Efficient Techniques for Accurate Visual Place Recognition

Master's Thesis in Robotics, Cognition, Intelligence

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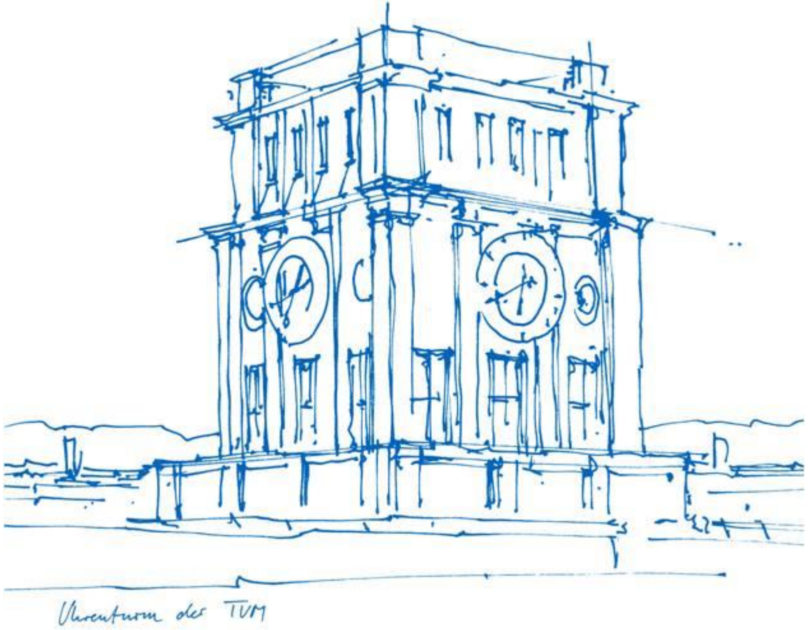
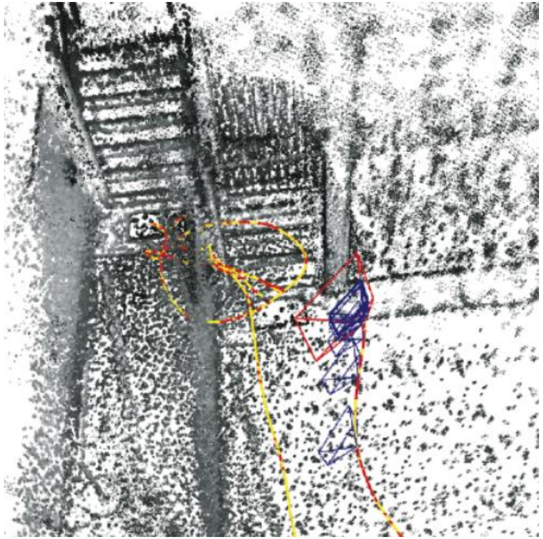


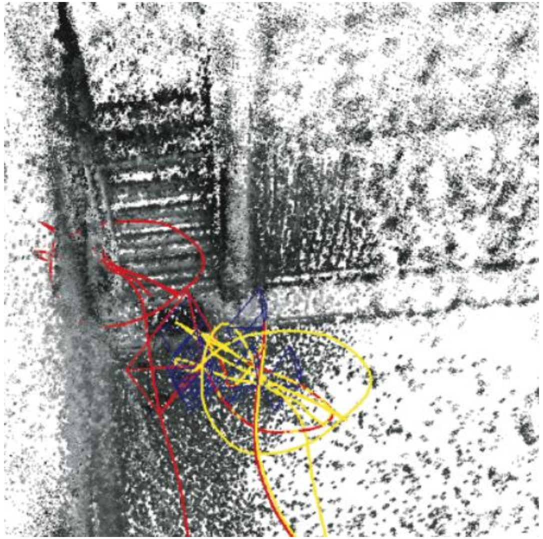
Introduction

Motivation, Problem Statement & Goals

Motivation

Loop Closure (Source: Gao *et al.* [1])





Problem Statement

Problem:

- Main performance drawback in SLAM / SfM: Image Matching
- Brute-force approach is extremely expensive
- Visual Place Recognition can be used to limit the search space

Extent of the Work:

- Visual Place Recognition based on local features
- Unordered image collections
- Pure appearance-based place recognition procedures
- Focus on efficient methods (real-time capability)

Goals of the Thesis

Overview of promising approaches:

- Visual place recognition, based on local features, pure image retrieval
- Additionally: Novel approach based on locality-sensitive hashing

Evaluation of place recognition methods:

- Newly developed benchmarking suite
- Parameter analysis, feature extractor influence, method comparison

