Filters in Image Processing

Analysing Images through Visual Descriptors

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May 14, 2018

Outline

1. Motivation

2. Basic idea for image descriptors

3. Image classification

4. Most common image descriptors
   - Haralick features
   - Local binary patterns (LBP)
   - MPEG-7 descriptors
   - Scale-invariant feature transform (SIFT)
   - Zernike features
   - Moment invariants

Motivation

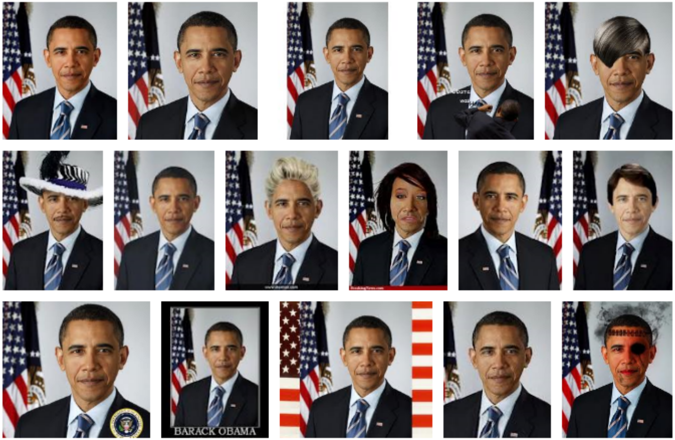
- Unknown image
- No meta information
- How to determine, what is in the image?

Motivation

- Results of a Google search for keyword '*obama*' (from Nov. 2011)

Motivation

- Results of searching for visually similar images of the official photo of president Obama (from Nov. 2011)



Basic idea for image descriptors

What are image descriptors?

- a smaller (a shorter) form of an image, which encodes some important image characteristics
- this image form is used in image recognition tasks including
  - comparing images
  - finding similar images
  - distinguish images

Desired properties

- fast computation (real-time tasks)
- invariance to scale, rotation, and distortion changes

Basic idea for image descriptors

Feature extraction
(via image descriptors)

$$\Rightarrow \begin{pmatrix} 135 \\ 94 \\ . \\ . \\ 102 \end{pmatrix}$$

$$\Rightarrow \begin{pmatrix} 132 \\ 91 \\ . \\ . \\ 103 \end{pmatrix}$$

$$\Rightarrow \begin{pmatrix} 32 \\ 59 \\ . \\ . \\ 10 \end{pmatrix}$$

Similarity evaluation
(image classification)

$$\begin{pmatrix} 135 \\ 94 \\ . \\ . \\ 102 \end{pmatrix} \overset{?}{\approx} \begin{pmatrix} 132 \\ 91 \\ . \\ . \\ 103 \end{pmatrix}$$

$$\begin{pmatrix} 135 \\ 94 \\ . \\ . \\ 102 \end{pmatrix} \overset{?}{\approx} \begin{pmatrix} 32 \\ 59 \\ . \\ . \\ 10 \end{pmatrix}$$

Image classification

Image classification

- includes a broad range of approaches to the identification of images.
- analyses the numerical properties of various image features and organizes data into categories – image classes (clusters).
- compares the feature vectors using a chosen metric $\Rightarrow$ close objects in feature space are considered visually similar and form clusters.

Image classes may be

- specified a priori by an analyst – supervised classification
- clustered automatically – unsupervised classification

Classification algorithms typically employ two phases

- *training phase* – a unique description of each classification category (training class) is created
- *testing phase* – feature-space partitions are used to classify image features

Image classification

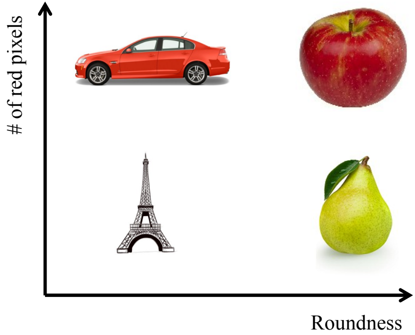
Most common classification methods

- *Cluster Analysis* – unsupervised method *k-means clustering*
- *Decision Trees* – non-parametric supervised method
- *Neural Networks* – statistical learning algorithms for supervised classification
- *Support Vector Machine (SVM)* – supervised classification, very popular
- *k-Nearest Neighbours algorithm (k-NN)* – simple, non-parametric, supervised method
- *Convolutional Neural Networks (CNN)* – learning based method

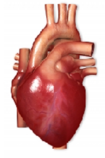
Image classification

Simple example: feature vector has 2 components

1. Roundness – x-axis
2. # of red pixels – y-axis



- What would be the feature vector of this query image?



