Computer Vision Systems Programming VO

Image Processing Recap

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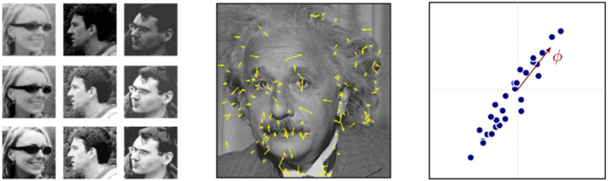
Topics

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

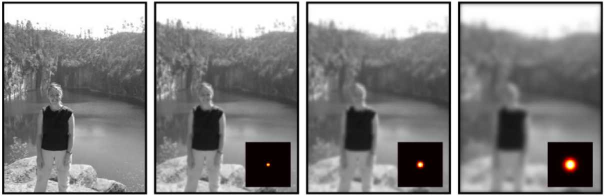
Different responses depending on kernel

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

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

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

Bright and dark regions indicate brightness changes

Images from Prince 2012

Direction of brightness changes can be valuable

- Texture characteristics

Use a Gabor filter as kernel h, which consists of

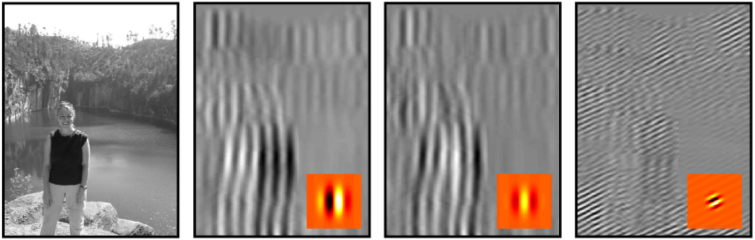
- A Gaussian for noise reduction
- A Sinusoid for change detection

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

Scale invariant blob detector

- A blob is an image region with similar intensity

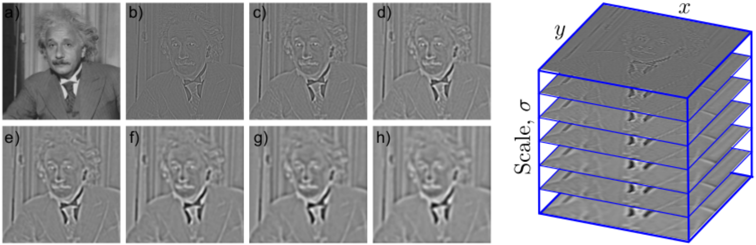
Blob detection accomplished via LoG filtering

- 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

Found local maxima are

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

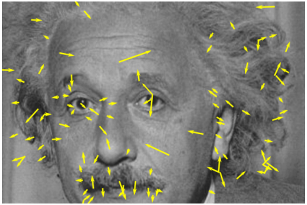


Image from Prince 2012

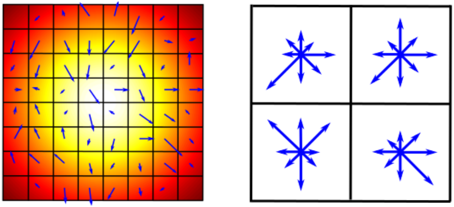
Local Descriptors

- 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

Computed from gradient histograms

Usually used together with SIFT interest points

- Compensate for scale, rotation



Images from Prince 2012

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 $\mathbf{x}$ by removing irrelevant features

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

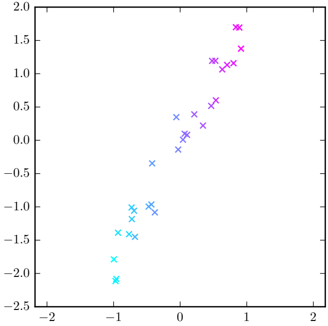
Advantages

- We get a better $\mathbf{x}$ automatically
- Facilitates data visualization

Dimensionality Reduction
PCA

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

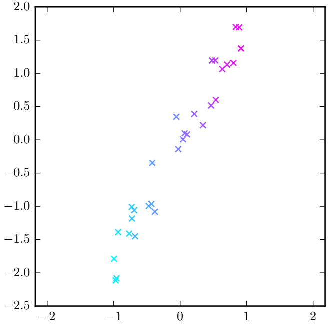
- Features are highly correlated



Dimensionality Reduction
PCA

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

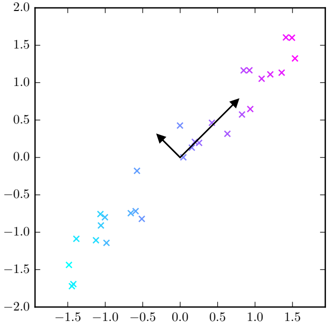
Spanned by directions of largest data variation



Standardize individual features (zero mean, unit stddev)

Compute covariance matrix Σ

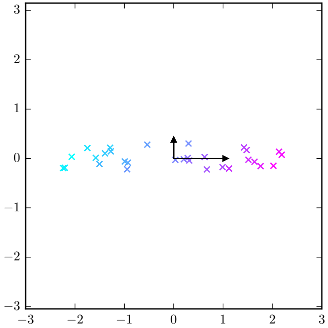
- Eigenvectors $\mathbf{u}_1, \mathbf{u}_2$ of Σ are sought direction vectors



Dimensionality Reduction
PCA

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

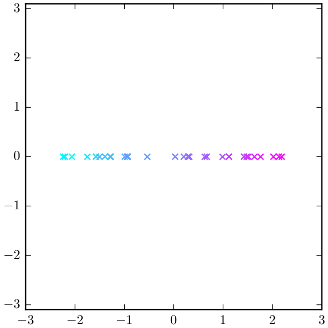
- $\mathbf{u}_1, \mathbf{u}_2$ are orthogonal, so U is a rotation matrix



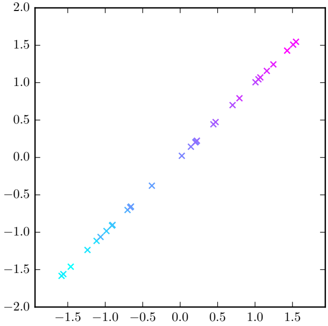
Dimensionality Reduction
PCA

Now we can simply drop features that vary little

- Encoded by the corresponding eigenvalues λ_1, λ_2



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



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

Bibliography

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