Efficient implementation:

- Open-source library containing multiple place recognition approaches
- Improving efficiency of existing algorithms

Visual Place Recognition

Theory & Methods

Definition

Visual:

- Visual appearance of places
- Not the only possible source of data

Place:

- Many different definitions depending on context
- In our context: Different places have different appearance
- Perceptual aliasing can be a challenge

Source: Cummins and Newman [2]

Recognition:

- Perceiving something which is previously known
- In computer vision: Classifying a detection (*what* in contrast to *if* and *where)*

Components

Image Description:

- Describing images: Local, global and hybrid approaches
- We focus on locally extracted features

Mapping:

- Remembering previously visited places
- In our case: Database containing image representations (inverse index)

Belief Generation:

- Decision whether a perceived place has been visited
- Image similarity measures

Visual Bag of Words

Origins:

- Text retrieval: Finding relevant documents in a large collection
- Assumption: Similar documents contain a similar distribution of words

Transfer to image retrieval:

- Extract visual words from images (clustering)
- Represent images by occurrence or distribution of words

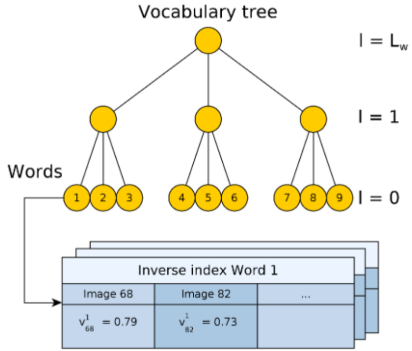
Advantages:

- Implicit pose invariance
- Simple and efficient implementation

Methods for Visual Place Recognition

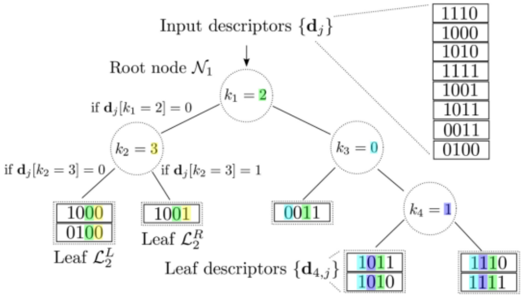
DBoW: Hierarchical Bag of Words [3]

- Vocabulary tree, constructed using hierarchical k-means++ clustering
- Cluster centers treated as terms in the bag-of-words scheme



HBST: Hamming Distance Embedding Binary Search Tree [4]

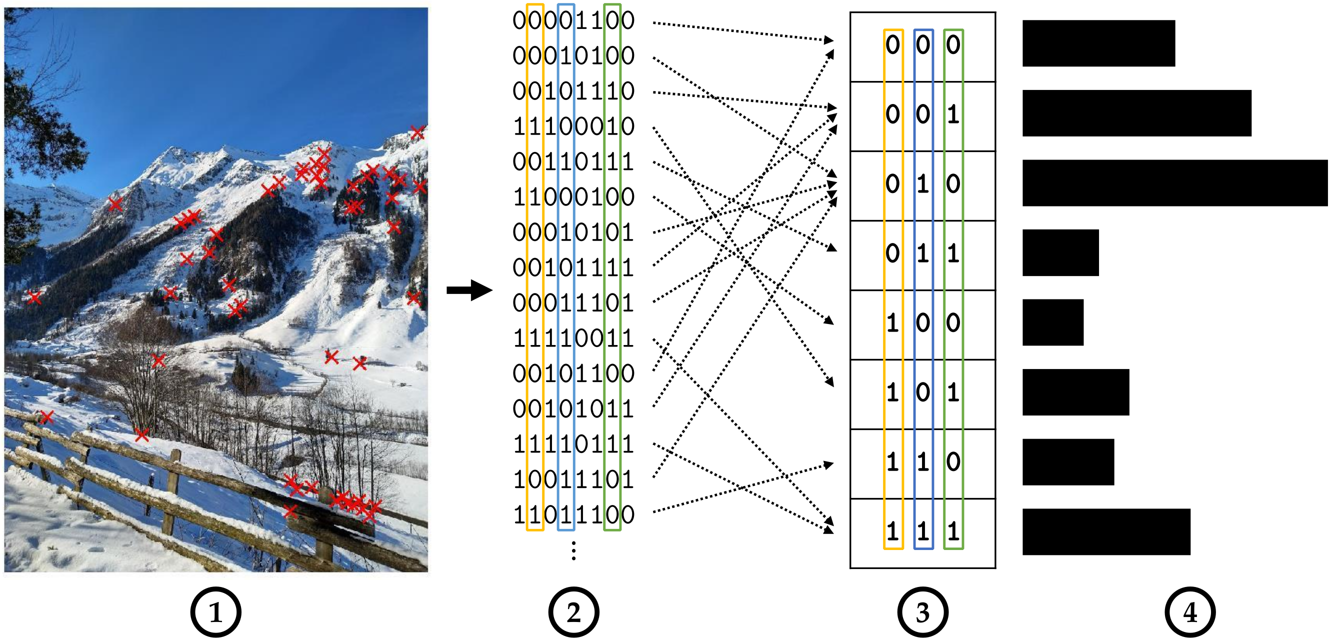
- Binary search tree, splitting based on bit indices
- Place recognition with voting scheme of descriptors in leaf nodes