Haralick features

- introduced in 1973 by Professor Haralick (see photo) from City University of New York
- popular approach for texture analysis
- Haralick features are still used in research
- based on so called *co-occurrence matrix*

Co-occurrence matrix

- is the distribution of co-occurring values at a given offset
- mathematically, the co-occurrence matrix C is defined as

$$C_{\Delta x,\Delta y}(i,j)=\sum_{p=1}^{n}\sum_{q=1}^{m}\begin{cases}1, & \text{if } I(p,q)=i \wedge I(p+\Delta x,q+\Delta y)=j \\ & \text{or } I(p,q)=i \wedge I(p-\Delta x,q-\Delta y)=j \\ 0, & \text{otherwise}\end{cases}$$

- i and j are the image intensity values of the image
- p and q are the spatial positions in the $n \times m$ image I
- the offset $(\Delta x,\Delta y)$ depends on the used direction θ and the distance d at which the matrix is computed

- $(\Delta x, \Delta y)$ represents the separation vector
- 4 orientations are usually considered
  - horizontal – separation vector $(1, 0)$ for distance 1
  - vertical – separation vector $(0, 1)$ for distance 1
  - main diagonal – separation vector $(1, 1)$ for distance 1
  - minor diagonal – separation vector $(1, -1)$ for distance 1

0	3	3
0	0	1
2	2	1

Original image I

#(0, 0)	#(0, 1)	#(0, 2)	#(0, 3)
#(1, 0)	#(1, 1)	#(1, 2)	#(1, 3)
#(2, 0)	#(2, 1)	#(2, 2)	#(2, 3)
#(3, 0)	#(3, 1)	#(3, 2)	#(3, 3)

General form of co-occurrence matrix for image I

Haralick features

Co-occurrence matrix

Original image I

0	3	3
0	0	1
2	2	1

$C_{1,0} =$

2	1	0	1
1	0	1	0
0	1	2	0
1	0	0	2

$C_{0,1} =$

2	0	2	1
0	2	0	1
2	0	0	0
1	1	0	0

$C_{1,1} =$

2	1	1	0
1	0	0	1
1	0	0	0
0	1	0	0

$C_{1,-1} =$

0	0	1	2
0	0	1	0
1	1	0	0
2	0	0	0

- because simple 8-bit images could have 256 intensity values, corresponding co-occurrence matrices will be very large
  - solution is to use quantization prior to the extraction process
- co-occurrence matrices are in the end normalized and averaged to form the final co-occurrence matrix C
- Note: All co-occurrence matrices are symmetric (why?)

Haralick features

Haralick suggested 14 features that could be derived from the matrix and form the feature vector of Haralick features

- entropy: $-\sum_{i=1}^{q}\sum_{j=1}^{q} C(i,j) \log C(i,j)$
- texture correlation: $\sum_{i=1}^{q}\sum_{j=1}^{q} |i-j| C(i,j)$
- texture homogeneity: $\sum_{i=1}^{q}\sum_{j=1}^{q} \frac{C(i,j)}{1+|i-j|}$
- and the others ... (q is the maximal intensity present in the image)

Bibliography

- R. M. Haralick, K. Shanmugam, and I. Dinstein. Textural Features for Image Classification. *IEEE Trans. on Systems, Man and Cyber.*, SMC-3(6):610–621, 1973.
- L. Tesař, D. Smutek, A. Shimizu, and H. Kobatake. 3D Extension of Haralick Texture Features for Medical Image Analysis. In *Proceedings of the Fourth IASTED International Conference on Signal Processing, Pattern Recognition, and Applications*, SPPRA '07, pages 350–355. ACTA Press, 2007.

