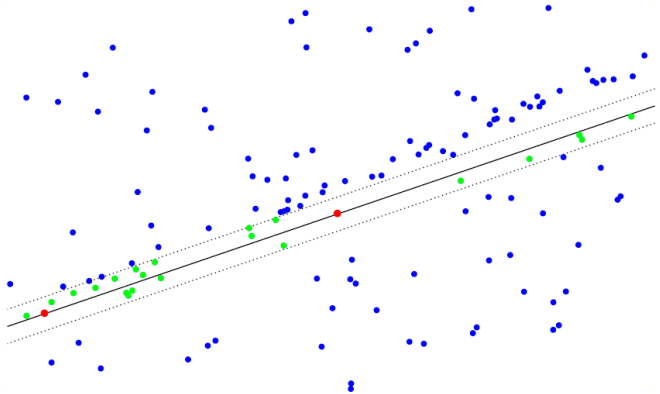

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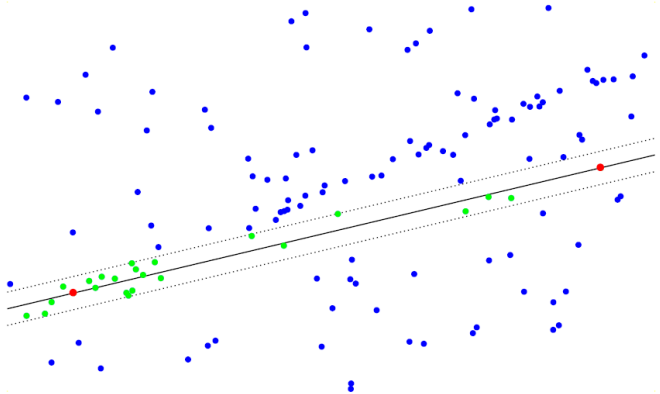

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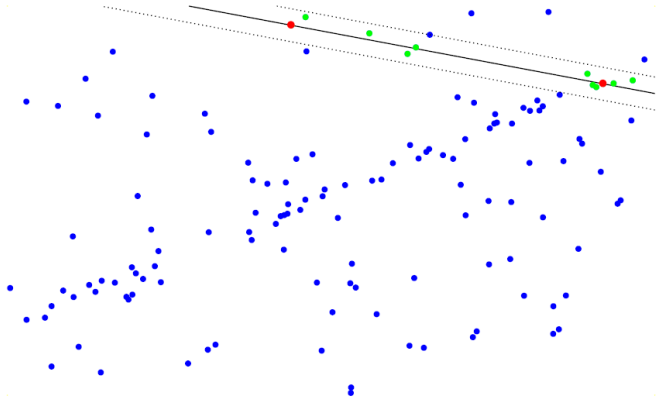

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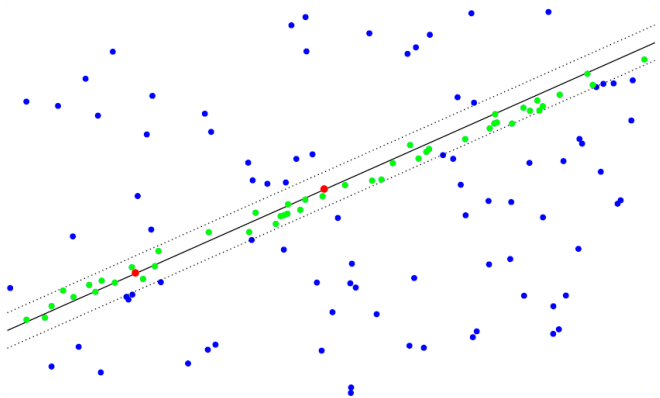

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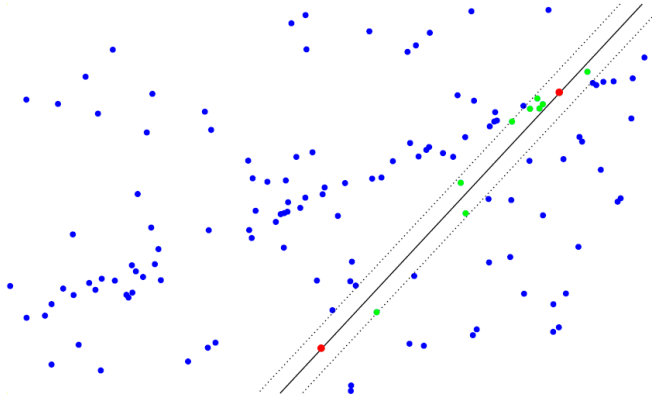

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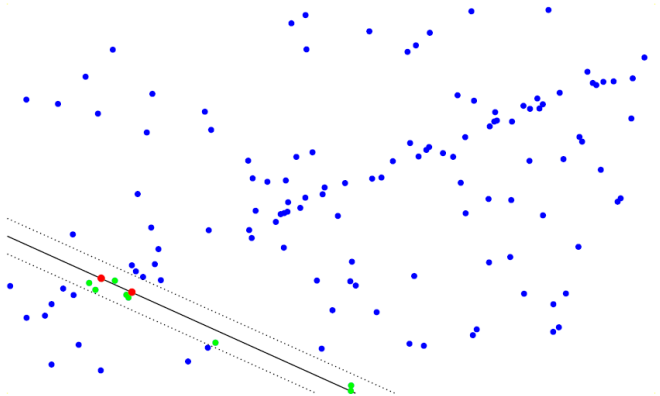

- Repeat: pick two points at random, draw line through them, count inlier points at fixed distance to line, keep best hypothesis so far

[3] Fischler and Bolles. CACM 1981. Random Sample Consensus: A Paradigm for Model Fitting With Applications to Image Analysis and Automated Cartography.

RANSAC

- X: data (tentative correspondences)
- n: minimum number of samples to fit a model
- $s(x;\theta)$: score of sample $\mathbf{x}$ given model parameters θ
- repeat:
  - hypothesis
    - draw n samples $H \subset X$ at random
    - fit model to H, compute parameters θ
  - verification
    - are data consistent with hypothesis? compute score $S = \sum_{\mathbf{x} \in X} s(\mathbf{x};\theta)$
    - if $S^* > S$, store solution $\theta^* := \theta$, $S^* := S$

RANSAC: Limitations

- Inlier ratio w (number of inliers in data / number of points in data) unknown
- Too expensive when minimum number of samples is large (e.g. $n > 6$) and inlier ratio is small (e.g. $w < 10\%$): 10^6 iterations for 1% probability of failure. (How?)

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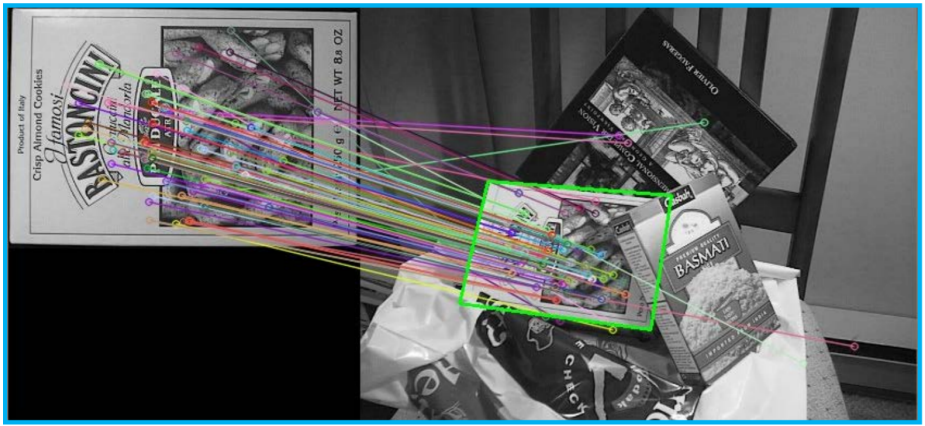
  - $1 - w^n \rightarrow$ probability that at least one of n points is an outlier $\implies$ a bad model will be estimated from this point set
  - $(1 - w^n)^k \rightarrow$ probability that algorithm never selects a set of n points which all are inliers, where $k \rightarrow$ number of iterations

RANSAC Applications

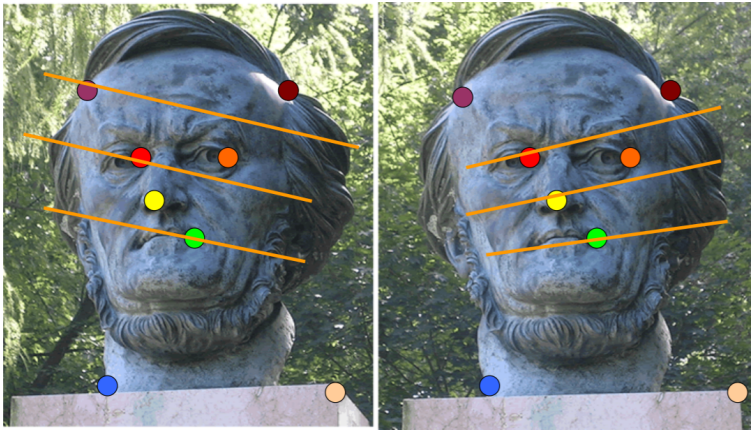
Rotation



Credit: Aaron Bobick, Washington University in St. Louis

RANSAC Applications

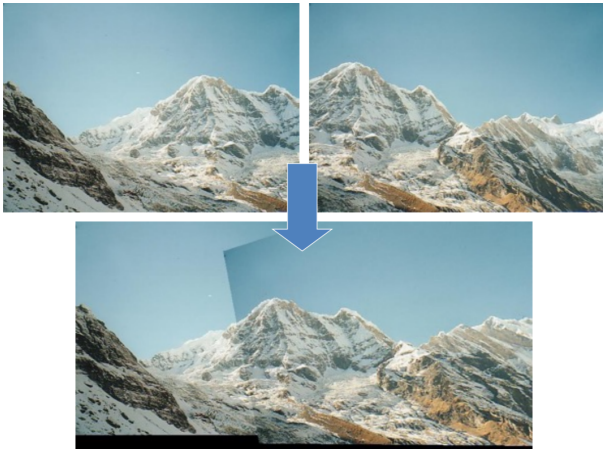
Estimating transformation matrix (also called **fundamental matrix**) relating two views



Credit: Derek Hoeim, UIUC

RANSAC Applications

Computing a **homography** (e.g., image stitching)



Credit: Ali Farhadi, Univ of Washington

Homework

Readings

- Chapter 4.3, 6.1, Szeliski, *Computer Vision: Algorithms and Applications*
- Papers on the respective slides (for more information)

References


Martin A. Fischler and Robert C. Bolles. "Random Sample Consensus: A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography". In: *Commun. ACM* 24.6 (June 1981), 381–395.


Bruce D. Lucas and Takeo Kanade. "An Iterative Image Registration Technique with an Application to Stereo Vision". In: *Proceedings of the 7th International Joint Conference on Artificial Intelligence - Volume 2*. IJCAI'81. Vancouver, BC, Canada: Morgan Kaufmann Publishers Inc., 1981, 674–679.


Richard Szeliski. *Computer Vision: Algorithms and Applications*. Texts in Computer Science. London: Springer-Verlag, 2011.


Avrithis, Yannis, Deep Learning for Vision (2018). URL: https://sif-dlv.github.io/ (visited on 05/21/2020).


Hoiem, Derek, CS 543 - Computer Vision (Spring 2011). URL: https://courses.engr.illinois.edu/cs543/sp2017/ (visited on 04/25/2020).