HashBoW: Hashing-Based Bag of Words

- Clustering based on Locality-Sensitive Hashing (LSH)
- Hash codes treated as terms in the bag-of-words scheme
- Training: Entropy maximization of hash codes

HashBoW: Image Representation



Evaluation

Benchmarking Suite, Contents & Results

Benchmarking Suite

Data Preparation

- Download of datasets
- Conversion into unified format
- Python, YAML

Data Processing

- Feature extraction
- Place recognition methods
- Output of results
- C++, OpenCV, YAML

Results Evaluation

- Analyze and visualize results
- Accuracy and run time
- Python, Jupyter Notebook

Evaluation Contents

Methods:

- DBoW3
- HBST
- HashBoW

Feature Extractors:

- AKAZE
- BRISK
- ORB

Datasets:

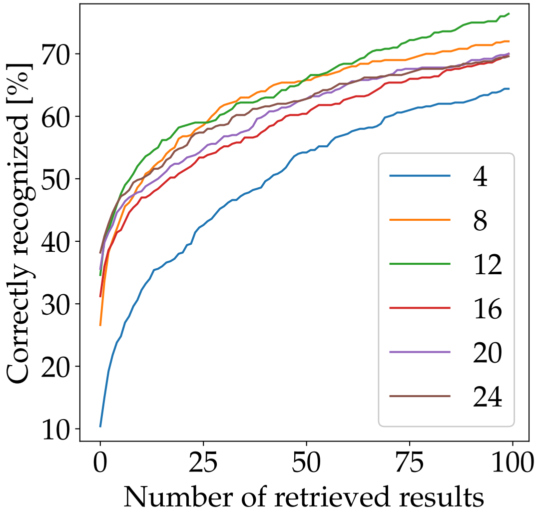
- Oxford Buildings
- Paris Buildings
- INRIA Holidays

Metrics:

- Percentage of correctly recognized places
- Recall
- Cumulated run time

Evaluation

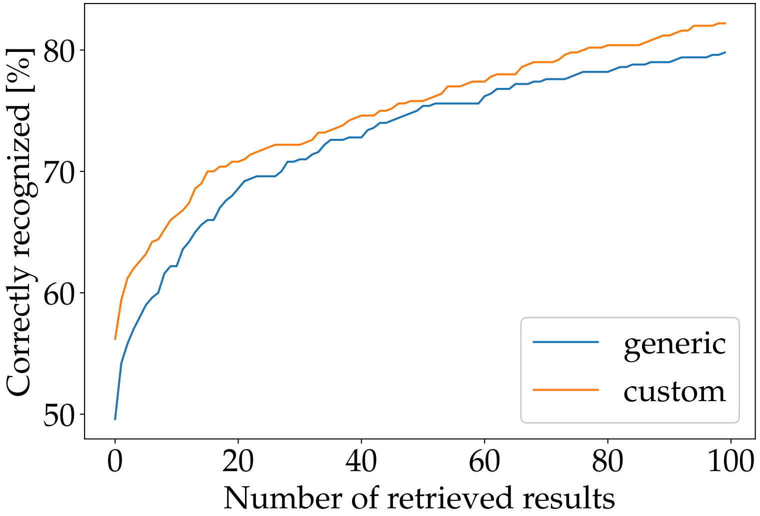
Parameter Analysis: HashBoW



Bits	Add	Query
4	0.12 s	0.19 s
8	0.15 s	1.23 s
12	0.27 s	3.19 s
16	0.56 s	2.09 s
20	0.84 s	1.11 s
24	1.19 s	0.71 s