Local binary patterns (LBP)

- introduced in 1994 by Ojala (upper photo) and Pietikäinen (lower photo) from University of Oulu, Finland
- descriptor became famous after generalization in 2002
- originally proposed for face recognition
- currently used also in (bio)medical image analysis, motion analysis, eye localization, fingerprint recognition, and many others

Local binary patterns (LBP)

Original approach (1994)

Idea: Texture can be described by the pattern and its strength

LBP pattern

1. each pixel is compared with its 8 neighbours
2. if the intensity value of neighbouring pixel is greater than or equal to the value of examined pixel's intensity, write 1 (otherwise, write 0)

Example

7	1	9
2	5	5
6	0	3

Threshold

1	0	1
0		1
1	0	0

Local binary patterns (LBP)
Original approach (1994)

Idea: Texture can be described by the pattern and its strength

LBP pattern

3. take the digits from top-left corner in clockwise order and interpret them as decimal number
4. this decimal number represents the pattern

Example

7	1	9
2	5	5
6	0	3

⇨

Threshold

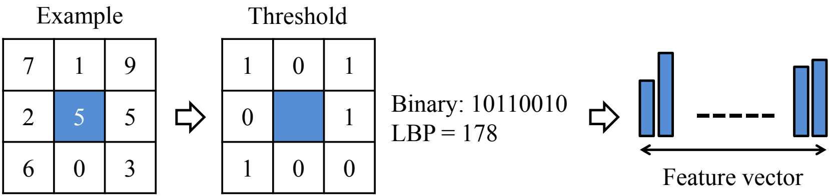
1	0	1
0		1
1	0	0

Binary: 10110010
LBP = 178

Idea: Texture can be described by the pattern and its strength

Strength of the pattern

5. decimals from entire image are used to form histogram (256 bins – why?)
6. concatenation of the normalized histogram values gives us the feature vector

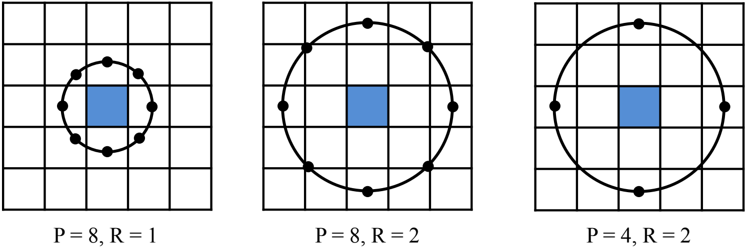


Local binary patterns (LBP)

Generalization of LBP (2002)

Idea: No limitation to the size of the neighbourhood and the number of sampling points

- parameter P - number of sampling points
- parameter R - size of the neighbourhood

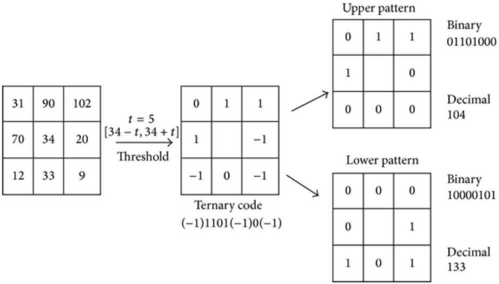


- when the sampling point is not in the centre of the pixel, bilinear interpolation is used

Local binary patterns (LBP)

LBP descriptor has many variants and modifications

- *Median binary patterns* – thresholding against the median within the neighbourhood
- *Local ternary patterns* – solving problem of nearly constant areas



- and the others . . .

Local binary patterns (LBP)

Bibliography

- T. Ojala, M. Pietikäinen, and D. Harwood. Performance evaluation of texture measures with classification based on Kullback discrimination of distributions. In *12th IAPR Intern. Conf. on Patt. Recog. Vol. 1 - Conf. A: Computer Vision and Image Processing*, pages 582–585, Oct. 1994.
- T. Ojala, M. Pietikäinen, and T. Maenpaa. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 24(7):971–987, July 2002.
- M. Pietikäinen, A. Hadid, G. Zhao, and T. Ahonen. Computer Vision Using Local Binary Patterns. Computational imaging and vision. Springer Verlag, London, 2011.