Deep Learning for Computer Vision

Hough Transform

Vineeth N Balasubramanian

Department of Computer Science and Engineering
Indian Institute of Technology, Hyderabad

Acknowledgements

- Most of this lecture's slides are based on lectures of **Deep Learning for Vision** course taught by Prof Yannis Avrithis at Inria Rennes-Bretagne Atlantique, as well as the **Computer Vision** course taught by Prof Mubarak Shah/Alper Yilmaz at the University of Central Florida

Line Fitting

- We have already seen a couple of line fitting algorithms: *Least squares fit* and *RANSAC*
- How do they perform when multiple lines are present?

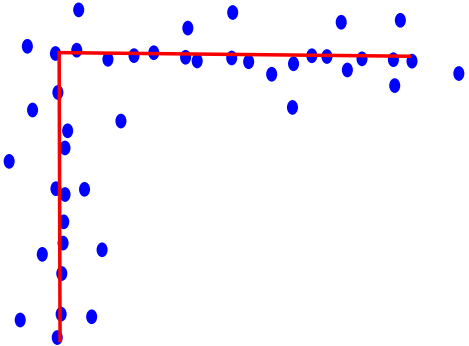


Figure 1: Example line configuration in an image.

Line Fitting: Hough Transform

- Hough, *Method and means for recognizing complex patterns*, U.S. Patent No. 3,069,654, Dec 1962
- Line equation in Cartesian co-ordinates is:
  - $y = mx + c$ $\quad$ m is slope, c is y-intercept
- Rearranging it slightly, we get:
  - $c = (-x)m + y$ $\quad$ which for a specific point (x_i, y_i) becomes $c = (-x_i)m + y_i$
- This can be thought of as the equation of line in parameter space; i.e in the (m, c) coordinate system with slope $-x_i$ and c-intercept y
- Each point in parameter space is a model

Source: Alper Yilmaz, Mubarak Shah, Fall 2011 UCF

Line Fitting: Hough Transform

- N samples needed to fit a model (2 points to fit a line)
- But even one sample brings some information
- In the space of all possible models, vote for ones that satisfy a given sample
- Collect votes for all samples, and seek for consensus

Source: Yannis Avrithis, Deep Learning for Vision, Spring 2019 SIF

Hough Transform: Polar Parametrization

- The Cartesian formulation is problematic for vertical lines. Why?

Hough Transform: Polar Parametrization

- The Cartesian formulation is problematic for vertical lines. Why?
  - The slope is unbounded for vertical lines.
- Consider a polar parametrization of the line:
  - $\rho = x \cos\theta + y \sin\theta$
  - ρ is distance of line from origin and θ is angle made by normal to x-axis
  - For given line, $\rho \geq 0$ and $0 \leq \theta \leq 360^\circ$ are bounded

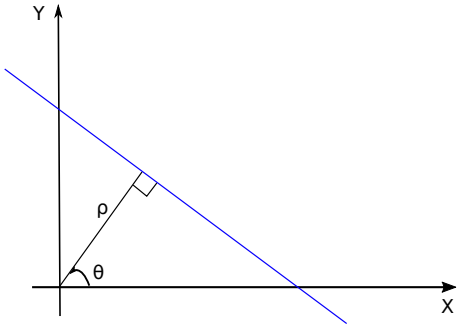


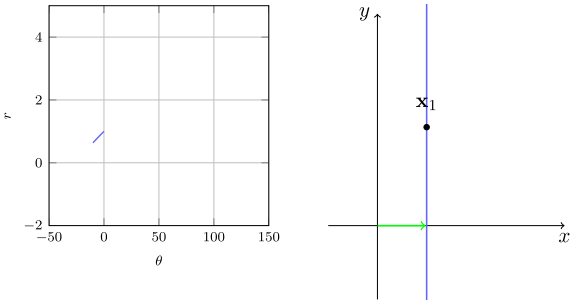
Figure 2: The ρ, θ parametrization.

Source: Alper Yilmaz, Mubarak Shah, Fall 2011 UCF

Hough Transform: Polar Parametrization

- A point (x_i, y_i) '*votes*' for many points in parameter space $\rightarrow$ **Hough Voting**
- Each line through a point (x_1, y_1) is a vote for a point in parameter space which satisfies $\rho = x_1 \cos\theta + y_1 \sin\theta$

voting in parameter space



Source: Yannis Avrithis, Deep Learning for Vision, Spring 2019 SIF

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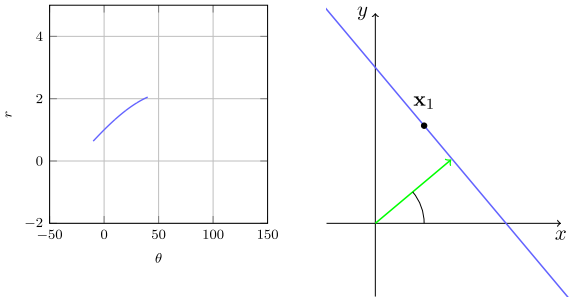

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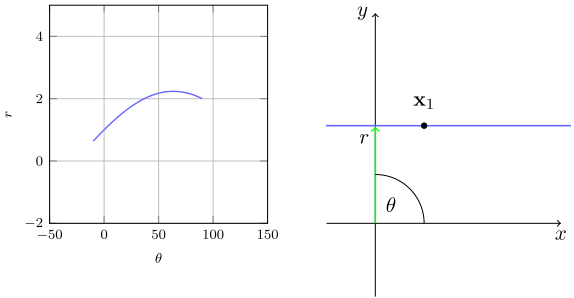

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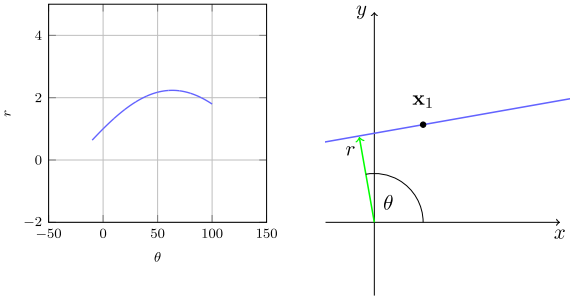

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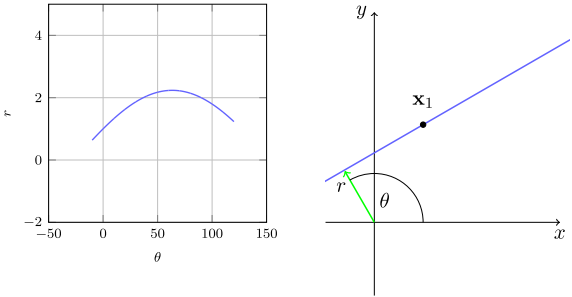
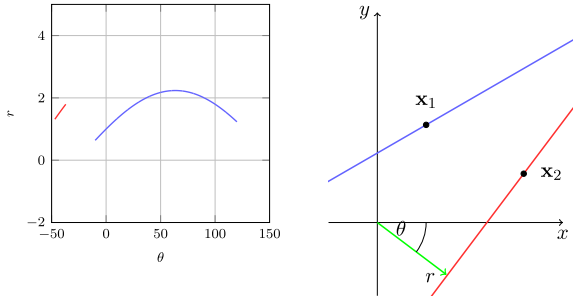


Source: Yannis Avrithis, Deep Learning for Vision, Spring 2019 SIF

Hough Transform: Polar Parametrization

- Each line through a point (x_2, y_2) is a vote for a point in parameter space which satisfies $\rho = x_2 \cos\theta + y_2 \sin\theta$

voting in parameter space



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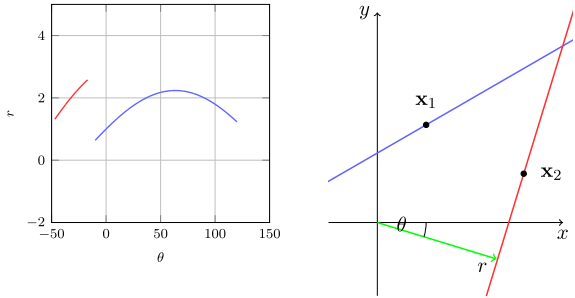

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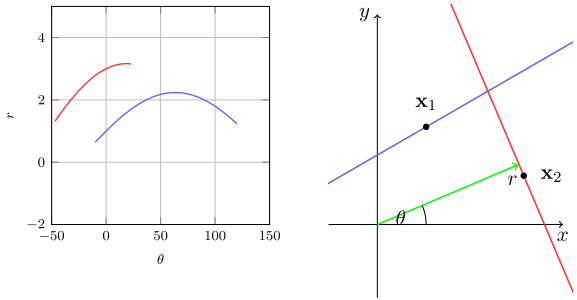

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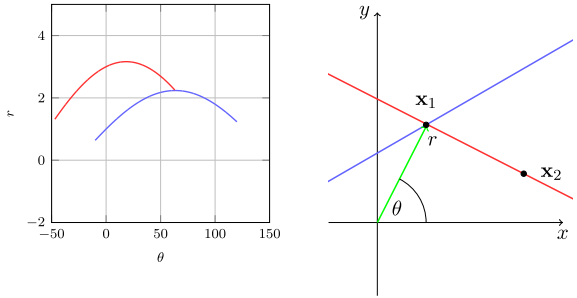

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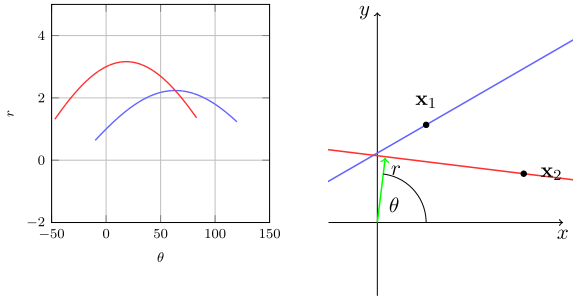


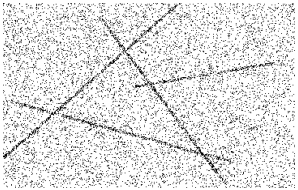
Source: Yannis Avrithis, Deep Learning for Vision, Spring 2019 SIF

Hough Voting

procedure HOUGH VOTING(X, Θ)
    X: data Θ: quantized parameter $\theta_{min}, ..., \theta_{max}$
    A: accumulator array, initially zero
    for $(x, y) \in X$ **do**
        for $\theta \in \Theta$ **do**
            $\rho = x \cos\theta + y \sin\theta$
            $\triangleright$ for each set of model parameters consistent with a sample, increment A
            $A[\theta, \rho] = A[\theta, \rho] + 1$
        end for
    end for
    Non-maximum Suppression: detect local maxima in A
end procedure

Source: Yannis Avrithis, Deep Learning for Vision, Spring 2019 SIF

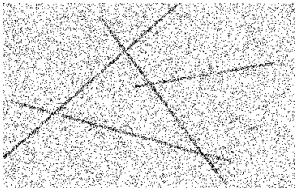
Line Detection



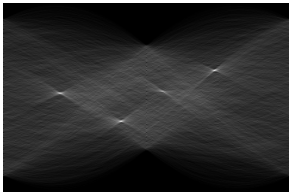
points

Source: Yannis Avrithis, Deep Learning for Vision, Spring 2019 SIF

Line Detection



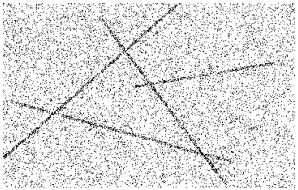
points



accumulator

Source: Yannis Avrithis, Deep Learning for Vision, Spring 2019 SIF

Line Detection



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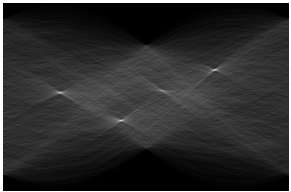
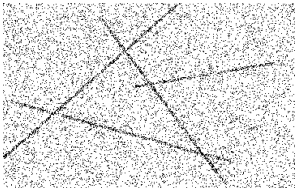


accumulator

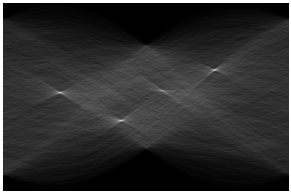
local maxima

Source: Yannis Avrithis, Deep Learning for Vision, Spring 2019 SIF

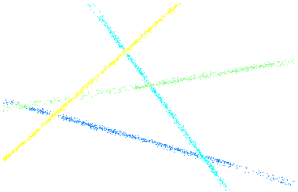
Line Detection



points



accumulator



labels

local maxima

Source: Yannis Avrithis, Deep Learning for Vision, Spring 2019 SIF

Hough Transform: Finding Circles

- Circle fitting similar to line fitting
  - $(x - x_0)^2 + (y - y_0)^2 - r^2 = 0$
- What are the dimensions of accumulator A for circle fitting?

