#### **Image Retrieval through Codebooks**

#### Marián Labuda

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- Principles
- System Architecture
- Visual Vocabularies
- Experimental results
- Conclusion

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### • Principles

- local feature extraction from a set of images
- conversion of features to visual words (quantization)
- using text retrieval technology

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- Basic operations
  1) Indexing
  - Feature extraction list of local image features
    - features as descriptors (high dimensional vectors)
  - Quantization images as text documents
    - quantization through visual vocabulary
    - simple text string instead of high dimensional vector
  - Storage visual words in inverted index

### 2) Querying

- Feature extraction a list of local image features for a given image
- Quantization the query image as a list of keywords
- Searching in an inverted index using text retrieval engine
  - answer ranking according to similarity
- Post-processing e.g. spatial verification

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#### **Feature extraction**

- image content described by image features

- image features global features (e.g. color histogram)- local features (e.g. SIFT, SURF, MSER, ...)
- pros. & cons. of local image features
- extraction of features creates descriptors
- computation complexity of high dimensional descriptors

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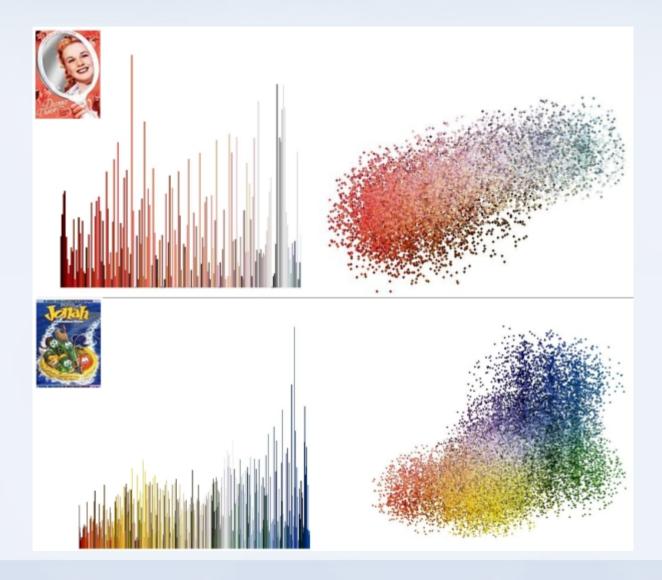
#### SIFTs



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#### **Color Histogram**



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- System Architecture
- **MESSIF framework** data abstraction - feature extraction
  - Web UI
- Lucene Core indexing and searching
- My implementation visual vocabulary
  - similarity modification
  - post-processing

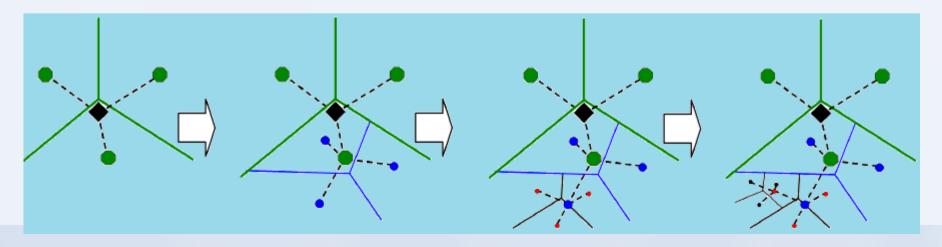
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- Lucene Core
  - full-text search engine
- usage of inverted files
- high performance
- supports various types of queries
- ranked searching
- using Lucene is provided through class *LuceneAlgorithm* combines Lucene Core library and MESSIF framework

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#### Visual Vocabulary

- provide quantization of local image descriptors
- visual vocabulary as a bottleneck of Image Retrieval System
- images as sets of quantized features
- some words can occur too often, others very few
  - later we can filter them as stop words (analogy to prepositions, ...)



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- My implementation Visual vocabulary
- abstract class AbstractVisualVocabulary
- simple implementation and integration of a new visual vocabulary
- implemented visual vocabularies:
  - K-means
  - *MDPV* (*metric distance permutation vocabulary*)
- efficiency of the given visual vocabulary

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#### Visual vocabularies - hierarchical k-means

- hierarchical k-means provides a faster way to quantize descriptors than flat
- a visual word as a path from the root to a leaf node

#### **Demo application**

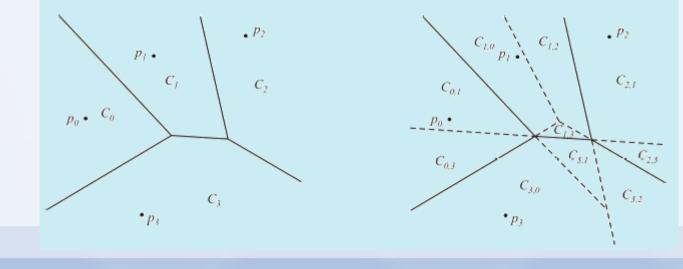
- deployed at http://mufin.fi.muni.cz/subimages-lucene/random
- oxford building dataset (~5000 images)
- 6 hierarchical k-means
- 10 descriptors in node