MPEG in general

- Motion Picture Experts Group (MPEG) – developed digital audiovisual compression standards (in 1988)
- MPEG-1 (1993) – the first standard for audio and video MP3
- MPEG-2 (1995) – generic coding of moving pictures and associated audio information
- MPEG-4 (1998) – coding of audio-visual objects
- MPEG-7 (2002) – multimedia content description interface (including Visual descriptors)

MPEG-7 descriptors

- part of MPEG-7 visual standard
- standardized low-level descriptors for different domains
- many contributors, joining editor B. S. Manjunath (see photo)
- first public release in 2002

MPEG-7 descriptors

Division

MPEG-7 visual descriptor are divided to 4 groups

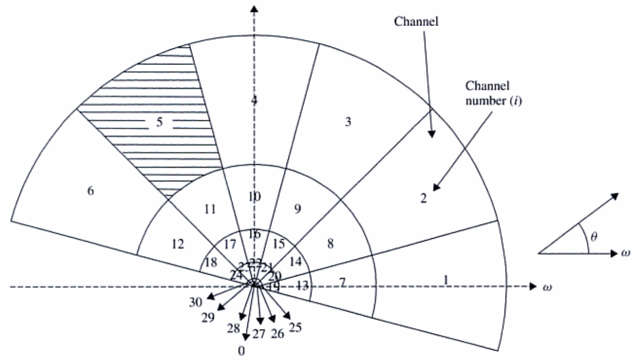
- Colour descriptors – robust to viewing angle, translation, and rotation of the regions of interest (ROI),
  6 features are included here
- Texture descriptors – contain important structural information of intensity variations and their relationship to the surrounding environment, 3 features are included here
- Shape descriptors – techniques for describing and matching shape features of 2D and 3D, 3 features are included here
- Motion descriptors – description of motion features in video sequences, 4 features are included here

MPEG-7 texture descriptors consist of three feature extractors

- Homogeneous Texture Descriptor (HTD) – characterizes the region texture using the mean energy and the energy deviation from the set of frequency channels
- Texture Browsing Descriptor (TBD) – specifies the perceptual characterization of the texture, which is similar to human perception
- Edge Histogram Descriptor (EHD) – spatial distribution of edges in the image

Notice: We will briefly describe HTD and EHD.

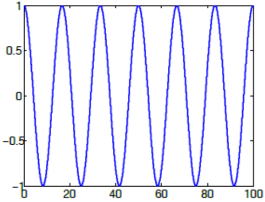
2D frequency plane is partitioned into 30 channels



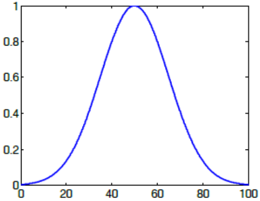
- partitioning uniform along the angular direction and not uniform along the radial direction (in octave scale)

The individual channels are convolved using Gabor filters

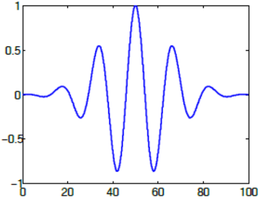
- introduced in 1946 by Dennis Gabor (see photo) for 1D signal
- the filter is obtained by modulating a sinusoid with a Gaussian function
- it responds to some frequency in a localized part of the signal



(a) Sinusoid

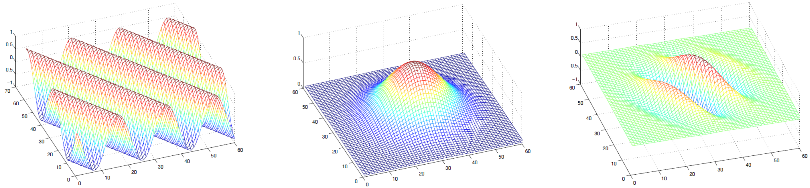


(b) Gaussian function



(c) Gabor filter

Extension of Gabor filters to 2D



(a) (b) (c)

The (s, r)-th channel, where s is radial index and r is angular index, is modelled in frequency domain as

$$G_{s,r}(\omega, \theta) = \exp\left[\frac{-(\omega-\omega_s)^2}{2\sigma_s^2}\right].\exp\left[\frac{-(\theta-\theta_r)^2}{2\tau_r^2}\right]$$

- σ_s and τ_r are standard deviation of the Gaussian in radial and angular direction, respectively
- $\theta_r = 30^\circ \times r$, where $r \in \{0, 1, 2, 3, 4, 5\}$
- $\omega_s = \omega_0 \times 2^{-s}$, where $s \in \{0, 1, 2, 3, 4\}$ and ω_0 is the highest frequency

