Description, detection and matching of image features – SIFT and Nearest Neighbor Search

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Outline:

I. the **S**cale **I**nvariant **F**eature **T**ransform (SIFT)

a) feature detection in scale-space

b) descriptor construction

II. extending SIFT using PCA

a) introduction to **P**rincipal **C**omponent **A**nalysis

b) the PCA-reduced SIFT descriptor

c) comparison of SIFT and PCA-SIFT

III. identifying objects using approximate nearest neighbor search

a) building a database of object features

b) matching features to the database

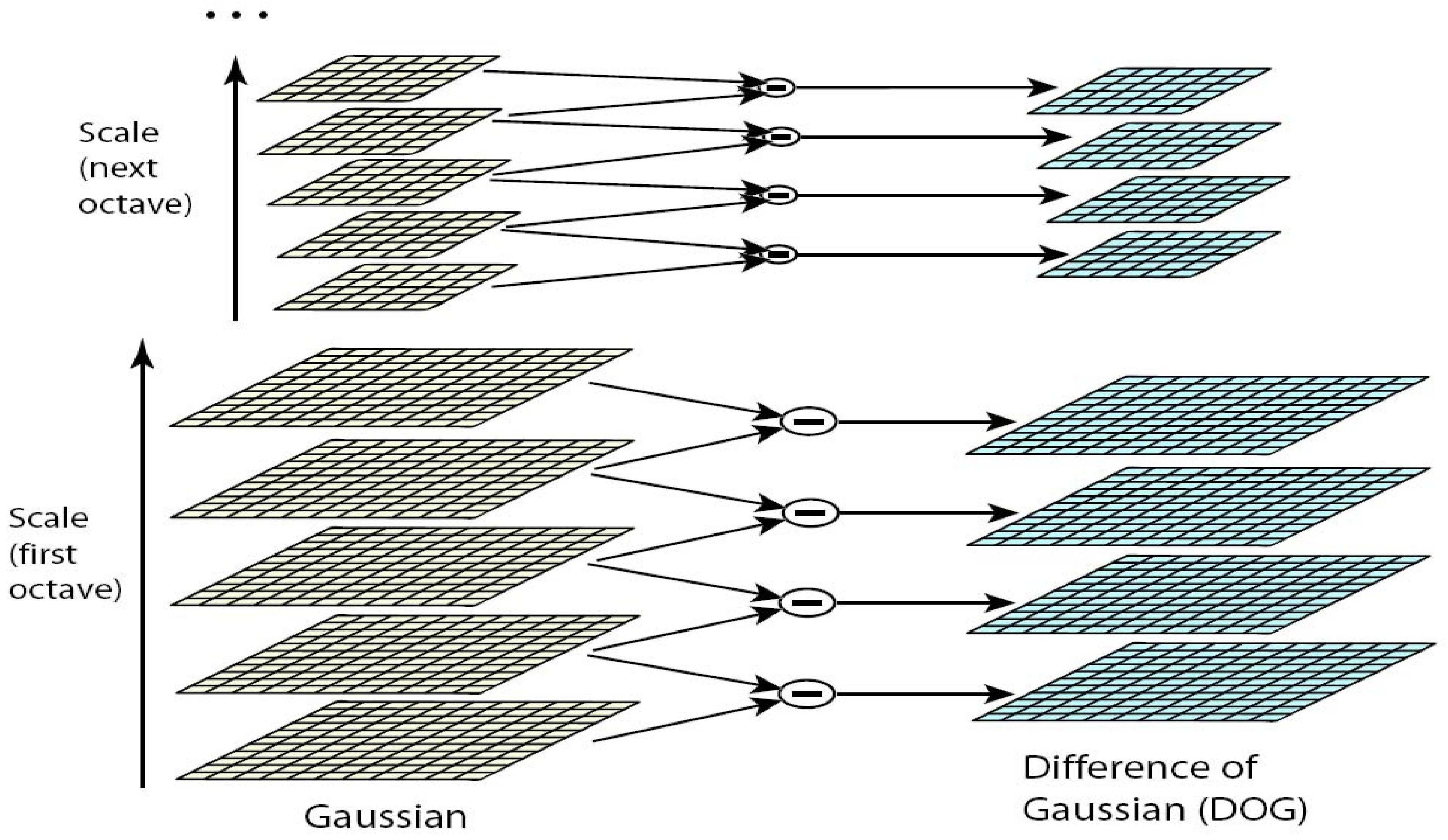
The **S**cale **I**nvariant **F**eature **T**ransform (SIFT)

- Attributes of the SIFT descriptor:
  - Invariant to location, rotation and scale
  - Also invariant to linear changes in lighting
  - Not fully affine invariant

- The steps of building a SIFT-descriptor
  1. Keypoint localization in scale-space
  2. Elimination of weak keypoints
  3. Assigning rotation
  4. Construction of the descriptor

