

Computer Vision Systems Programming VO

Image Processing Recap

Christopher Pramerdorfer

Computer Vision Lab, Vienna University of Technology

Topics

Brief *Image Processing* (IP) recap

Assuming you are already familiar with it



Images from Prince 2012

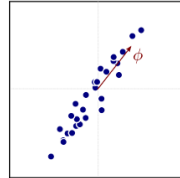


Image Processing Recap

We use IP to extract good features from images

- ▶ Preprocessing step for CV
- ▶ IP has great influence on CV performance

What are good features? More on this later

Let's recap some basic IP methods

- ▶ No details, this is not an IP lecture

Linear Filtering

Used for many low-level tasks

Pixel values are linear combination of neighbor values

Computed via *convolution* (or correlation) with kernel h

Different responses depending on kernel

$$f'(x, y) = \sum_{i,j} f(x - i, y - j)h(i, j)$$

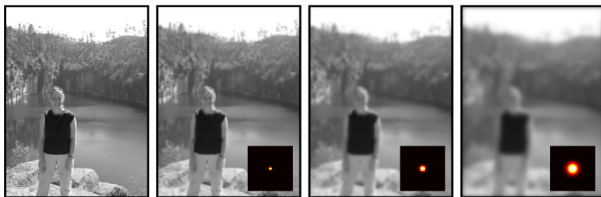
Linear Filtering

Noise Reduction

Gain robustness to noise via image blurring

Can be performed by using a 2D Gaussian as kernel h

$$h(i, j) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{i^2 + j^2}{2\sigma^2}\right)$$



Images from Prince 2012

Linear Filtering

Detecting Brightness Changes – LoG Filter

Brightness changes can be valuable information

- ▶ Object boundaries, textured regions

Use a Laplacian of Gaussian (LoG) filter as kernel h

- ▶ Gaussian for noise reduction
- ▶ Laplacian approximates $\nabla^2 = f_{xx} + f_{yy}$

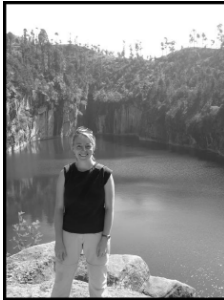
LoG filters respond to intensity changes

- ▶ Regardless of direction
- ▶ At a frequency defined by σ of Gaussian

Linear Filtering

Detecting Brightness Changes – LoG Filter

Bright and dark regions indicate brightness changes



Images from Prince 2012

Linear Filtering

Detecting Brightness Changes – Gabor Filter

Direction of brightness changes can be valuable

- ▶ Texture characteristics

Use a Gabor filter as kernel h , which consists of

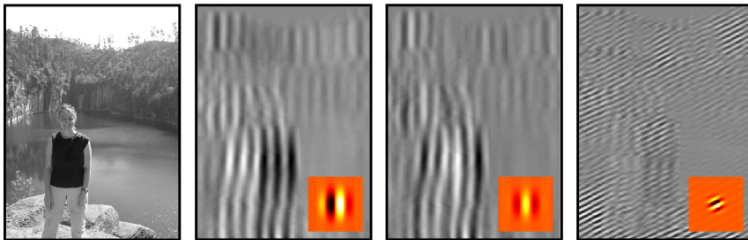
- ▶ A Gaussian for noise reduction
- ▶ A Sinusoid for change detection

Gabor filters respond to intensity changes at a

- ▶ Phase and orientation defined by the Sinusoid
- ▶ Frequency defined by the Gaussian and Sinusoid

Linear Filtering

Detecting Brightness Changes – Gabor Filter



Images from Prince 2012

Interest Point Detection

Interest points (keypoints) are

- ▶ Distinctive locations in images
- ▶ Invariant and robust to image transformations

Can be detected reliably in multiple images of same object

- ▶ Used for object detection, structure from motion

Interest Point Detection

SIFT Keypoints

Scale invariant blob detector

- ▶ A *blob* is an image region with similar intensity

Blob detection accomplished via LoG filtering

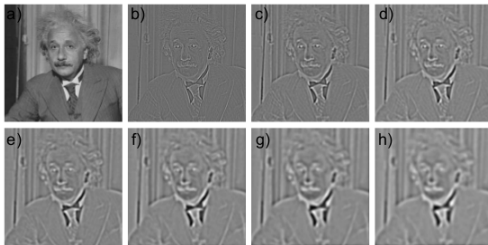
- ▶ LoG filter responds to blobs of size that depends on σ

Scale invariance is achieved by

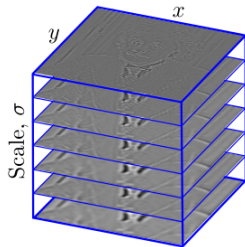
- ▶ Applying LoG filter with multiple σ
- ▶ Finding local maxima in resulting scale-space

Interest Point Detection

SIFT Scale Space



Images from Prince 2012



Interest Point Detection

SIFT Keypoints

Found local maxima are

- ▶ Discarded unless on image corners
- ▶ Assigned an orientation via gradient histograms (slide 15)