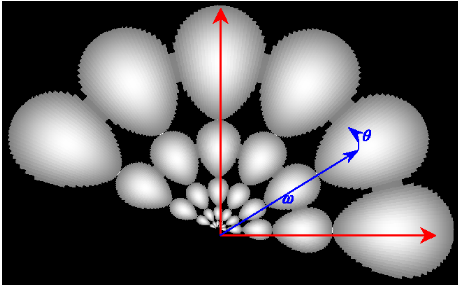
MPEG-7 descriptors

Homogeneous Texture Descriptor (HTD)

The syntax of the HTD is as follows:

$$\text{HTD} = [f_{DC}, f_{SD}, e_1, e_2, ..., e_{30}, d_1, d_2, ..., d_{30}]$$

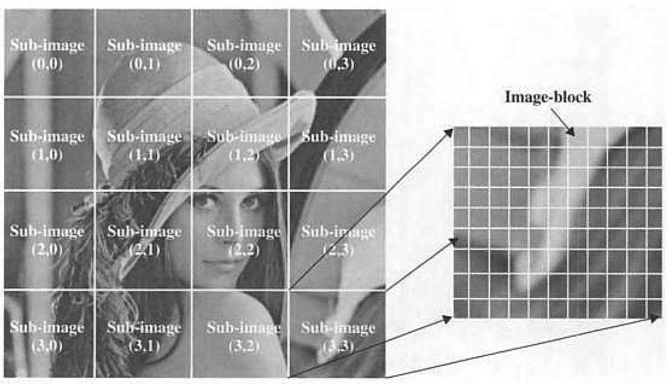
- f_{DC} is the mean of the image
- f_{SD} is the standard deviation of the image
- e_i and d_i are non-linearly scaled and quantized mean and standard deviation of the i^{th} channel ($i \in \{1, 2, .., 30\}$)



MPEG-7 descriptors
Edge Histogram Descriptor (EHD)

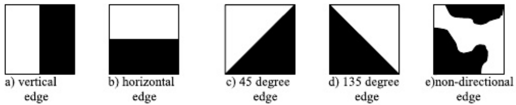
EHD represents the local edge distribution in the image

- divide image space in 4×4 sub-images
- each sub-image divided into non-overlapping squared image blocks (1100 image blocks)



EHD represents the local edge distribution in the image

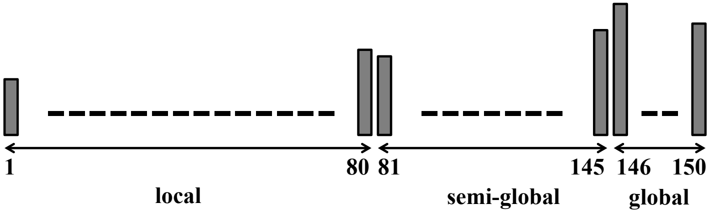
- each image block is classified into one of the 5 edge categories or as non-edge block



- classification is done by applying corresponding edge detector and thresholding

Feature vector of EHD consists of three types of bins

- local – 4 × 4 sub-images × 5 types of edges
- semi-global – grouping of sub-images in predefined way (horizontal, vertical, ...)
- global – 1 bin for every type of edges



MPEG-7 descriptors

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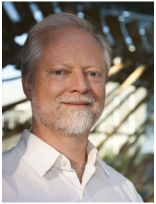
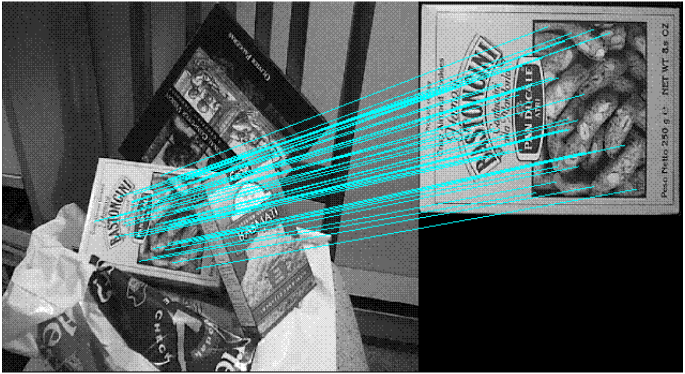
- B. S. Manjunath, P. Salembier, and T. Sikora, editors. Introduction to MPEG-7: Multimedia Content Description Interface. *Wiley & Sons, Inc.*, New York, USA, Apr. 2002.