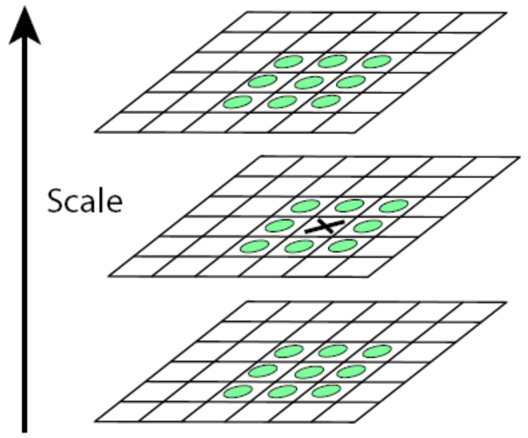
SIFT – keypoint detection

- Scale invariance is obtained by searching for features in scale-space
- Decreasing scale is simulated by repeatedly applying Gaussian blurring to the image
- Subtracting each image from its direct neighbors generates a series of Difference-of-Gaussian images that are a close approximation to LoG


. . .
Scale (next octave)
Scale (first octave)
Gaussian
Difference of Gaussian (DOG)

SIFT – keypoint detection

- Detect keypoint candidates by comparing each point to its 8 neighbors on the same scale and each of its 9 neighbors one scale up and down



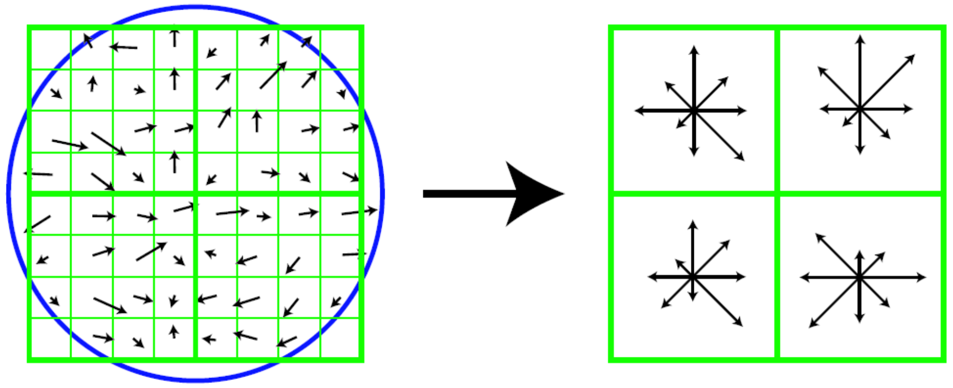
- Every point that is bigger or smaller than each of its neighbors is a keypoint candidate
- Eliminate candidates that are located on an edge or have poor contrast
- Instead of using this detection method, every other detector supplying a location and scale can be utilized

SIFT – orientation invariance

- An orientation histogram with 36 bins is computed from the image gradients around the keypoint
- The maximum orientation is assigned to this keypoint
- For each other orientation within 80% of the maximum orientation, a new keypoint with this orientation is created
- Each keypoint is rotated in direction of its orientation thus normalizing it

SIFT – descriptor construction

- The area around the keypoint is divided into 4 x 4 subregions



- Build an orientation histogram with 8 bins for each subregion; gradient values are weighted by a Gaussian window
- This results in a vector with 128 dimensions (4 x 4 x 8)
- Normalize this vector to unit length (grants invariance to multiplicative changes in lighting)

PCA – **P**rincipal **C**omponent **A**nalysis

- Used to lower the dimensionality of a dataset with a minimal information loss
- Chooses a new coordinate system with the first axis pointing in direction of the greatest variance in the dataset; accordingly for second, third, ... axis
- By eliminating axis with a low variance, the dimensionality is reduced but only little information is lost
- Mathematically this is done by a eigenvector decomposition of the covariance matrix of this dataset

PCA-SIFT: a dimensionality reduced descriptor

- Due to its high dimensionality and the computational cost caused by this, PCA can greatly improve SIFT
- PCA-SIFT replaces the original SIFT-descriptor
- The matrix used to project into the PCA-based n dimensional space will be called projection matrix
- The steps to creating a PCA-SIFT-descriptor are:

    1. Compute or load a projection matrix
    2. Detect keypoints
    3. Project the image patch around the keypoint by multiplying it with the projection matrix

PCA-SIFT: computing a projection matrix

- Select a representative set of pictures and detect all keypoints in these pictures
- For each keypoint:
  - Extract an image patch around it with size 41 x 41 pixels
  - Calculate horizontal and vertical gradients, resulting in a vector of size 39 x 39 x 2 = 3042
- Put all these vectors into a k x 3042 matrix A where k is the number of keypoints detected
- Calculate the covariance matrix of A:

$$A = A - mean(A)$$

$$cov A = A^T A$$

PCA-SIFT: computing a projection matrix

- Compute the eigenvectors and eigenvalues of covA
- Select the first n eigenvectors; the projection matrix is a n x 3042 matrix composed of these eigenvectors
- n can either be a fixed value determined empirically or set dynamically based on the eigenvalues
- The projection matrix is only computed once and saved