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#### •Visual vocabularies - MDPV

- idea of metric distance permutation vocabulary – based on a small number of pivots and recursivelly defines voronoi cells

- provides finer granularity than k-means
- faster and requires less space than k-means
- visual words as a sequence of more pivots (5 or 10 are used at most)



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- My implementation Similarity modification
  - text based retrieval systems often use tf-idf scoring
    tf term frequency "How many times does the term occur in the document (in one image)?"
    idf inverse document frequency "How many documents
    - (images) contain the given term in whole collection?"
  - Lucene provides an easy way to implement own similarity
  - definition of similarity by scoring
  - score computation:

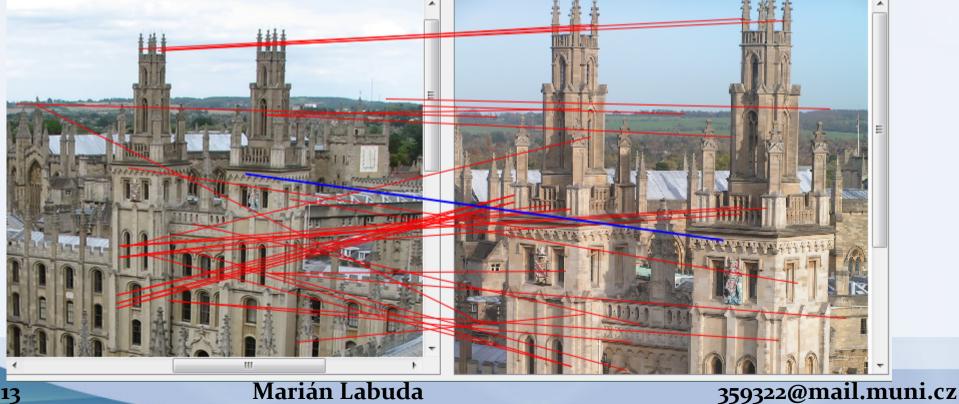
 $score(q, d) = coord(q, d) * \Sigma(tf(t \in d) * idf(t) * t.getBoost())$ 

- experimentally determined the best similarity on the ukbench dataset

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- My implementation Post-processing
- RANSAC RANdom SAmple Consensus
- geometric verification

- not enough improvement on the given vocabularies – fine-grained words



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#### • Experimental results

#### - Ukbench dataset contains 5 (almost) different datasets

- CD CD covers
- moving moving vehicles
- CD+moving combination of CD and moving datasets
- flip some flipped versions of normal dataset
- normal test set

 locators of similar images example: sift100000
 sift100001
 sift100002
 sift100003

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- Experimental results (continue)
  - similarity tests based on the matrix of different settings:
    - term frequency weights
    - inverse document frequency weights
    - overlap weights
- compared to ukbench results visual words provided by authors
- comparison based on relationship to flat ukbench results
  - slightly better results in effectiveness better retrieval
  - slightly worse results in speed

- "best" similarity: tf = 1  $idf = (\ln \frac{N}{N_i})^2$   $coord = (\frac{overlap}{maxOverlap})^3$ N - total count of documents overlap - terms of query in document  $N_i$  - documents count containing term maxOverlap - count of query terms

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#### • Experimental results (continue 2)

- how many of the ground-truth images occured in top 4:

| Dataset       | My Similarity | Customized | Ukbench |
|---------------|---------------|------------|---------|
| CD            | 2,9583        | 2,9344     | 2,8956  |
| movie         | 2,8912        | 2,8762     | 2,8285  |
| CD & movie    | 2,9528        | 2,9326     | 2,8844  |
| flip          | 2,9609        | 2,9548     | 3,0144  |
| test          | 3,1414        | 3,1498     | 3,1664  |
| Average value | 2,9809        | 2,9696     | 2,9579  |

- each dataset consists of 10200 images
- every image has 3 other ground-truth images
- Customized similarity is same as My Similarity except the tf
- customized similarity count with term frequency as  $\sqrt{f}$  instead of 1

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- Experimental results (continue 3)
- unfortunately I was not able to reproduce their results with any similarity
- stop words did not provide more precise results
- term frequency can be fully omited
- index time is up to 2 minutes

- searching of 10200 queries on database consisting of 10200 documents takes from 6 to 10 minutes (39 – 60 ms per image)

- experiments on Lenovo T430s – 8 GB RAM

- Intel Core i7 3520M (2,9 GHz, 2 cores)



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#### Conclusion

- image retrieval system based on visual vocabularies and inverted files are as strong as the vocabulary

- term frequency can be fully omited

- usage of stop words depends on vocabulary
- inverted index provides fast and scalable solution

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