Hough Transform: Finding Circles

- Circle fitting similar to line fitting
  - $(x - x_0)^2 + (y - y_0)^2 - r^2 = 0$
- What are the dimensions of accumulator A for circle fitting?
  - 3D accumulator with dimensions x_0, y_0, r
- Fix one of the parameters (generally radius is fixed) and loop for the rest
- Increment accumulator A
- Find local maxima in A

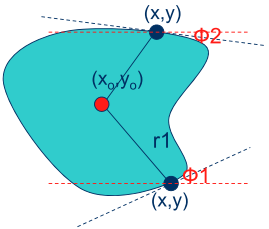
Source: Alper Yilmaz, Mubarak Shah, Fall 2011 UCF

Source: Ioannis Gkioulekas, 16-385 Computer Vision, Spring 2020, CMU

Generalized Hough Transform

- Used for shapes with no analytical expression
- Involves a training phase where R-table is computed
- Given object of interest, compute R-table as follows:
  - Compute centroid (x_c, y_c).
  - For each edge point (x_i, y_i), compute distance to centroid r_i and find edge orientation ϕ_i.
  - Construct a table of angles and r-values

Φ1	r1, r2, r3 …
Φ2	r14, r21, r23 …
Φ3	r41, r42, r33 …
Φ4	r10, r12, r13 …



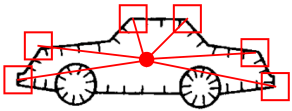
Source: Alper Yilmaz, Mubarak Shah, Fall 2011 UCF

Generalized Hough Transform

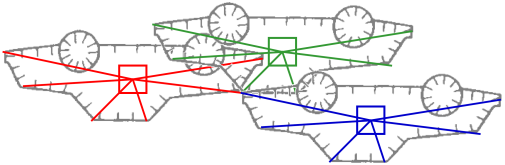
1: **procedure** GENERALIZED HOUGH TRANSFORM($X, R, A[x_c, y_c]$)
2: X: data R: R-table $A[x_c, y_c]$: Accumulator array with quantization $x_{c_{\min}}, \cdots, x_{c_{\max}}$ and $y_{c_{\min}}, \cdots, y_{c_{\max}}$
3: A: accumulator array, initially zero
4: **for** $(x, y) \in X$ **do**
5: **for** each $(r_i, \phi_i) \in R$ **do**
6: $x_c = x + r_i \cos \phi_i$
7: $y_c = y + r_i \sin \phi_i$
8: $A[x_c, y_c] = A[x_c, y_c] + 1$
9: **end for**
10: **end for**
11: Non-maximum Suppression: detect local maxima in A
12: **end procedure**

Generalized Hough Transform: Example

- **Build model:** Record coordinates relative to reference point
- **Test phase:** Each point votes for all possible coordinates of reference point



Model image



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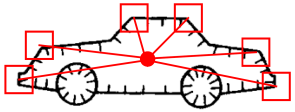
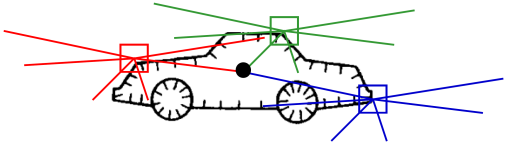
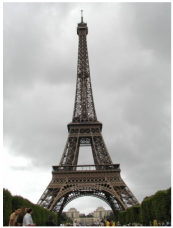


Model image



Test image

Generalized Hough Transform: Example

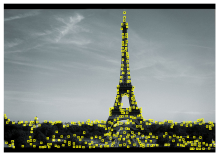


Model image

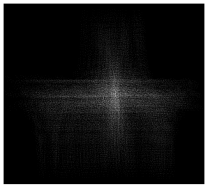
Test image

Generalized Hough Transform: Example

Model image points



Test image points



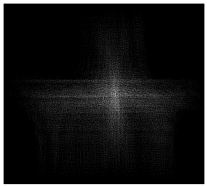
Accumulator

Local Maxima

Generalized Hough Transform: Example

Model image points

Test image with location



Accumulator

Local Maxima

Hough Transform

- Can be used for detection of:
  - shapes
  - objects, including multiple instances
- Advantages
  - Deals with occlusion well
  - Robust to noise
- Disadvantages
  - Can be computationally expensive
  - Setting parameters is not easy

Source: Ioannis Gkioulekas, 16-385 Computer Vision, Spring 2020, CMU

Homework

Readings

- Chapter 4.3, Szeliski, *Computer Vision: Algorithms and Applications*

Questions

- How would you use Hough transform to detect ellipses, squares and rectangles?
- Your friend working in a diagnostics startup asks you how to use Hough transform to automatically count Red Blood Cells in a blood sample. What would you advise your friend?

References

Richard O. Duda and Peter E. Hart. "Use of the Hough Transformation to Detect Lines and Curves in Pictures". In: *Commun. ACM* 15.1 (Jan. 1972), 11–15.

John Illingworth and Josef Kittler. "A survey of the Hough transform". In: *Computer vision, graphics, and image processing* 44.1 (1988), pp. 87–116.

Richard Szeliski. *Computer Vision: Algorithms and Applications*. Texts in Computer Science. London: Springer-Verlag, 2011.

Deep Learning for Computer Vision

From Points to Images: Bag-of-Words and VLAD Representations

Vineeth N Balasubramanian

Department of Computer Science and Engineering
Indian Institute of Technology, Hyderabad

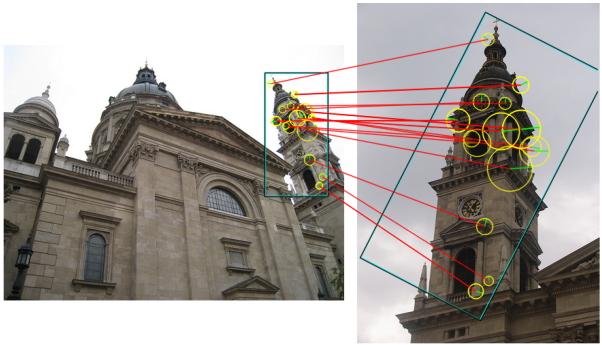
Acknowledgements

- Most of this lecture's slides are based on lectures of **Deep Learning for Vision** course taught by Prof Yannis Avrithis at Inria Rennes-Bretagne Atlantique

Review

So far:

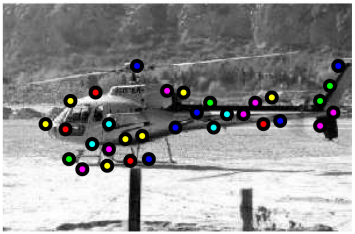
- Descriptors for matching features between different views of the same scene/object
  - Used in image stitching, image retrieval, etc.

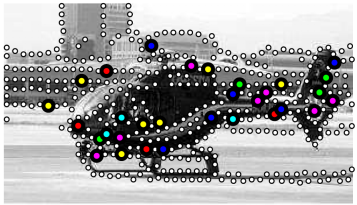


Source: Yannis Avrithis, Deep Learning for Vision, Spring 2019 SIF

Review

- Can the same descriptors be used for matching different instances of the object?
  - Used in image classification, detection, etc.





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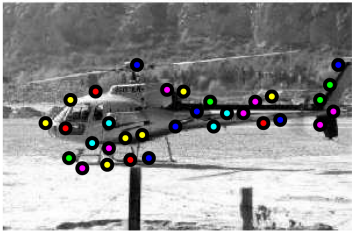
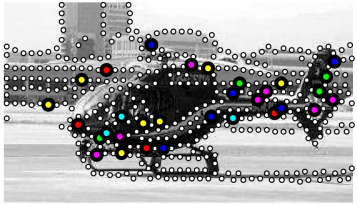




Rigid transformations may not work here. Can we discard geometry for now, and bring it back in other ways?

Source: Yannis Avrithis, Deep Learning for Vision, Spring 2019 SIF

Our First Attempt: Bag-of-Words (BoW)

Samples

Our First Attempt: Bag-of-Words (BoW)

Samples

Form Vocabulary

Our First Attempt: Bag-of-Words (BoW)

Samples

Form Vocabulary

Histogram

Our First Attempt: Bag-of-Words (BoW)

1) John likes to watch movies. Mary likes movies too.

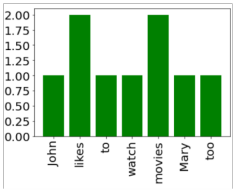
2) Mary also likes to watch football games..

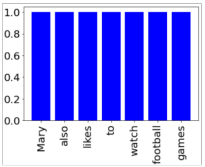
Samples

"John","likes","to","watch","movies","Mary","likes","movies","too"

"Mary","also","likes","to","watch","football","games"

Form Vocabulary





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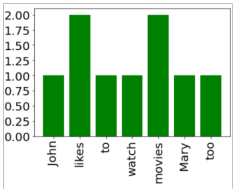

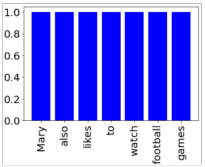

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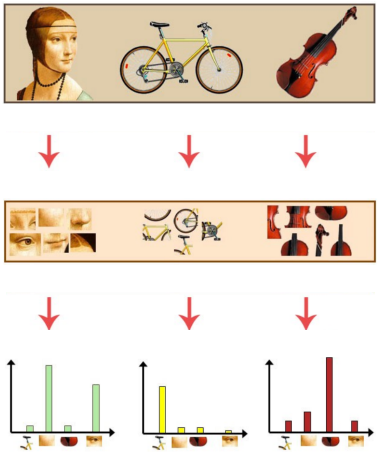

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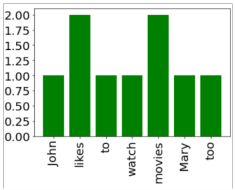
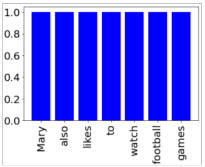
Samples

Uses of Bag-of-Words?





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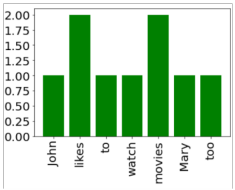
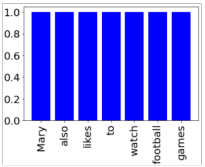
Samples

Uses of Bag-of-Words?