PCA-SIFT: building the descriptor

- Input: a keypoint location in scale-space and an orientation
- Extract a 41 x 41 patch around the keypoint at the given scale, rotated to its orientation
- Calculate 39 x 39 horizontal and vertical gradients, resulting in a vector of size 3042
- Multiply this vector using the precomputed n x 3042 projection matrix
- This results in a PCA-SIFT descriptor of size n

Comparison of SIFT and PCA-SIFT

- SIFT:
  - • Dimensions: 128
  - - High dimensionality
  - - not fully affine invariant
  - + less empiric knowledge required
  - + easier implementation
- PCA-SIFT:
  - • Dimensions: variable, recommended is 20 or less
  - - not fully affine invariant
  - - projection matrix needs representative set of pictures; this matrix will then only work for pictures of this kind
  - + lower dimensionality while retaining distinctiveness leads to greatly reduced computational cost

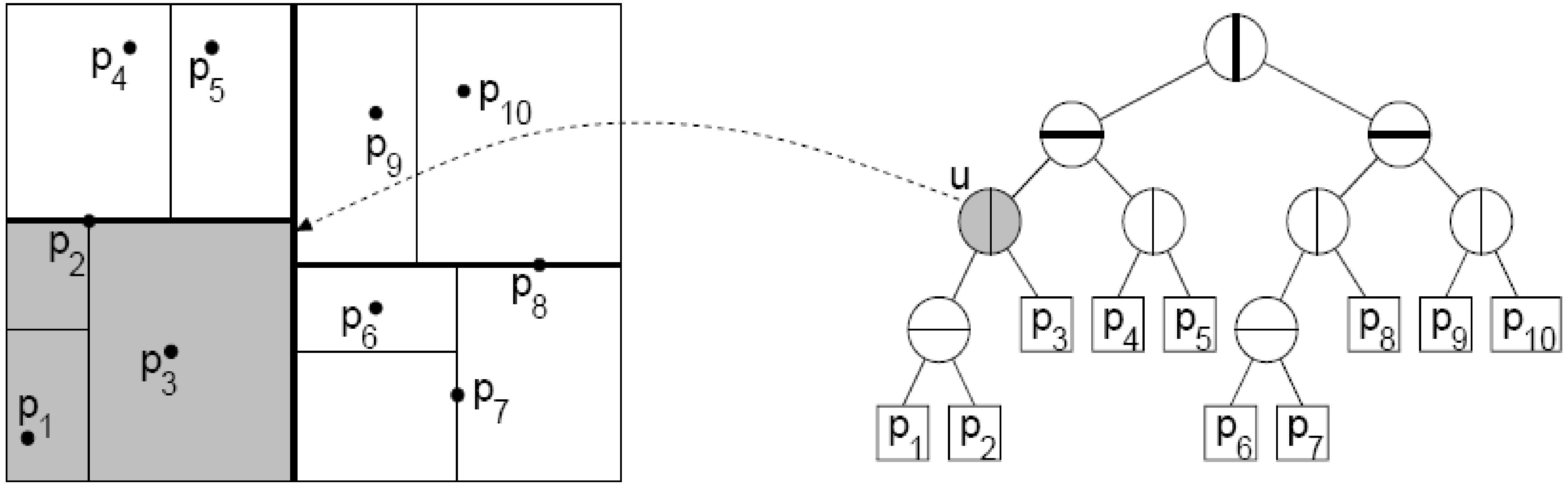
Approximate nearest neighbor search

- To finally identify objects, we need to match features extracted from real-time pictures to a database with features from these objects
- Algorithms used for nearest neighbor search are exponential in the dimensionality of the search-space
- If we allow a small error to be made, the search time can be significantly reduced
- Since the input data contains errors anyway, this will not greatly impair matching quality
- Our project uses the ANN-library by *David M. Mount* and *Sunil Arya*

Building the database

- A set of pictures from the object to be detected is scanned for features; every feature is treated as a point in multi-dimensional space
- The ANN-library provides two types of binary trees for data storage:
  - kd-trees: the root node is the smallest hypercube containing all points; each node that contains more than a given number of points is divided into two child-nodes based on a splitting rule
  - bd-trees: same as kd-trees, in addition these may decide to shrink the hypercubes instead of splitting them
- The main problems arise from highly clustered points

Example tree



The tree starts with a hypercube containing all points

Every node that has more than one point in it is split along the dimension of maximum spread at the median

Points that lie on a line may be counted to either adjacent node

Searching the database

- The database can be searched for the k nearest neighbors of a point, making a maximum error of a factor (1 + ε)
- ANN implements two possible search strategies:
  - **Standard search:** requires less memory but may take longer
  - **Priority search:** uses a priority queue to speed up searching
- Querying for more than one nearest neighbor does not increase searchtime but helps estimating the quality of the matches

Thank you for your attention!