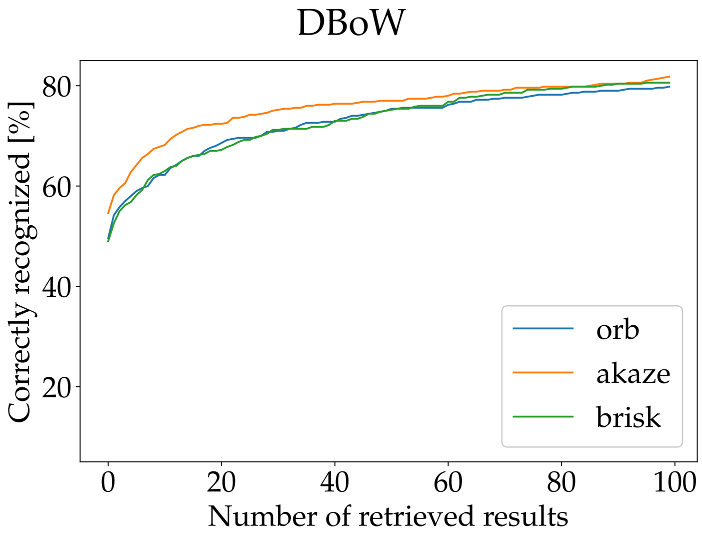
Evaluation

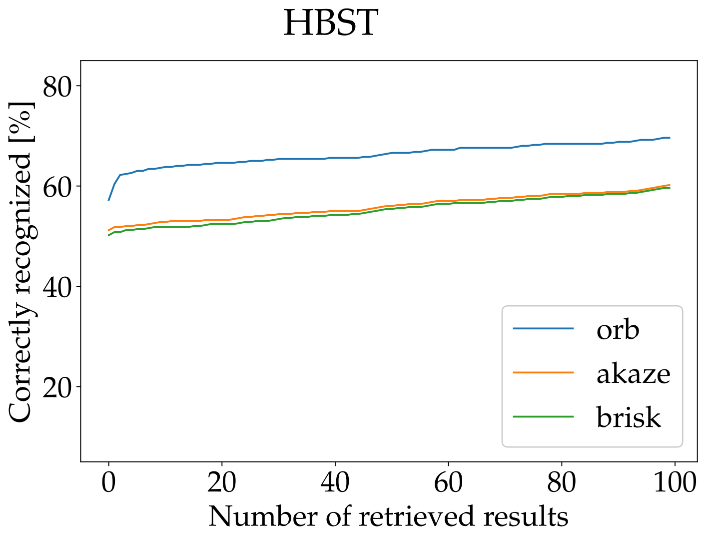
Influence of Training Dataset (DBoW)



Evaluation

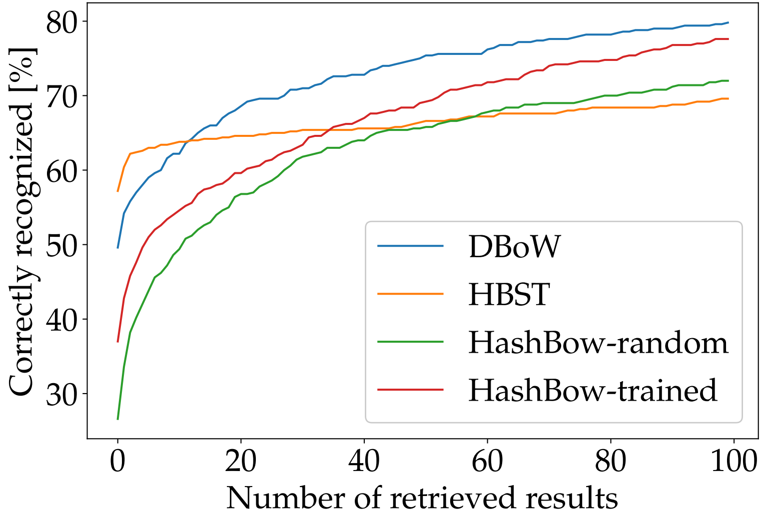
Influence of Feature Extractor: DBoW & HBST





Evaluation

Final Method Comparison



Method	Add	Query
DBoW	14.15 s	10.27 s
HBST	5.09 s	2.67 s
HashBoW-random	0.15 s	1.23 s
HashBoW-trained	0.32 s	3.74 s

→ HashBoW-random: 8 bits, random bit sampling
→ HashBoW-trained: 12 bits, entropy maximized hash codes

Efficient Implementation

Motivation, Structure & Improvements

Motivation & Goals

Motivation:

- Structure of different bag-of-words approaches is very similar
- No reference collection of algorithms available
  → Performance, code quality and usage can vary widely
- DBoW: Accurate but comparatively slow

Goals of the new library:

- Well-documented: Easy to use and understand
- Extensible: New methods can be added easily
- Lightweight: Straightforward to incorporate
- Efficient reference implementations