- Retrieval
- Classification





Histogram

BoW for Retrieval[1]

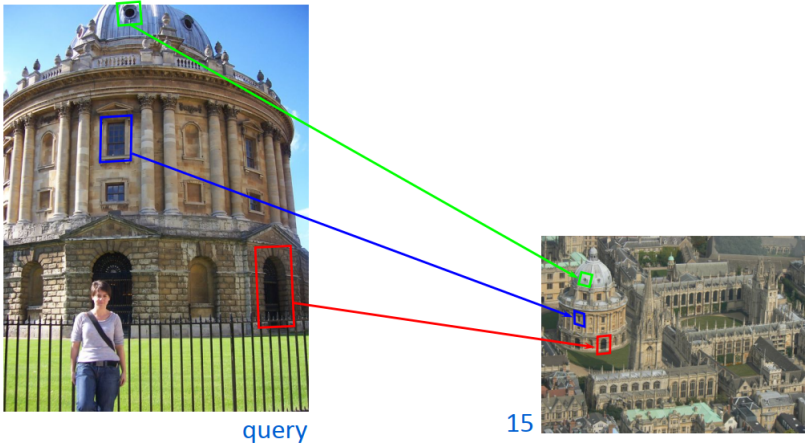
query

15

Query vs dataset image

[1] Sivic and Zisserman, Video Google: A Text Retrieval Approach to Object Matching in videos, ICCV 2003

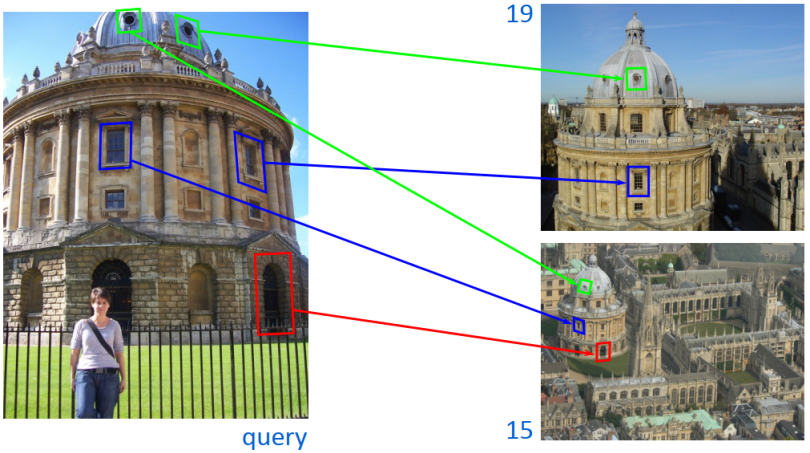
BoW for Retrieval[1]



Pairwise descriptor matching

[1]Sivic and Zisserman, Video Google: A Text Retrieval Approach to Object Matching in videos, ICCV 2003

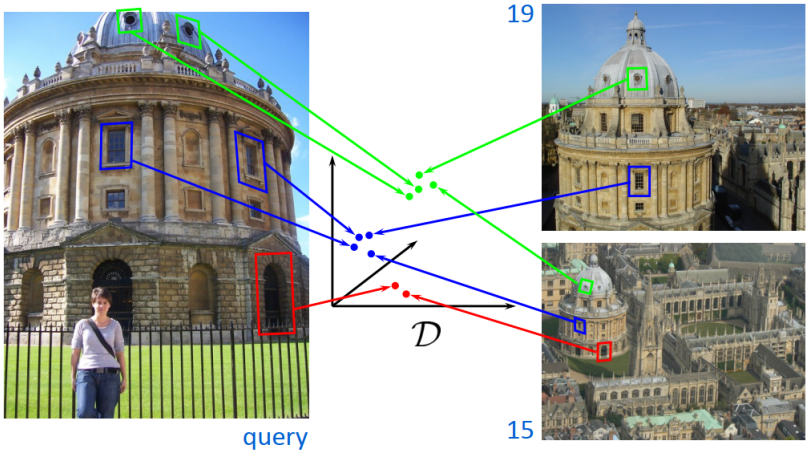
BoW for Retrieval[1]



Pairwise descriptor matching for every dataset image

[1]Sivic and Zisserman, Video Google: A Text Retrieval Approach to Object Matching in videos, ICCV 2003

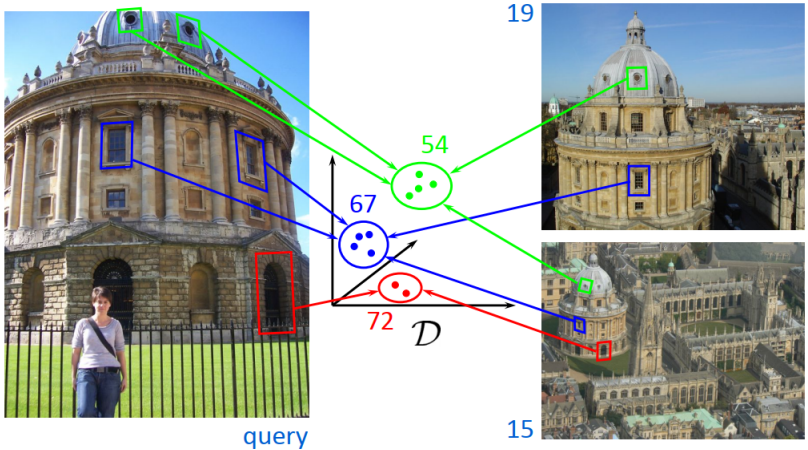
BoW for Retrieval[1]



Similar descriptors should all be nearby in the descriptor space

[1] Sivic and Zisserman, Video Google: A Text Retrieval Approach to Object Matching in videos, ICCV 2003

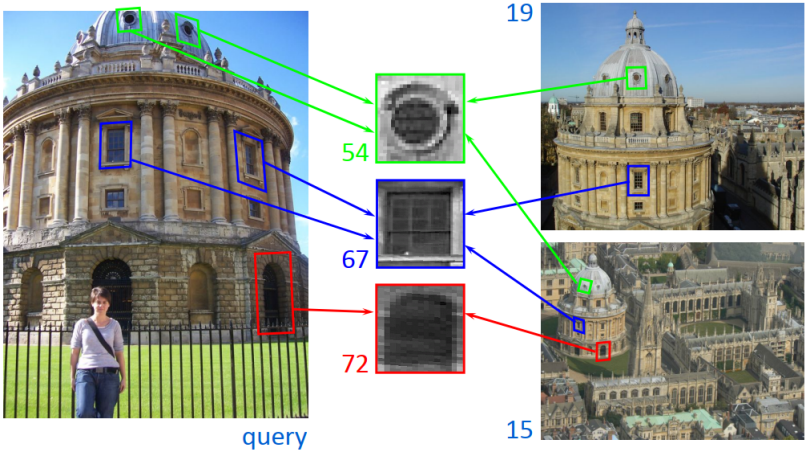
BoW for Retrieval[1]



Quantize them into visual words

[1] Sivic and Zisserman, Video Google: A Text Retrieval Approach to Object Matching in videos, ICCV 2003

BoW for Retrieval[1]



Now visual words act as a proxy. No pairwise matching needed

[1] Sivic and Zisserman, Video Google: A Text Retrieval Approach to Object Matching in videos, ICCV 2003

BoW for Retrieval

- Each image is represented by a vector $\mathbf{z} \in \mathbb{R}^k$, where k is size of codebook
  - Each element $z_i = w_i n_i$ where w_i is a fixed weight per visual word and n_i number of occurrences of this word in the image

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- Given a set of n images represented by matrix $Z \in \mathbb{R}^{k \times n}$ (each image as a column) and query image $\mathbf{q}$, we need a vector of similarities:

$$s = S_{\text{BoW}}(Z, \mathbf{q}) := Z^\top \mathbf{q}$$

and then sort s by descending order

- Note: With L_2-normalization, this is equivalent to measuring Euclidean distance: for vectors $\mathbf{z}$ and $\mathbf{q}$, $||\mathbf{z} - \mathbf{q}||^2 = 2(1 - \mathbf{z}^T\mathbf{q})$

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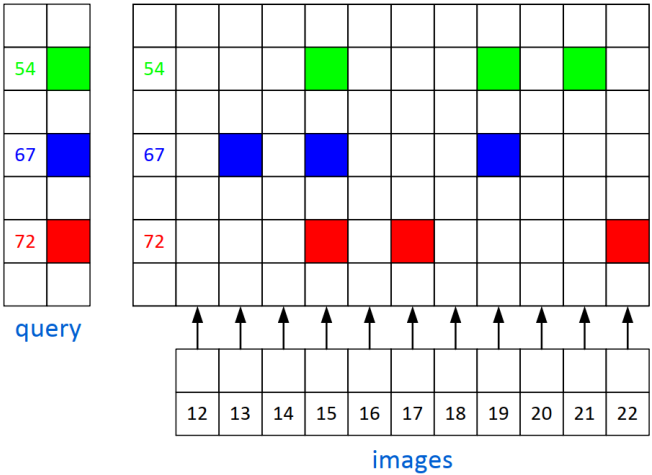
- When $k \gg p$, where p is the number of features per image on average, Z and $\mathbf{q}$ are sparse
- Rather than check whether a word is contained in an image, check which images contain a given word

BoW for Retrieval: Inverted File Index[2]



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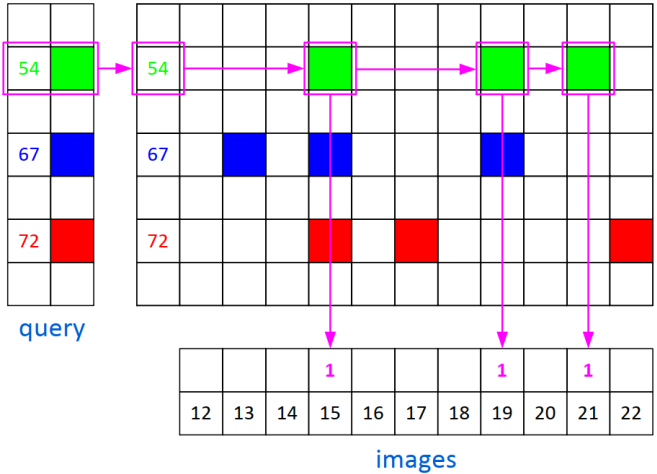

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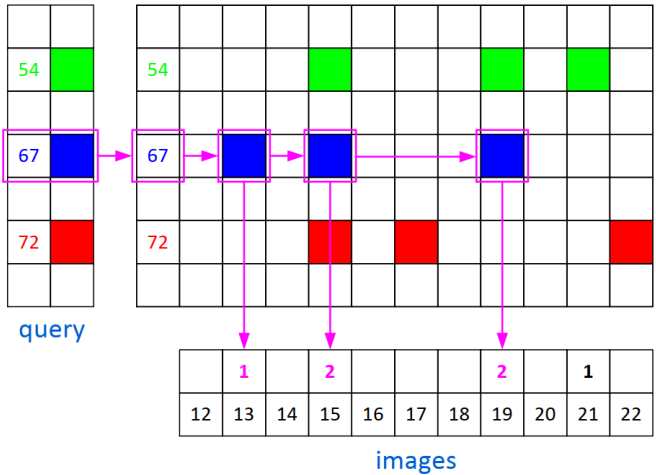

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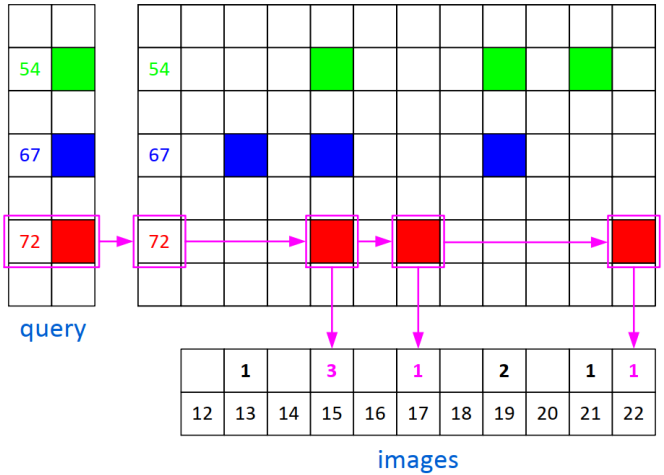

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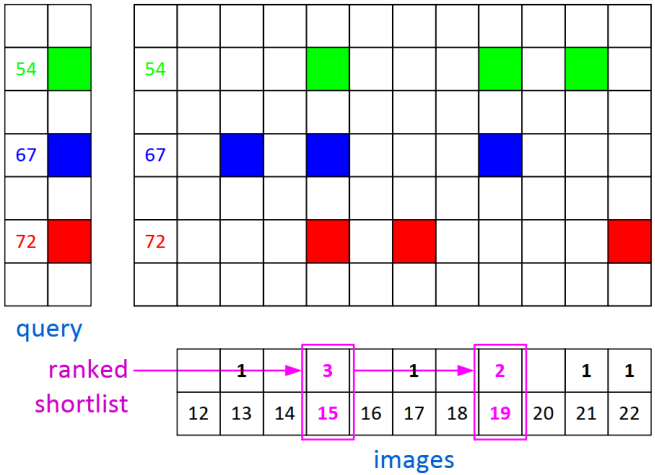

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BoW for Classification

How?