Scale-invariant feature transform (SIFT)



- presented in 2004 (first article in 1999) by David Lowe (see photo) from University of British Columbia (UCB), Canada
- patented by UCB for commercial purposes
- local feature extraction (robust to occlusion)
- similar to human visual system
- extracting distinctive invariant features

Scale-invariant feature transform (SIFT)



- demonstration of SIFT descriptor
- finding corresponding parts of the image
- query image (in the right) is identified as a part of the image in the left

Scale-invariant feature transform (SIFT)

SIFT consists of key point detection and key point descriptor

Key point detection

- location of the peaks in scale space
- key point localization
- orientation assignment

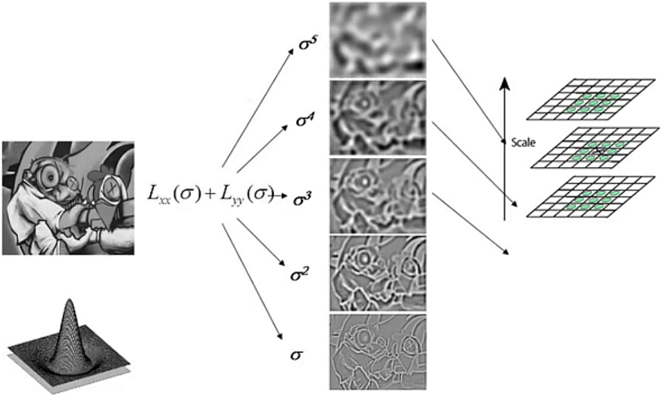
Key point descriptor

- describing the key point as a vector
- could be used with other key point detections

Key points are derived as local extreme point in scale space of Laplacian-of-Gaussian (LoG)

- derive LoG with various σ values
- for each point, compare it in $3 \times 3 \times 3$ neighbourhood (3D image from the scale spaces)
- if central point is an extreme point (maxima or minima), consider it as a key point

Key points are derived as local extreme points in scale space of Laplacian-of-Gaussian (LoG)

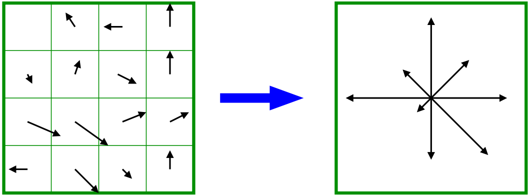


Key point localization consists of

- eliminating outliers (poorly localized along the edges)
- searching for best scales for all extreme points
- comparing to some threshold

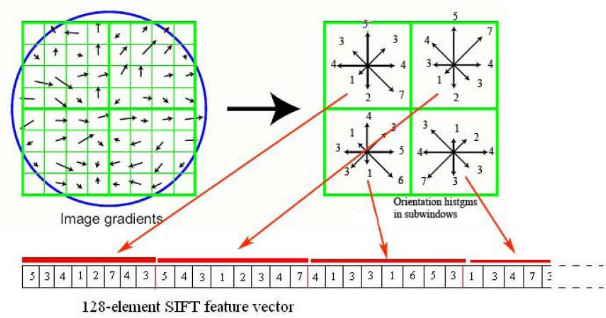
Orientation assignment to key points

- to achieve rotation invariance
- at each point compute central difference (magnitude and direction)
- for each key point, build the weighted histogram of directions (36 bins $\implies$ per 10°), weights are gradient magnitudes
- select the peak as the direction of the key point (could be more, within 80% of max peak)
- any further calculations are done relative to this orientation



Extracting of local image descriptors at key points

- compute relative orientation! and magnitude in 16×16 (depicted only 8×8) neighbourhood at key point
- form weighted histogram (8 bins) for 4×4 regions
- concatenate 16 histograms in one vector of 128 dimensions which represents the SIFT feature vector



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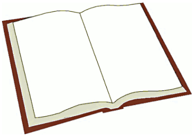
- D. Lowe. Distinctive Image Features from Scale-Invariant Keypoints. *International Journal of Computer Vision*, 2004.