Library Structure

Descriptors

- Binary: std::bitset
- Real-valued: Eigen::Matrix
- Additional wrapper template

BoW Generators

- Abstract base class defines interface
- Actual implementation in derived classes
- Currently implemented: HashBoW, DBoW

BoW Vectors

- Mimics std::vector interface
- Contains word identifiers and values
- Additional normalization functionality

Database

- Generic database implementation
- Inverted index for fast queries
- Scoring: L_1, L_2, Cosine Similarity

Improvements

HashBoW

Training procedure:

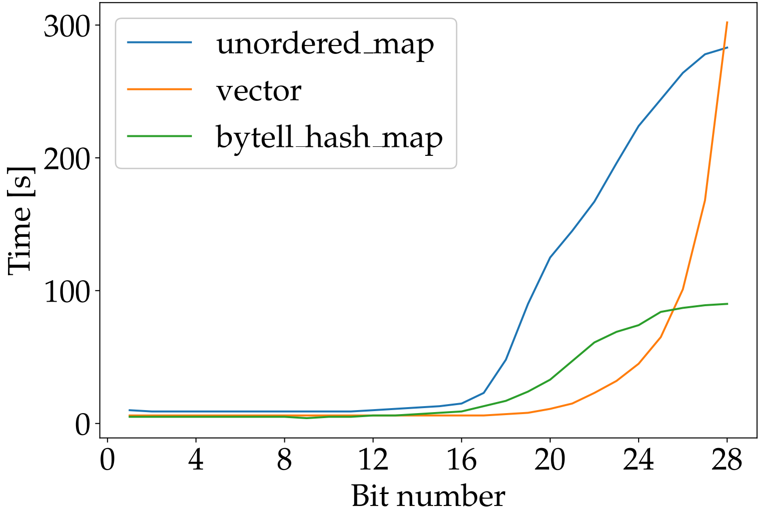
- Entropy maximization of hash codes
- Count associated descriptors for every hash code
- Trade-off between run time and memory efficiency for large hash codes

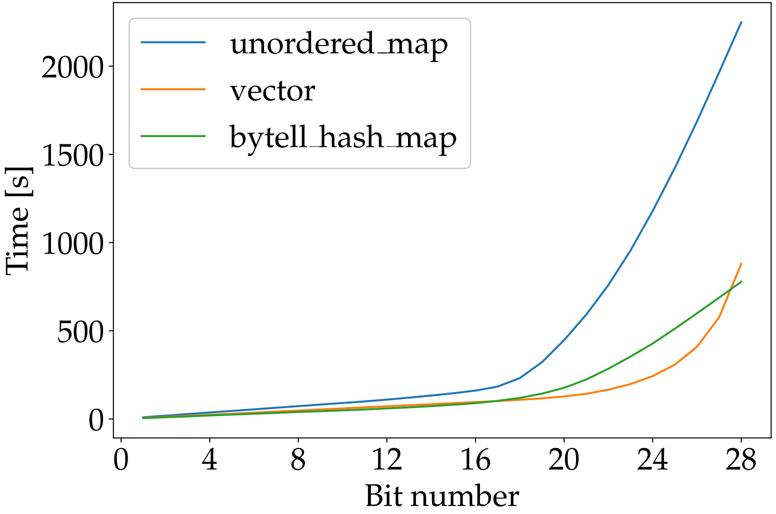
Choice of container:

- std::unordered_map: Memory-efficient but slow
- std::vector: Fast (at first) but memory-inefficient
- ska::bytell_hash_map [5]: Good compromise

Improvements

HashBoW: Container Performance





Improvements

DBoW

Descriptors:

- Change cv::Mat to std::bitset / Eigen::Matrix
- Faster in mean and distance calculation

Bag-of-words vectors:

- Change std::map to std::unordered_map
- Constant instead of logarithmic complexity (search & insert)

Improvements

DBoW

Inverted index:

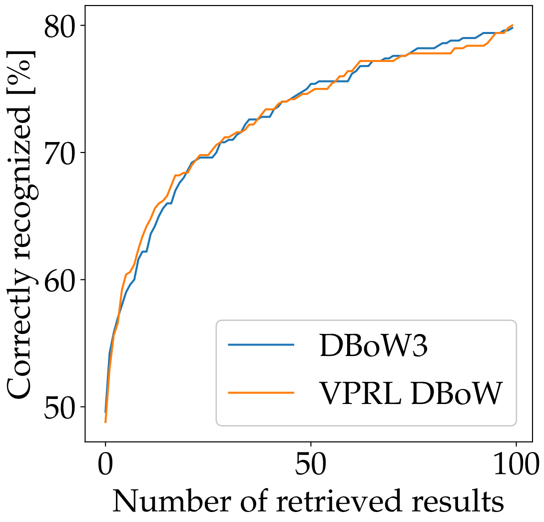
- Change std::vector<std::list> to std::unordered_map<std::vector>
- Improves run-time and memory efficiency