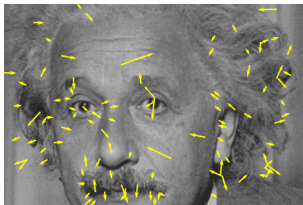


Image from Prince 2012

Local Descriptors

Compact representations of contents of an image region

Usually computed at interest point locations

Invariant in conjunction with suitable interest points

Pool information locally to achieve robustness

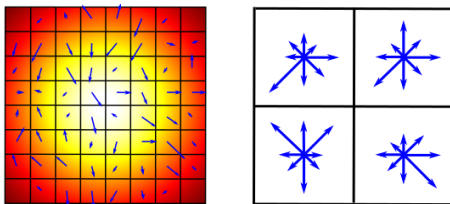
Local Descriptors

SIFT Descriptor

Computed from gradient histograms

Usually used together with SIFT interest points

- Compensate for scale, rotation



Images from Prince 2012

Local Descriptors

SIFT Descriptor

SIFT descriptors are

- ▶ Invariant to scale and rotation (interest points)
- ▶ Invariant to global intensity changes (gradients)
- ▶ Robust to small affine transformations (pooling)

Dimensionality Reduction

Reduce the dimensionality of x by removing irrelevant features

- ▶ Irrelevant means redundant or not discriminative (e.g. noise)

Advantages

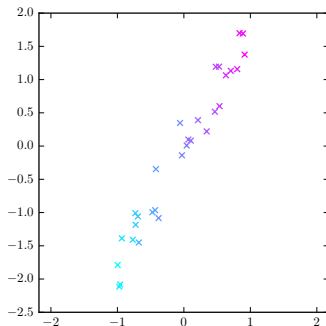
- ▶ We get a better x automatically
- ▶ Facilitates data visualization

Dimensionality Reduction

PCA

Assume the following data (30 samples $\mathbf{x}_1 \cdots \mathbf{x}_{30}$, $\dim(\mathbf{x}) = 2$)

- Features are highly correlated

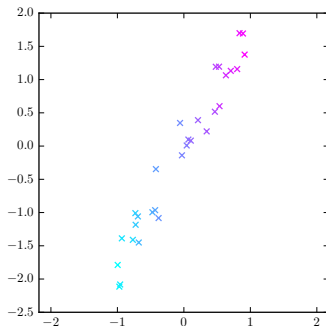


Dimensionality Reduction

PCA

We want to map the \mathbf{x}_k to a linear subspace

Spanned by directions of largest data variation



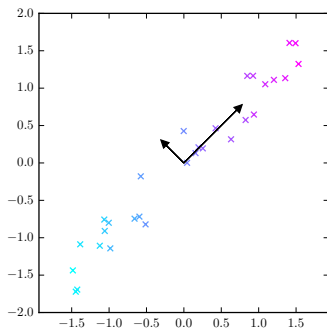
Dimensionality Reduction

PCA

Standardize individual features (zero mean, unit stddev)

Compute covariance matrix Σ

- Eigenvectors $\mathbf{u}_1, \mathbf{u}_2$ of Σ are sought direction vectors

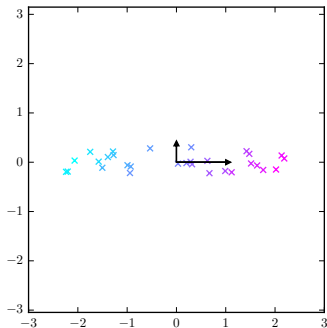


Dimensionality Reduction

PCA

Represent \mathbf{x}_k in the $U = (\mathbf{u}_1, \mathbf{u}_2)$ basis, $\mathbf{x}_k^r = U^\top \mathbf{x}_k$

- $\mathbf{u}_1, \mathbf{u}_2$ are orthogonal, so U is a rotation matrix

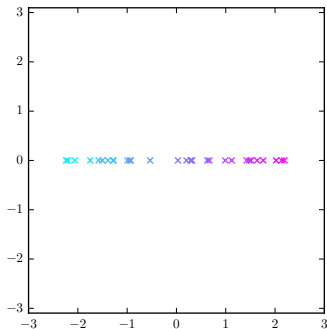


Dimensionality Reduction

PCA

Now we can simply drop features that vary little

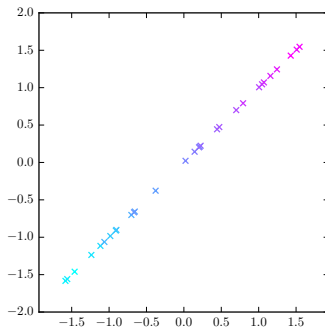
- ▶ Encoded by the corresponding eigenvalues λ_1, λ_2



Dimensionality Reduction

PCA

If desired we can approximate \mathbf{x}_k by multiplying with U



Dimensionality Reduction

PCA

This method is called *Principal Component Analysis (PCA)*

Used to find features that retain e.g. 99% of variance

- ▶ Often leads to a significant dimensionality reduction

Used to perform *whitening*

- ▶ To obtain uncorrelated features with same variance
- ▶ Needed by some ML algorithms

Prince, S.J.D. (2012). *Computer Vision: Models Learning and Inference*. Cambridge University Press.