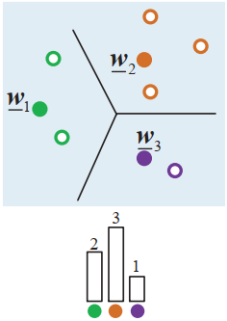
BoW for Classification

- Each image represented by $\mathbf{z} \in \mathbb{R}^k$; each element z_i the number of occurrences of visual word c_i in the image.

BoW for Classification

- Each image represented by $\mathbf{z} \in \mathbb{R}^k$; each element z_i the number of occurrences of visual word c_i in the image.
- **Naive Bayes:** Chose maximum posterior probability of class $\mathbf{C}$ given image $\mathbf{z}$ assuming features are independent $\rightarrow$ linear classifier with parameters estimated by visual word statistics on training set
- **Support Vector Machine (SVM):** Images $\mathbf{z}_1, \mathbf{z}_2$ compared using a kernel function $\phi(\cdot)$; if $\phi(\mathbf{z}_1)^T \phi(\mathbf{z}_2) = \mathbf{z}_1^T \mathbf{z}_2$, this is again a linear classifier

Extension of BoW: Vector of Locally Aggregated Descriptors (VLAD)



(BoW)

- Yields a scalar frequency
- Limited information

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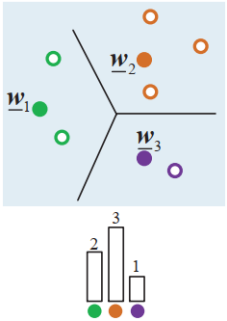

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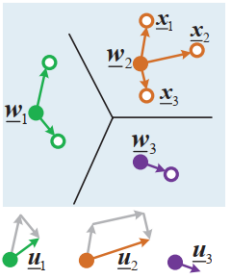
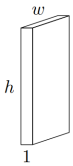


(VLAD)

- Yields a vector per visual word
- Comparatively more information, resulting in better discrimination by classifier

Credit: Li Liu

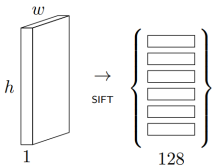
BoW Vs VLAD



- 3-channel RGB input $\rightarrow$ 1-channel gray-scale

Credit: Yannis A

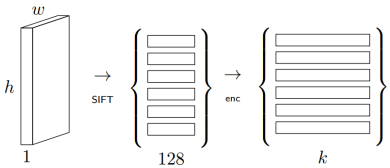
BoW Vs VLAD



- 3-channel RGB input $\rightarrow$ 1-channel gray-scale
- Set of $\sim$ 1000 features $\times$ 128-dim SIFT descriptors

Credit: Yannis A

BoW Vs VLAD



- 3-channel RGB input $\rightarrow$ 1-channel gray-scale
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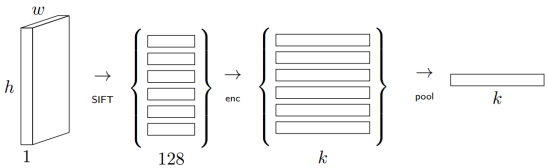

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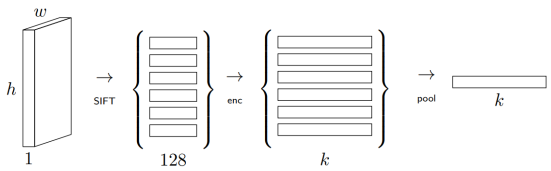

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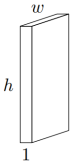

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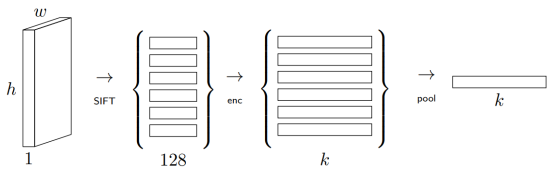
Credit: Yannis A

BoW Vs VLAD



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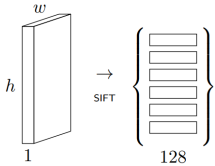

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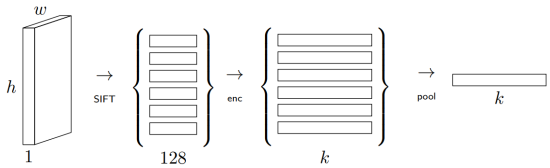
BoW Vs VLAD



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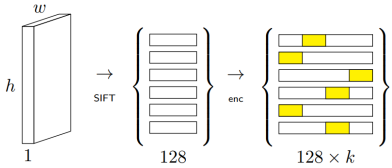

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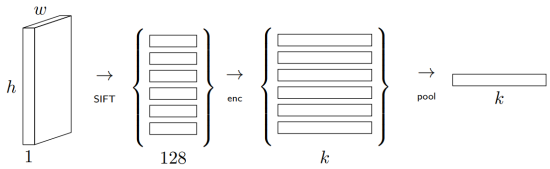
Credit: Yannis A

BoW Vs VLAD



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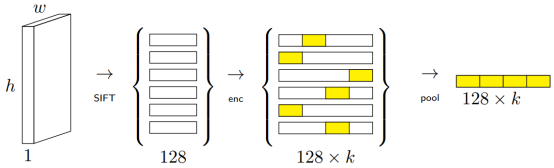

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Credit: Yannis A

Homework

Readings

- Chapter 14.3, 14.4, Szeliski, *Computer Vision: Algorithms and Applications*

Questions

- What is the connection of BoW to the k-means clustering algorithm?
- How would you now use k-means variants such as hierarchical k-means and approximate k-means to extend BoW? (*Hint: Look up vocabulary trees!*)

References

J Sivic and A Zisserman. "Video Google: A text retrieval approach to object matching in videos". In: ICCV. 2003.

Gabriella Csurka et al. "Visual categorization with bags of keypoints". In: *Workshop on statistical learning in computer vision, ECCV*. Vol. 1. 1-22. 2004, pp. 1–2.

Richard Szeliski. *Computer Vision: Algorithms and Applications*. Texts in Computer Science. London: Springer-Verlag, 2011.

Deep Learning for Computer Vision

Image Descriptor Matching

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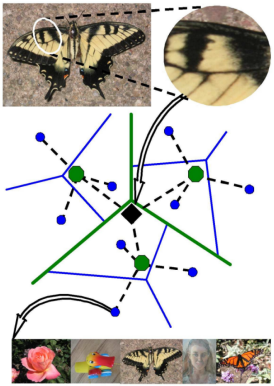
Acknowledgements

- Most of this lecture's slides are based on lectures of **Deep Learning for Vision** course taught by Prof Yannis Avrithis at Inria Rennes-Bretagne Atlantique

Review[1]

Hierarchical k-means and BoW:



- Apply hierarchical k-means and build a fine partition tree
- Descriptors descend from root to leaves by finding nearest node at each level
- Image represented by $x_i = w_i n_i$ as in BoW
- Dataset searched by inverted files at leaves
- No principled way of defining w_i across levels
- Distortion minimized only locally; points can get assigned to leaves that are not globally nearest

[1] Nister and Stewenius, Scalable Recognition With a Vocabulary Tree, CVPR 2006

Image Descriptor Matching: Options So Far

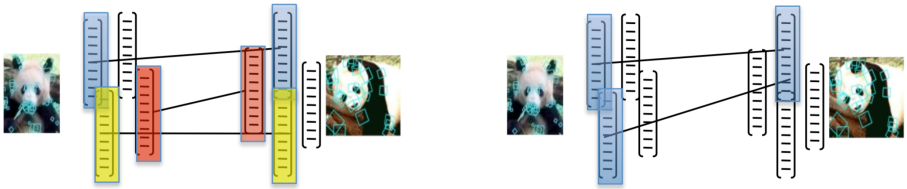
Nearest Neighbor Matching:

- Use each feature in a set to independently index into second set. Any problems you see?

Image Descriptor Matching: Options So Far

Nearest Neighbor Matching:

- Use each feature in a set to independently index into second set. Any problems you see?
- Ignores possibly useful information of co-occurrence $\Longrightarrow$ fails to distinguish between instances where an object has varying numbers of similar features since multiple features may be matched to a single feature in the other set



Source: Alberto Del Bimbo, UNIFI, Italy

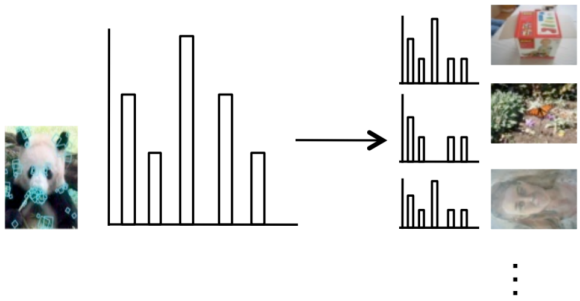
Image Descriptor Matching: Options So Far

Bag-of-Words Matching: Any glaring limitation?

Image Descriptor Matching: Options So Far

Bag-of-Words Matching: Any glaring limitation?

- Can only compare entire images to one another and does not allow partial matchings
- This implies an **all-all** matching; it is often preferable to have a **one-one** matching instead



Source: Alberto Del Bimbo, UNIFI, Italy

Generalizing Descriptor Matching using Kernels[2]

- Consider an image described by a set of n descriptors (features) $X = \{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_n\}$, each of d dimensions

[2] Tolias et al, To Aggregate or Not to aggregate: Selective Match Kernels for Image Search, CVPR 2013

Generalizing Descriptor Matching using Kernels[2]

- Consider an image described by a set of n descriptors (features) $X = \{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_n\}$, each of d dimensions
  - Descriptors typically quantized using k-means clustering
  - Quantizer $q : R^d \rightarrow C \subset R^d$ maps each descriptor to a representative descriptor, a.k.a **visual word**
  - $C = \{\mathbf{c}_1, \mathbf{c}_2, \cdots, \mathbf{c}_k\}$ is a codebook consisting of k visual words.