- Lecture on YouTube ▸ Link



Zernike Features

Zernike polynomials in 2D

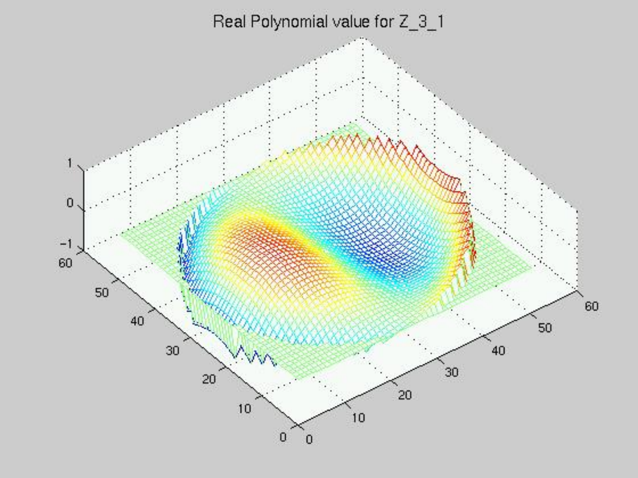
$$V_{nl}(x,y) = \sum_{m=0}^{\frac{n-l}{2}} (-1)^m \frac{(n-m)!}{m!\left(\frac{n-2m+l}{2}\right)!\left(\frac{n-2m-l}{2}\right)!} \left(x^2+y^2\right)^{\frac{n}{2}-m} e^{il\theta},$$

where

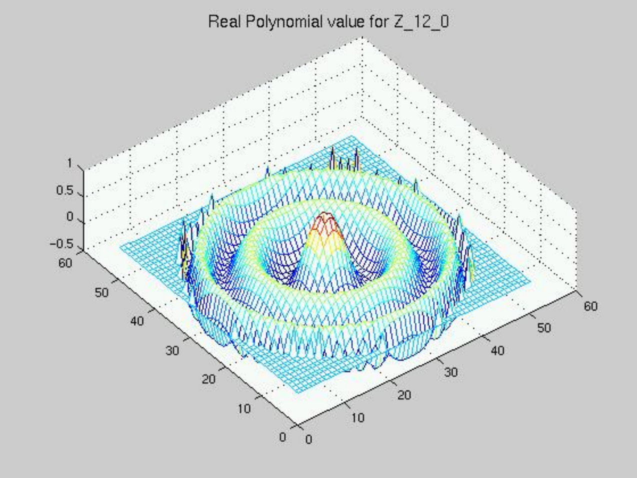
- $0 \leq l \leq n$
- $(n-l)$ is even
- $\theta = \tan^{-1}\left(\frac{y}{x}\right)$
- $x^2 + y^2 \leq 1$
- individual V_{nl} are orthogonal.

Frederik Zernike (1888-1966)

