Content-based multimedia retrieval

Georgios Tziritas Computer Science Department http://www.csd.uoc.gr/~tziritas



Content retrieval in real world

User intention : browsing, surfing, classification, search

Data scope : personal collection, domain specific, archives, Web

Query formation : key-word, free-text, example, sketch



W. Zhou, H. Li and Q. Tian, Recent Advance in Content-based Image Retrieval: A Literature Survey, Arxiv, Sept.201

User / Data / Query



Query modality



It is difficult to precisely express the expected visual content by a query. The quality of the query has a significant impact on the retrieval results.

W. Zhou, H. Li and Q. Tian, Recent Advance in Content-based Image Retrieval: A Literature Survey, Arxiv, Sept.2017

Similarity measures / learning

Agreement with semantics It is difficulty to describe a high-level semantic concept with low-level visual features Noise resistance Computational efficiency Object scale Distance properties **Image similarity**

$$S(\mathcal{X}, \mathcal{Y}) = \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} k(x, y)$$

=
$$\sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} \phi(x)^T \phi(y)$$

=
$$\Psi(\mathcal{X})^T \Psi(\mathcal{Y}).$$

feature extraction feature encoding database indexing

Clustering (hierarchical, grouping, mixtures)

Classification

Face detection : color

Skin color detection Color system YcbCr, HSV



Face detection : texture

Subband analysis Discrete Wavelet Frames





Spring 2018

Face detection



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Face detection : learning



Convolutional neural network



Face recognition

Subband analysis (Discrete Wavelet Transform)

Localisation of characteristic areas

Alignment



Face recognition



Text detection and recognition



Text detection and recognition



Object (class) detection



Image analysis / Statistical model / Learning

Content descriptors

Low level content description (color, texture, shape) MPEG-7

Local visual features invariant to geometric transforms



Scale Invariant Feature Transform



It can well capture the invariance to rotation and scaling transformation and is robust to illumination change

Int. Journal on Computer Vision, 2002

Key-points





Selection

Scale Invariant Feature Transform

SIFT Local patch 16x16 pixels at key-point Subdivision to 16 sub-blocks of size 4x4 pixels Histogram of gradient orientation (8 bins) Descriptor 8x4x4=128 dimensions



D. Lowe, Distinctive image features from scale-invariant keypoints, *Int. Journal on Computer Vision*, 2004

Bag of visual words

Compact representation

It may be based on SIFT features (a) for an object or (b) for a video frame Grouping SIFT features to form object or frame description visual words Vector quantization for codebook creation (*k-means algorithm*) Grouping and matching a large number of SIFT descriptors is a computational challenge The quantization result of a single local feature can be regarded as a high-dimensional binary vector, where the non-zero dimension corresponds to the quantized visual word. Visual words are rich in encapsulation of basic visual characteristics, despite the inevitable uncertainty With small codebook and feature space coarsely partitioned, irrelevant features with large distance may also fall into the same cell. When the codebook size is large which means the feature space is finely partitioned, features proximate to the partition boundary are likely to fall into different cells. Spring 2018

Image retrieval : learning

Neural network

Learning by training content representation similarity criterion (classification)

Bridging the semantic gap

Pretraining in large base / adaptation to specific classes



Indexing

Image index refers to a database organizing structure to assist for efficient retrieval of the target images.

Inverted file indexing

Sparse matrix : Rows correspondent to images and columns denote visual words Each visual word is followed by an inverted file list of entries. In on-line retrieval, only those images sharing common visual words with the query image need to be checked. Thus, the number of candidate images to be compared is greatly reduced.

Hashing

Partition the feature space, so that similar images can be found in nearby areas The large dimension features are encoded into low-dimension binary codes for search by similarity Semantically similar data must have close binary codes

Geometric verification

By including contextual information, the discriminative capability of visual codebook can be greatly enhanced. Loose spatial consistency from some spatially nearest neighbors can be imposed to filter false visual-word matches



B. Girod et al., Mobile visual search, IEEE Signal Processing Magazine, 201

Image scoring

Feature distance

$$D(I_q, I_m) = \left(\sum_{i=1}^{N} |q_i - m_i|^p\right)^{\frac{1}{p}}$$

BoVW : weighted visual word histogram

Weighting visual words

Term frequency in the document

Inverse document frequency



Mobile visual search





B. Girod et al., Mobile visual search, IEEE Signal Processing Magazine, 201

Compact feature description : compressed histogram of gradient

Gradient at key-points



VQ constellations

B. Girod et al., Mobile visual search, IEEE Signal Processing Magazine, 201

Compact feature description : location histogram

The interest points are spatially clustered It is possible to compress feature location data efficiently





B. Girod et al., Mobile visual search, IEEE Signal Processing Magazine, 2011

Indexing / query

Vocabulary hierarchical tree

An approximate nearest neighbor search is achieved by propagating the query feature vector from the root node down the tree by comparing the corresponding child nodes and choosing the closest one.



B. Girod et al., Mobile visual search, IEEE Signal Processing Magazine, 201

Speech / music discrimination





Feature extracted on frames : mean over standard deviation