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  - $C = \{\mathbf{c}_1, \mathbf{c}_2, \cdots, \mathbf{c}_k\}$ is a codebook consisting of k visual words.
- To compare two image representations X and Y, let us define a general family of matching kernels:

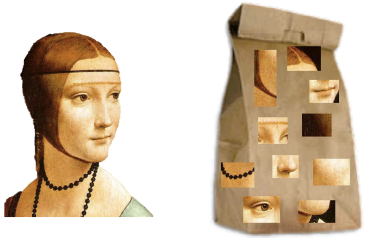
$$K(X, Y) = \gamma(X)\gamma(Y) \sum_{\mathbf{c} \in C} M(X_c, Y_c) \tag{1}$$

where $X_c = \{\mathbf{x} \in X : q(\mathbf{x}) = \mathbf{c}\}$ is the set of descriptors assigned to the same visual word, M is a within-cell matching function, and γ is a normalization function

[2] Tolias et al, To Aggregate or Not to aggregate: Selective Match Kernels for Image Search, CVPR 2013

Bag of Words Matching[3]

Recall: BoW model characterizes an image solely by visual words



- Cosine similarity in BoW model can be defined by defining M as:

$$M(X_c, Y_c) = \sum_{\mathbf{x} \in X_c} \sum_{\mathbf{y} \in Y_c} 1$$

Image Credit: Fei-Fei, Fergus and Torralba, Recognizing and Learning Object Categories, CVPR 2007 Tutorial

[3] Jegou et al, Aggregating local descriptors into a compact image representation, CVPR 2010

Hamming Embedding for Matching[4]

- In addition to being quantized, each descriptor $\mathbf{x}$ is binarized as $\mathbf{b}_x$.
- Score is computed between all pairs of descriptors assigned to the same visual word as:

$$M(X_c, Y_c) = \sum_{\mathbf{x} \in X_c} \sum_{\mathbf{y} \in Y_c} 1[h(\mathbf{b}_x, \mathbf{b}_y) \leq \tau]$$

where $h(\cdot, \cdot)$ is the Hamming distance between two binary vectors, and τ is a threshold to count matched pairs

[4] Jegou et al, Aggregating local descriptors into a compact image representation, CVPR 2010

VLAD Matching[5]

- **Recall:** For each visual word, VLAD performs *pooling* by constructing a vector representing the sum of residuals as:

$$V(X_c) = \sum_{\mathbf{x} \in X_c} r(\mathbf{x}) \qquad \text{where} \qquad r(\mathbf{x}) = \mathbf{x} - q(\mathbf{x})$$

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VLAD Matching[5]

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$$V(X_c) = \sum_{\mathbf{x} \in X_c} r(\mathbf{x}) \qquad \text{where} \qquad r(\mathbf{x}) = \mathbf{x} - q(\mathbf{x})$$

- A $d \times k$ vector is constructed for an image X as follows:

$$V(X) = (V(X_{c_1}), V(X_{c_2}), V(X_{c_3}), .., V(X_{c_k}))$$

- Matching kernel now defined as:

$$M(X_c, Y_c) = V(X_c)^T V(Y_c) = \sum_{\mathbf{x} \in X_c} \sum_{\mathbf{y} \in Y_c} r(\mathbf{x})^T r(\mathbf{y})$$

[5] Jegou et al, Aggregating local descriptors into a compact image representation, CVPR 2010

Aggregated Selective Match Kernel (ASMK)[6]

- ASMK is a combination of two borrowed ideas:
  - Non-linear selective function (from Hamming Embedding)
  - Pooling Residuals (from VLAD)
- Matching kernel M is expressed as:

$$M(X_c, Y_c) = \sigma_\alpha(\hat{V}(X_c)^T \hat{V}(Y_c))$$

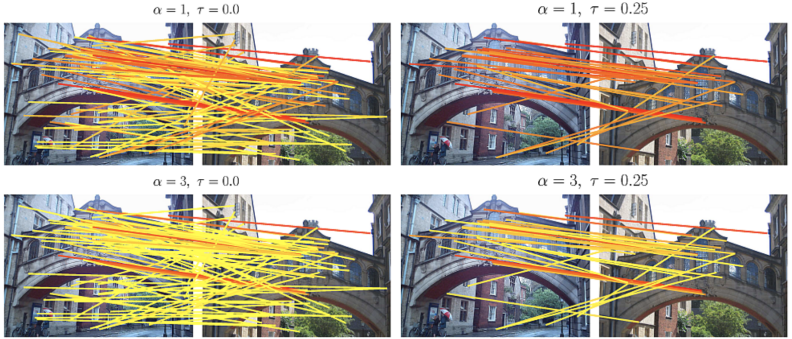
where σ_α is a non-linear function given by:

$$\sigma_\alpha(u) = \begin{cases} \text{sign}(u)|u|^\alpha & \text{if } u > \tau \\ 0 & \text{otherwise} \end{cases}$$

and $\hat{V}(X_c) = V(X_c)/||V(X_c)||$ and $V(X_c)$ is VLAD representation discussed earlier

[6] Tolias et al, To Aggregate or Not to aggregate: Selective Match Kernels for Image Search, CVPR 2013

Aggregated Selective Match Kernel (ASMK)



- ASMK matching with different values of distance threshold and selectivity parameter
- Yellow corresponds to 0 similarity and red to maximum similarity per image pair, as defined by selective function
- Larger selectivity drastically down-weights false correspondences
- This replaces hard thresholding in the Hamming Embedding method

Aggregated Selective Match Kernel (ASMK)

ASMK Example: Each visual word is drawn with a different color

Efficient Match Kernels[7]

- Instead of threshold-based matching functions (as used in HE), we can use a continuous function $\kappa(\mathbf{x}, \mathbf{y})$ and avoid using computationally intensive codebooks:

$$K(X, Y) = \gamma(X)\gamma(Y) \sum_{\mathbf{x} \in X} \sum_{\mathbf{y} \in Y} \kappa(\mathbf{x}, \mathbf{y})$$

- Such a function $K(X, Y)$ can be decomposed into an inner product of $\Phi(X)$ and $\Phi(Y)$
- To do that, we learn a low-dimensional feature map ϕ such that $\kappa(x, y) = \phi(x)^T \phi(y)$ and:

$$K(X, Y) = \left(\gamma(X) \sum_{\mathbf{x} \in X} \phi(x) \right)^T \left(\gamma(Y) \sum_{\mathbf{y} \in Y} \phi(y) \right) = \Phi(X)^T \Phi(Y)$$

[7] Bo and Sminchisescu, Efficient Match Kernels between Sets of Features for Visual Recognition, NeurIPS 2009

Homework

Readings

- Tolias *et al.* To Aggregate or Not to aggregate: Selective Match Kernels for Image Search. CVPR 2013
- Chapter 14.4, Szeliski, *Computer Vision: Algorithms and Applications*

References

Liefeng Bo and Cristian Sminchisescu. "Efficient Match Kernels between Sets of Features for Visual Recognition". In: *Proceedings of the 22nd International Conference on Neural Information Processing Systems*. NIPS'09. Vancouver, British Columbia, Canada: Curran Associates Inc., 2009, 135–143.

H. Jégou et al. "Aggregating local descriptors into a compact image representation". In: *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*. 2010, pp. 3304–3311.

Richard Szeliski. *Computer Vision: Algorithms and Applications*. Texts in Computer Science. London: Springer-Verlag, 2011.

G. Tolias, Y. Avrithis, and H. Jégou. "To Aggregate or Not to aggregate: Selective Match Kernels for Image Search". In: *2013 IEEE International Conference on Computer Vision*. 2013, pp. 1401–1408.

Deep Learning for Computer Vision

Pyramid Matching

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Indian Institute of Technology, Hyderabad

Acknowledgements

- Most of this lecture's slides are based on lectures of **Deep Learning for Vision** course taught by Prof Yannis Avrithis at Inria Rennes-Bretagne Atlantique

Recall: Descriptor Matching

- Given two images with descriptors $X, Y \subset \mathbb{R}^d$, $X_c = \{\mathbf{x} \in X : q(\mathbf{x}) = \mathbf{c}\}$ where q maps vector $\mathbf{x}$ to its nearest centroid, bag-of-words similarity on C is given by:

$$s_{BoW}(X, Y) \propto \sum_{\mathbf{c} \in C} w_c |X_c||Y_C| = \sum_{\mathbf{c} \in C} w_c \sum_{\mathbf{x} \in X_c} \sum_{\mathbf{y} \in Y_c} 1 \tag{1}$$

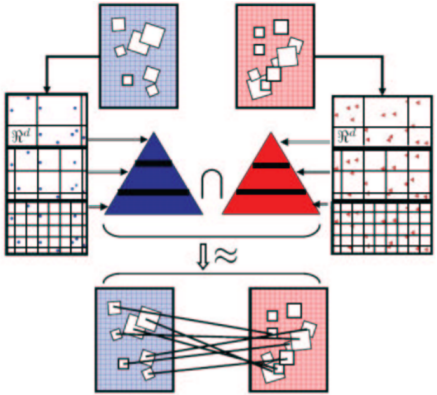
- More general form:

$$K(X, Y) := \gamma(X)\gamma(Y) \sum_{\mathbf{c} \in C} w_c M(X_c, Y_c)$$

where M is a within-cell matching function, and $\gamma(X)$ serves for normalization

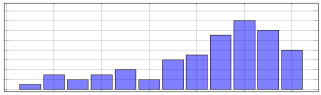
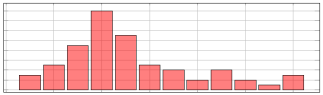
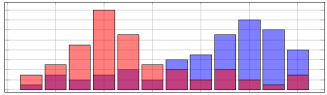
Going Beyond Single-level Matching: Pyramid Match Kernel (PMK)[1]

- **Pyramid matching:** an efficient method that maps unordered feature sets to multi-resolution histograms
- Computes a weighted histogram intersection to find implicit correspondences based on finest resolution histogram cell where a matched pair first appears
- Approximates similarity measured by optimal correspondences between feature sets of unequal cardinality



[1]Grauman and Darrell, The Pyramid Match Kernel: Discriminative Classification with Sets of Image Features, IEEE ICCV 2005, Vol 2, pp. 1458–1465

Histogram Intersection[2]

- Given two histograms $\mathbf{x}, \mathbf{y}$ of b bins each, their **histogram intersection** is:

$$\kappa_{HI}(\mathbf{x}, \mathbf{y}) = \sum_{i-1}^{b} \min(x_i, y_i)$$

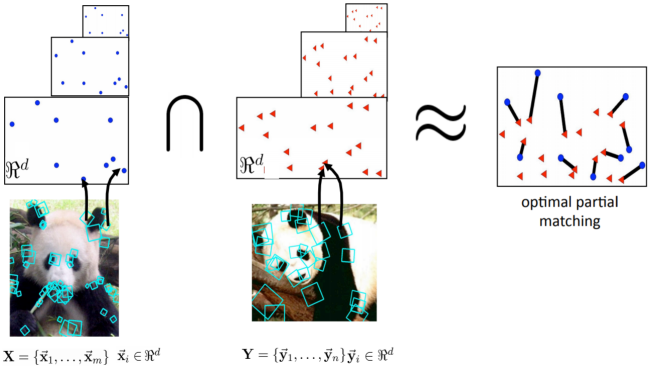
- This is related to L_1 distance as:

$$||\mathbf{x} - \mathbf{y}||_1 = ||\mathbf{x}||_1 + ||\mathbf{y}||_1 - 2\kappa_{HI}(\mathbf{x}, \mathbf{y})$$