Zernike polynomials in 2D – Examples

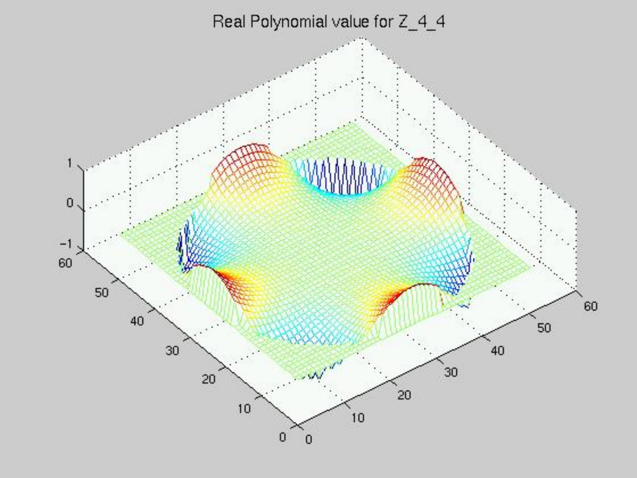


Zernike polynomials in 2D – Examples



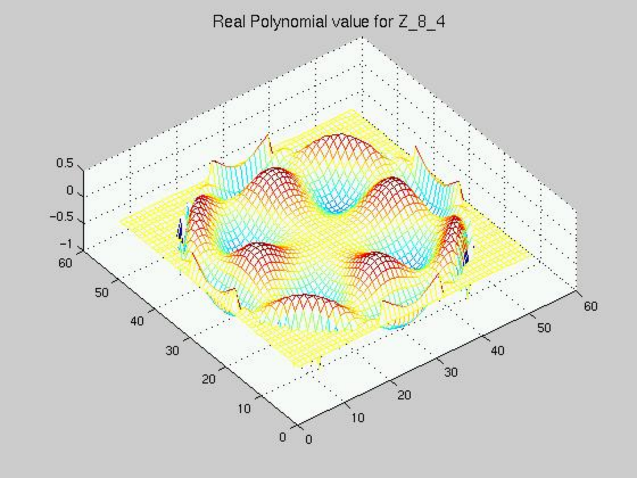
Zernike Features

Zernike polynomials in 2D – Examples



Zernike Features

Zernike polynomials in 2D – Examples



Zernike Features

Definition

Let be given an inner product

$$Z_{nl} = \frac{n+1}{\pi} \sum_x \sum_y V^*_{nl}(x,y) f(x,y),$$

where

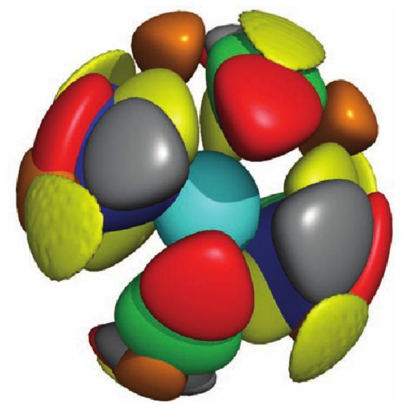
- $f(x,y)$ is an analyzed image a
- V_{nl} is a selected Zernike polynomial.

Then scalar $|Z_{nl}|$ is called a Zernike feature/descriptor.

Notice: $Z_{nl} \in \mathbb{C}$

Zernike Features in 3D

3D Zernike polynomial



- Novotni, M., Klein, R. Shape retrieval using 3D Zernike descriptors, Computer-Aided Design, Volume 36, Issue 11, Solid Modeling Theory and Applications,r 2004, 1047–1062
- Grandison, S., Roberts, C., Morris, R. J. The Application of 3D Zernike Moments for the Description of Model-Free Molecular Structure, Functional Motion, and Structural Reliability, Journal of Computational Biology. March 2009, 16(3): 487-500

Moment Invariants

Definition

- The 2-D moment of order $(p+q)$ of a digital image $f(k,l)$ of size $M \times N$ is defined as:

$$m_{pq} = \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} k^p l^q f(k,l)$$

  where $p = 0, 1, 2, \ldots$ and $q = 0, 1, 2, \ldots$ are integers.

- The central moment of order $(p+q)$ is defined as

$$\mu_{pq} = \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} (k - \bar{k})^p (l - \bar{l})^q f(k,l)$$

  where

$$\bar{k} = \frac{m_{10}}{m_{00}} \quad \text{and} \quad \bar{l} = \frac{m_{01}}{m_{00}}$$

Definition (cont.)

- The normalized central moments are defined as

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{c}}$$

where

$$c = \frac{p+q}{2} + 1 \quad \text{for} \quad p+q = 2, 3, \ldots$$

Now, let us define several moment invariants that are insensitive to

- translation
- scale
- change
- mirroring
- rotation

Moment Invariants

Seven invariants

$$
\begin{aligned}
\phi_1 &= \eta_{20} + \eta_{02} \\
\phi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\
\phi_3 &= (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \\
\phi_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\
\phi_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12}) \left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] \\
&\quad +(3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03}) \left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right] \\
\phi_6 &= (\eta_{20} - \eta_{02}) \left[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right] \\
&\quad +4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \\
\phi_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12}) \left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] \\
&\quad +(3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03}) \left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right]
\end{aligned}
$$

You should know the answers . . .

- Build your own 10B descriptor for any grayscale image. Explain the maning of individual parts of the feature vector.
- Explain the way of efficient comparsion of two randomly chosen RGB color images.
- Describe the construction of so called *co-occurrence matrix*. How would you observe large scale (spanned over more than 3 pixels) texture details?
- Why do LBP feature vectors possess histograms with 256 bins?
- Which way may we compute the mean gradient direction of a selected 4×4 region?
- Propose an extension of standard Haralick features to work with 3D image data.
- How would you apply Zernike polynomial to an incoming image of any size so that you could compute the corresponding Zernike feature?