Additional improvements:

- More modern C++
- Improved documentation
- Small changes to further improve run time

Improvements

DBoW: Accuracy and run time



Method	Train	Add	Query
DBoW3	74 m 12 s	14.22 s	10.42 s
VPRL DBoW (ours)	14 m 41 s	3.12 s	1.98 s

Conclusion

Contributions & Future Work

Main Contributions

1. Overview and evaluation of efficient techniques for visual place recognition
2. Novel hashing-based bag-of-words approach
3. Benchmarking suite which is easy to use and extend
4. Efficient and well-documented library for bag-of-words methods

Future Work

Benchmarking Suite:

- More datasets, place recognition methods, evaluation metrics
- Different pipelines, e.g. loop closure detection

Library:

- More methods & database implementations
- DBoW: Direct Index

HashBoW:

- Performance improvements: Different hashing function, locality-preserving hashing
- Extension to real-valued descriptors

Check out the code

Benchmarking Suite:
https://gitlab.vision.in.tum.de/vpr/vpr_benchmark

VPR Library:
https://gitlab.vision.in.tum.de/vpr/vpr_library

Pretrained vocabularies & full evaluation data:
https://gitlab.vision.in.tum.de/vpr/vpr_data

Thank you for your attention.

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Literature

[1] X. Gao, R. Wang, N. Demmel, and D. Cremers, "LDSO: Direct sparse odometry with loop closure," in *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2018, pp. 2198–2204.

[2] M. Cummins and P. Newman, "Probabilistic appearance based navigation and loop closing," in Proceedings 2007 IEEE International Conference on Robotics and Automation, 2007, pp. 2042–2048

[3] D. Gálvez-López and J. D. Tardós, "Bags of binary words for fast place recognition in image sequences," *IEEE Transactions on Robotics*, vol. 28, no. 5, pp. 1188–1197, 2012.

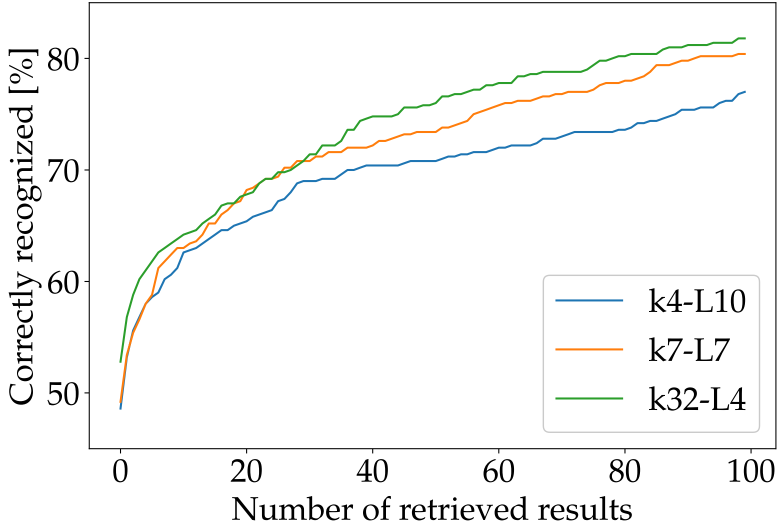
[4] D. Schlegel and G. Grisetti, "HBST: A hamming distance embedding binary search tree for feature-based visual place recognition," *IEEE Robotics and Automation Letters*, vol. 3, no. 4, pp. 3741–3748, 2018 .