[2] Swain and Ballard, Color Indexing, IJCV 1991, pp 11–32

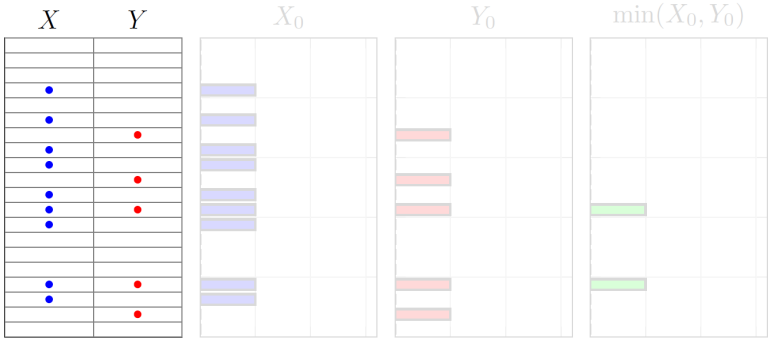
Pyramid Match Kernel (PMK)[3]

Weighted sum of histogram intersections at different levels of two images approximates their optimal pairwise matching



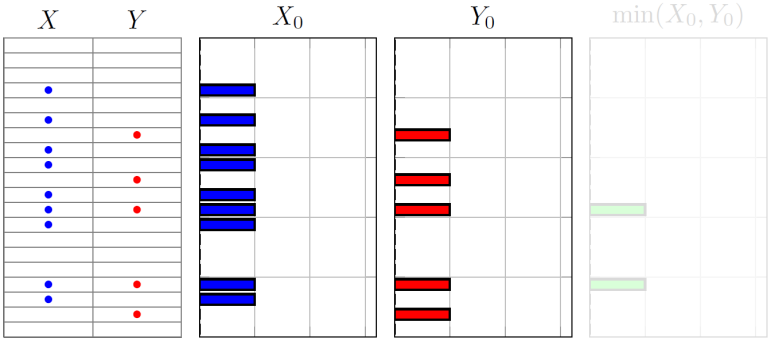
[3] Grauman and Darrell, The Pyramid Match Kernel: Discriminative Classification with Sets of Image Features, IEEE ICCV 2005, Vol 2, pp. 1458–1465

Pyramid Match Kernel: Method



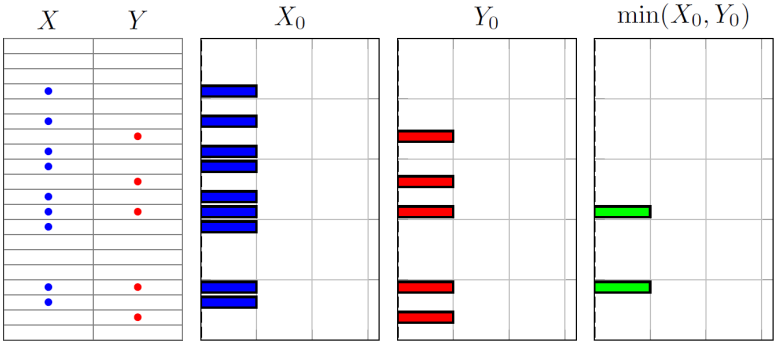
- 1-D point sets X, Y on grid of size 1

Pyramid Match Kernel: Method



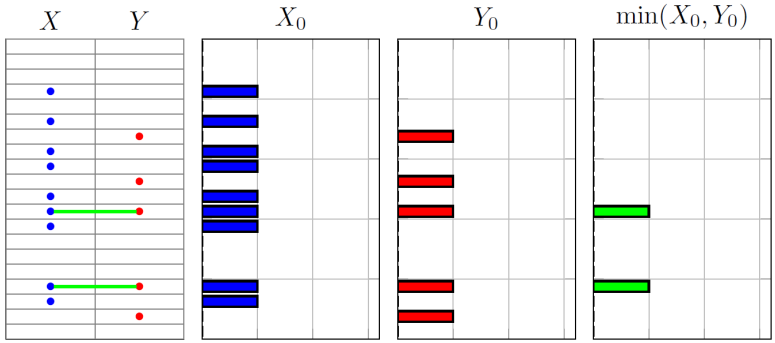
- 1-D point sets X, Y on grid of size 1 - level 0 histograms

Pyramid Match Kernel: Method



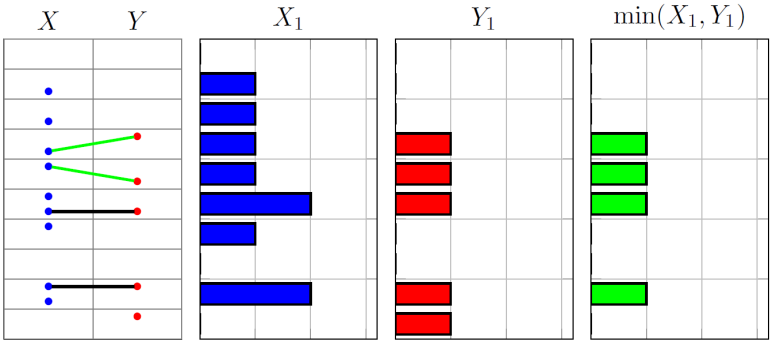
- 1-D point sets X, Y on grid of size 1 - level 0 histograms - intersection

Pyramid Match Kernel: Method



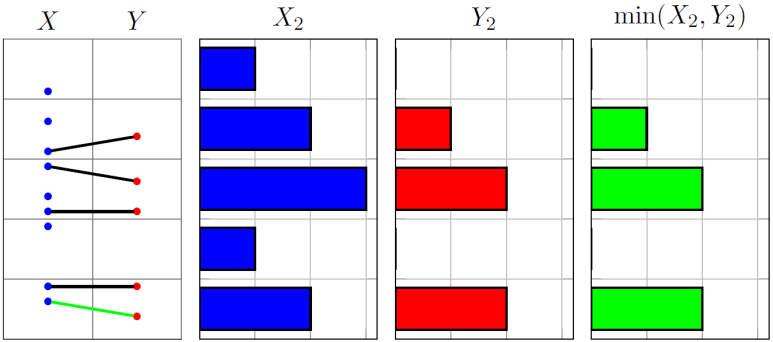
- 1-D point sets X, Y on grid of size 1 - level 0 histograms - intersection
- 2 matches weighted by 1
- Total similarity score: $2 \times 1 = 2$

Pyramid Match Kernel: Method



- 1-D point sets X, Y on grid of size 2 - level 1 histograms - intersection
- (2 matches weighted by 1) + (2 weighted by $\frac{1}{2}$)
- Total similarity score: $2 \times 1 + 2 \times \frac{1}{2} = 3$

Pyramid Match Kernel: Method



- 1-D point sets X, Y on grid of size 4 - level 2 histograms - intersection
- (2 matches weighted by 1) + (2 weighted by $\frac{1}{2}$) + (1 weighted by $\frac{1}{4}$)
- Total similarity score: $2 \times 1 + 2 \times \frac{1}{2} + 1 \times \frac{1}{4} = \mathbf{3.25}$

Pyramid Match Kernel

- Given a set $X = \{\mathbf{x}_1, \cdots, \mathbf{x}_n\} \subset \mathbb{R}^d$, where distances of elements range in $[1, D]$

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- Given two images with descriptors $X, Y \subset \mathbb{R}^d$, their **pyramid match** is:

$$
\begin{aligned}
K_\Delta(X, Y) &= \gamma(X)\gamma(Y) \sum_{i=0}^{L} \frac{1}{2^i} \Bigg(\underbrace{\kappa_{HI}(X_i, Y_i)}_{\text{Matches at this level}} - \underbrace{\kappa_{HI}(X_{i-1}, Y_{i-1})}_{\text{Matches at previous level}} \Bigg) \\
&= \gamma(X)\gamma(Y) \left(\frac{1}{2^L} \kappa_{HI}(X_L, Y_L) + \sum_{i=0}^{L-1} \frac{1}{2^{i+1}} \kappa_{HI}(X_i, Y_i) \right)
\end{aligned}
\tag{2}
$$

where $\gamma(X)$ serves for normalization

Pyramid Match Kernel

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$$= \gamma(X)\gamma(Y) \left(\frac{1}{2^L} \kappa_{HI}(X_L, Y_L) + \sum_{i=0}^{L-1} \frac{1}{2^{i+1}} \kappa_H(X_i, Y_i) \right)$$

where $\gamma(X)$ serves for normalization

Counts number of new pairs matched

PMK is a Positive Definite Kernel

- K_Δ can be written as a weighted sum of κ_{HI} terms, with non-negative coefficients
- κ_{HI} can be written as a sum of min terms
- min can be written as a dot product:

x	$\phi(x)$							
3	1	1	1	0	0	0	0	0
5	1	1	1	1	1	0	0	0
$\min(x, y) = 3$	1	1	1	0	0	0	0	0

- Therefore, so can K_Δ

PMK as an Embedding[4]

- There is an explicit embedding for κ_{HI}, therefore also for K_Δ. What could it be?

[4] Indyk and Thaper, Fast Image Retrieval via Embeddings, WSCTV. 2003

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- If $|X| \leq |Y|$ and $\pi : X \to Y$ is one-to-one, then $K_\Delta(X, Y)$ approximates the optimal pairwise matching:

$$\max_{\pi} \sum_{\mathbf{x} \in X} ||\mathbf{x} - \pi(\mathbf{x})||_1^{-1}$$

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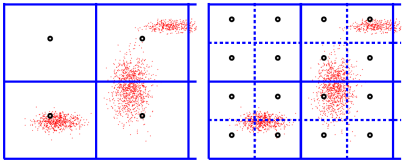
- This is similar to the **Earth mover's distance**:

$$\min_{\pi} \sum_{\mathbf{x} \in X} ||\mathbf{x} - \pi(\mathbf{x})||_1$$

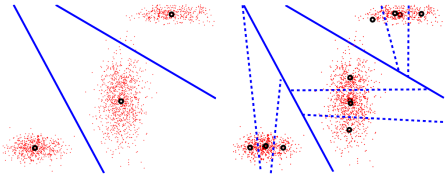
- But PMK is a *similarity* measure; it allows partial matching and does not penalize clutter, except for the normalization

[4] Indyk and Thaper, Fast Image Retrieval via Embeddings, WSCTV. 2003

PMK and Vocabulary Tree[5]



Uniform bins

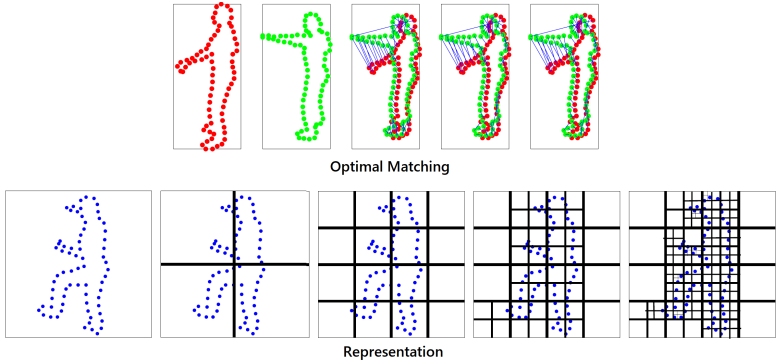


Vocabulary-guided bins

- Replace regular grid with hierarchical vocabulary cells
- Compared to vocabulary tree, there is a principle in assigning cell weights
- Still, its approximation quality can suffer at high dimensions

[5] Grauman and Darrell, Approximate Correspondences in High Dimensions, NeurIPS 2007

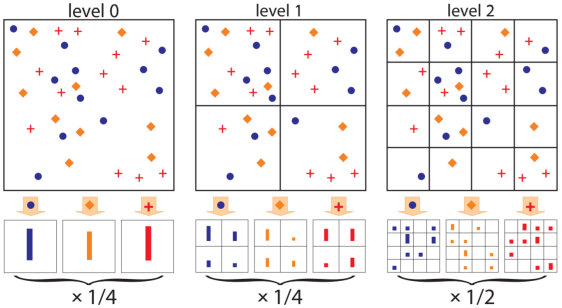
PMK and Spatial Matching[6]