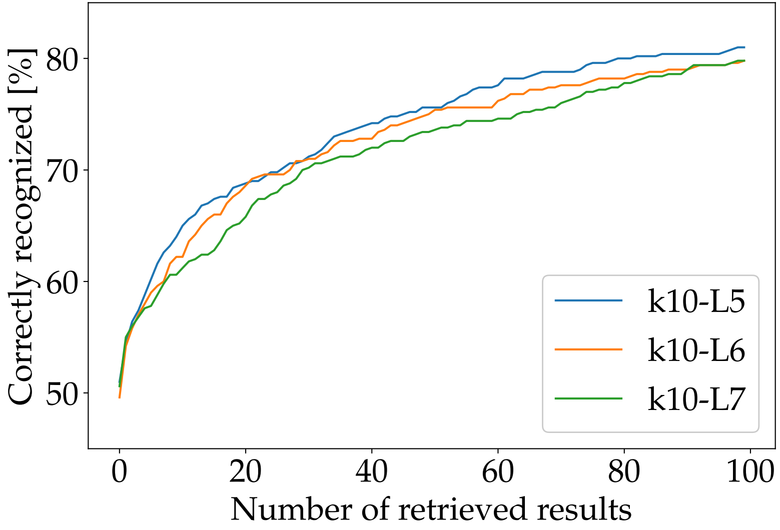
[5] M. Skarupke, *A new fast hash table in response to google's new fast hash table | probably dance*, May 28, 2018. [Online]. Available: https://probablydance.com/2018/05/28/a-new-fast-hash-table-in-response-to-googles-new-fasthash-table/ (visited on 2020-06-22).

Bonus Slides

Evaluation

Parameter Analysis: Vocabulary Tree Size / Structure (DBoW)





Evaluation

Parameter Analysis: Vocabulary Tree Size / Structure (DBoW)

Parameters	Training time
k = 4, L = 10	74 m 23 s
k = 7, L = 7	65 m 35 s
k = 32, L = 4	83 m 6 s

Parameters	Training time
k = 10, L = 5	64 m 41 s
k = 10, L = 6	74 m 12 s
k = 10, L = 7	78 m 35 s

Evaluation

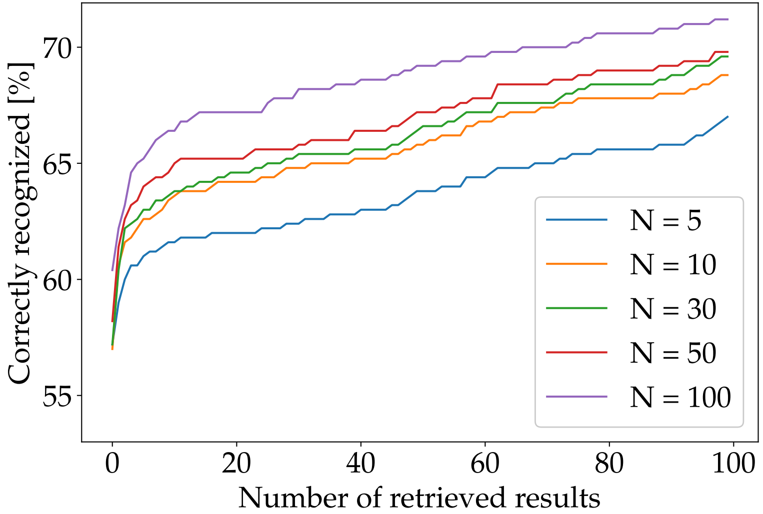
Parameter Analysis: Vocabulary Tree Size / Structure (DBoW)

Parameters	Add	Query
k = 4, L = 10	12.88 s	10.40 s
k = 7, L = 7	13.04 s	10.39 s
k = 32, L = 4	20.88 s	13.35 s

Parameters	Add	Query
k = 4, L = 10	9.95 s	19.00 s
k = 7, L = 7	14.33 s	10.42 s
k = 32, L = 4	17.74 s	10.80 s

Evaluation

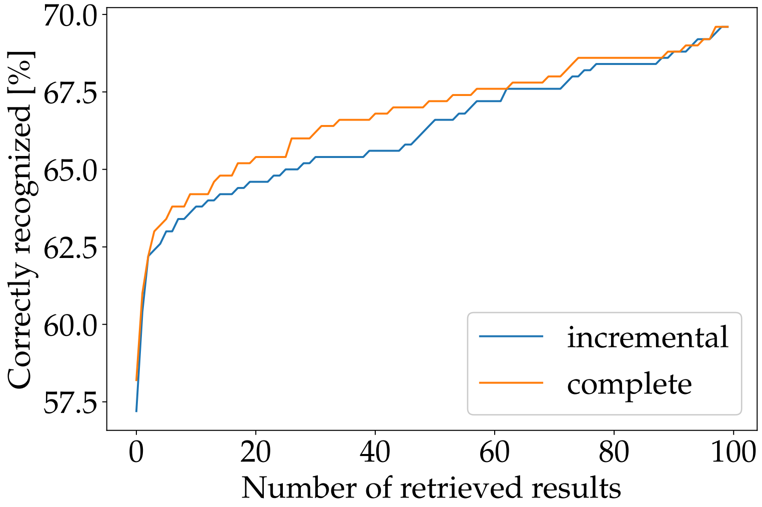
Parameter Analysis: Maximum Leaf Size (HBST)