- Same idea, applied to image 2-D coordinate space for spatial matching
- Matching cost is only based on point coordinates; No appearance

[6] Grauman and Darrell, Fast Contour Matching Using Approximate Earth Mover's Distance, CVPR 2004

Spatial Pyramid Matching (SPM)[7]

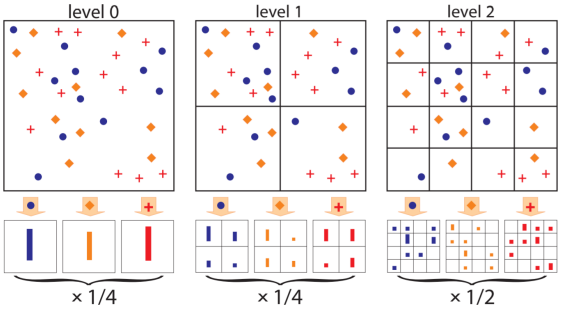


- If $X^{(j)}, Y^{(j)}$ are the feature coordinates of images X, Y with descriptors assigned to visual word j,

$$K_{SP}(X, Y) = \sum_{j=1}^{k} K_{\Delta}(X^{(j)}, Y^{(j)})$$

[7] Lazebnik et al, Beyond Bags of Features: Spatial Pyramid Matching for Recognizing Natural Scene Categories, CVPR 2006

Spatial Pyramid Matching (SPM)[7]



- Coupled with BoW, it is a set of joint appearance-geometry histograms
- Robust to deformation but not invariant to transformations; Applied for global scene classification

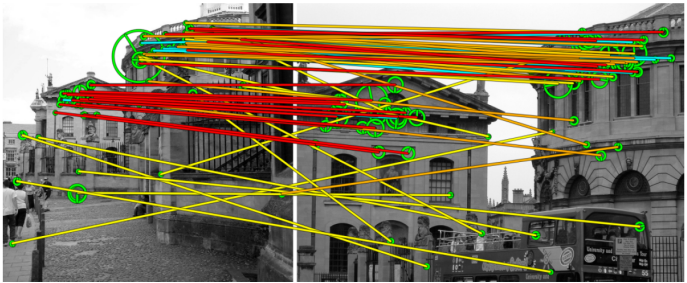
[7] Lazebnik et al, Beyond Bags of Features: Spatial Pyramid Matching for Recognizing Natural Scene Categories, CVPR 2006.

Hough Pyramid Matching (HPM)[8]

Fast Pyramid Matching

[8] Tolias and Avrithis, Speeded-up, relaxed spatial matching, ICCV 2011

Hough Pyramid Matching (HPM)[8]



Hough Pyramid Matching

- Work with a single set of correspondences instead of two sets of features
- Determine a transformation hypothesis by a pair of features and then use histograms to collect votes in the transformation space

[8] Tolias and Avrithis, Speeded-up, relaxed spatial matching, ICCV 2011

Hough Pyramid Matching

- A **local feature** p in image P has position $\mathbf{t}(p)$, scale $s(p)$ and orientation $\theta(p)$ given by matrix $R(p) \in \mathbb{R}^{2\times 2}$:

$$F(p) = \begin{pmatrix} s(p)R(p) & \mathbf{t}(p) \\ \mathbf{0}^\intercal & 1 \end{pmatrix}$$

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$$F(p) = \begin{pmatrix} s(p)R(p) & \mathbf{t}(p) \\ \mathbf{0}^\intercal & 1 \end{pmatrix}$$

- A **correspondence** $c = (p, q)$ is a pair of features $p \in P$, $q \in Q$ of two images P, Q and determines relative similarity transformation from p to q:

$$F(c) = F(q)F(p)^{-1} = \begin{pmatrix} s(c)R(c) & \mathbf{t}(c) \\ \mathbf{0}^\intercal & 1 \end{pmatrix}$$

with translation $\mathbf{t}(c) = \mathbf{t}(q) - s(c)R(c)\mathbf{t}(p)$, relative scale $s(c) = s(q)/s(p)$ and rotation $R(c) = R(q)R(p)^{-1}$ or $\theta(c) = \theta(q) - \theta(p)$

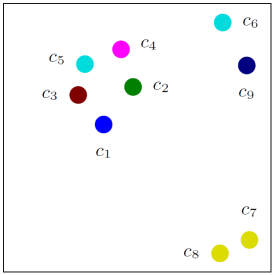
Hough Pyramid Matching

- The 4-DoF relative transformation represented by 4-D vector:

$$f(c) = (\mathbf{t}(c), s(c), \theta(c))$$

- To enforce one-to-one mapping, two correspondences $c = (p, q)$ and $c^{'} = (p^{'}, q^{'})$ are said to be **conflicting** if they refer to the same feature on either image, i.e., $p = p^{'}$ or $q = q^{'}$

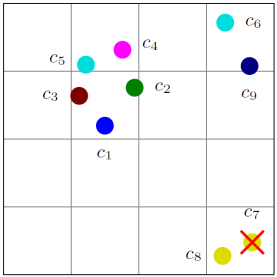
Hough Pyramid Matching



	p	q	similarity score
c_1			$(2+\frac{1}{2}2+\frac{1}{4}2)w(c_1)$
c_2			$(2+\frac{1}{2}2+\frac{1}{4}2)w(c_2)$
c_3			$(2+\frac{1}{2}2+\frac{1}{4}2)w(c_3)$
c_4			$(1+\frac{1}{2}3+\frac{1}{4}2)w(c_4)$
c_5			$(1+\frac{1}{2}3+\frac{1}{4}2)w(c_5)$
c_6			0
c_7			0
c_8			$(\frac{1}{4}6)w(c_8)$
c_9			$(\frac{1}{4}6)w(c_9)$

- Correspondence c weighted by $w(c)$, based e.g. on visual word

Hough Pyramid Matching



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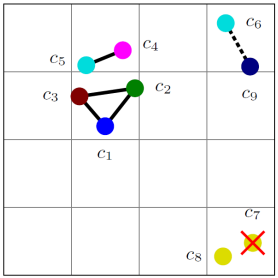
- Correspondence c weighted by $w(c)$, based e.g. on visual word
- Conflicting correspondences in same bin are **erased**

Hough Pyramid Matching



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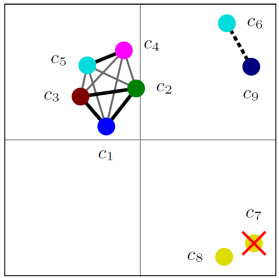
- Correspondence c weighted by $w(c)$, based e.g. on visual word
- Conflicting correspondences in same bin are **erased**
- In bin b with n_b correspondences, each correspondence groups with $[n_b - 1]_+$ others
- Level 0 Weight 1

Hough Pyramid Matching



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- Correspondence c weighted by $w(c)$, based e.g. on visual word
- Conflicting correspondences in same bin are **erased**
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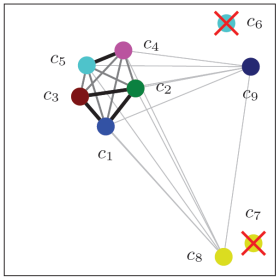
- Level 1 Weight $\frac{1}{2}$

Hough Pyramid Matching



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- Conflicting correspondences in same bin are **erased**
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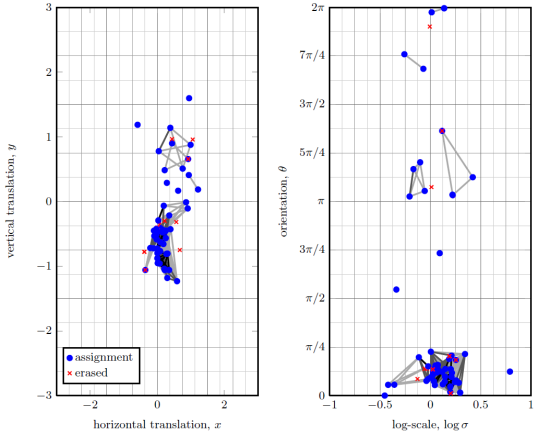
- Level 2 Weight $\frac{1}{4}$

Hough Pyramid Matching



- *Mode Seeking:* We are looking for regions where density is maximized in transformation space

Hough Pyramid Matching

- Linear in number of correspondences; no need to count inliers
- Robust to deformations and multiple matching surfaces, invariant to transformations
- Only applies to same instance matching

Homework

Readings

- Chapter 16.1.4, Forsyth and Ponce, *Computer Vision: A Modern Approach (2nd ed.)*

Other Resources

- Pyramid Match Kernel project page

References


Michael J. Swain and Dana H. Ballard. "Color Indexing". In: *Int. J. Comput. Vision* 7.1 (Nov. 1991), 11–32.


Piotr Indyk and Nitin Thaper. "Fast Image Retrieval via Embeddings". In: *WSCTV*. 2003.


Kristen Grauman and Trevor Darrell. "Fast Contour Matching Using Approximate Earth Mover's Distance". In: *IEEE CVPR*. Oct. 2004, pp. I–220.


K. Grauman and T. Darrell. "The Pyramid Match Kernel: Discriminative Classification with Sets of Image Features". In: *IEEE ICCV*. Nov. 2005, Vol 2, pp. 1458–1465.


Svetlana Lazebnik, Cordelia Schmid, and J. Ponce. "Beyond Bags of Features: Spatial Pyramid Matching for Recognizing Natural Scene Categories". In: *IEEE CVPR*. Vol. 2. Feb. 2006, pp. 2169 –2178.


Kristen Grauman and Trevor Darrell. "Approximate Correspondences in High Dimensions". In: *Neural Information Processing Systems*. 2007.


Giorgos Tolias and Yannis Avrithis. "Speeded-up, relaxed spatial matching". In: *IEEE ICCV*. 2011, pp. 1653–1660.


David Forsyth and Jean Ponce. *Computer Vision: A Modern Approach*. 2 edition. Boston: Pearson Education India, 2015.

Deep Learning for Computer Vision

Transitioning From Traditional Vision to Deep Learning

Vineeth N Balasubramanian

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Indian Institute of Technology, Hyderabad

Summarizing Topics So Far

Fundamental Operations

- **Convolution** is a unique operation
  - linear, shift-invariant
  - *Useful properties:* Commutative, Associative, Distributive (over addition)
- Forms basis of image operations and even modern-day neural networks working on images

Summarizing Topics So Far

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Common Pipeline in Traditional Vision Tasks

- Extract corners or patches in images $\rightarrow$ Extract descriptors
- Use banks of filters, such as Steerable filters or Gabor filters
- Use descriptors for tasks such as retrieval, matching or classification

Traditional Vision: High-level Abstractions

Image-Level Understanding

- Going from low-level image understanding to aggregation of descriptors
- Banks of filters capture responses at different scales and orientations
- Histograms can be viewed as "*encoding*" and "*pooling*"
- Similarities to the human visual system

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Local Features/Understanding

- Not all spatial regions important, depends on task (stereopsis, motion estimation, instance recognition compared to class recognition)
- Encoding makes features sparse
  - Many words in BoW have zero count
- Operators that detect local features can be viewed as "*convolution*" followed by some kind of "*competition*"

Traditional Vision: High-level Abstractions

Representing Images/Regions as Descriptors

- Learn descriptors/representations such that dot product is good enough for matching
- Some invariance to geometric transformations, designed or learned in certain cases

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Moving on to Deep Learning...

Although not by design, Deep Learning seems to build on some of the above principles, but in a learnable manner...we will see soon