Max. Leaf Size	Add	Query
5	9.69 s	2.10 s
10	4.58 s	2.25 s
30	5.15 s	2.71 s
50	6.20 s	3.22 s
100	8.85 s	4.61 s

Evaluation

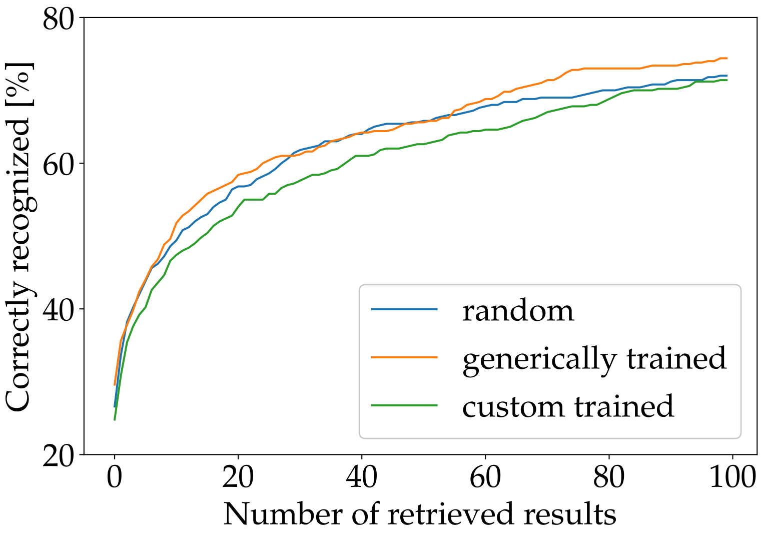
Tree Construction Strategy (HBST)

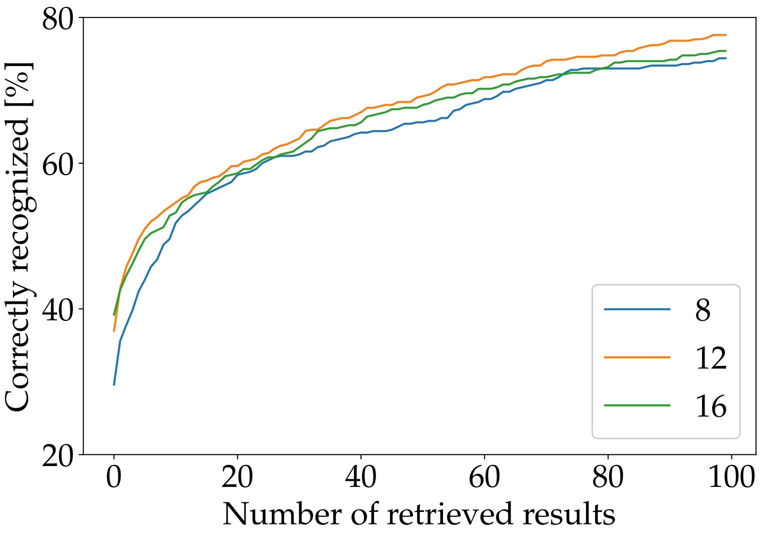


Construction	Add	Train
Incremental	5.17 s	-
Complete	0.02 s	103.27 s

Evaluation

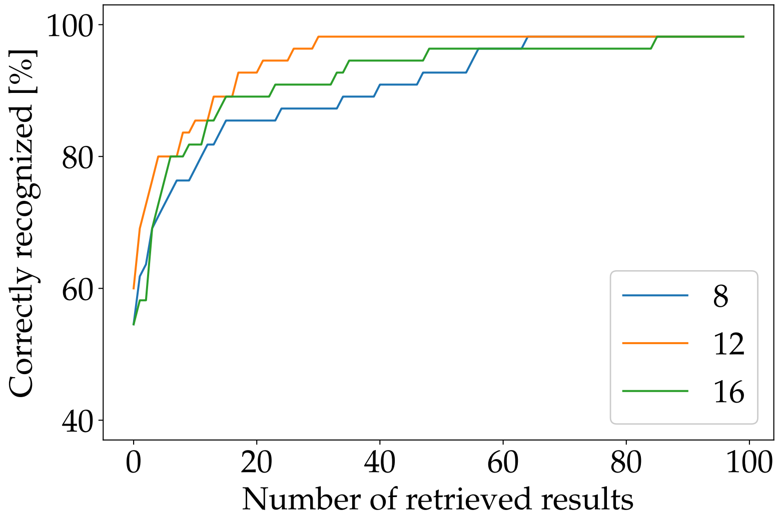
Training: HashBoW (Holidays)

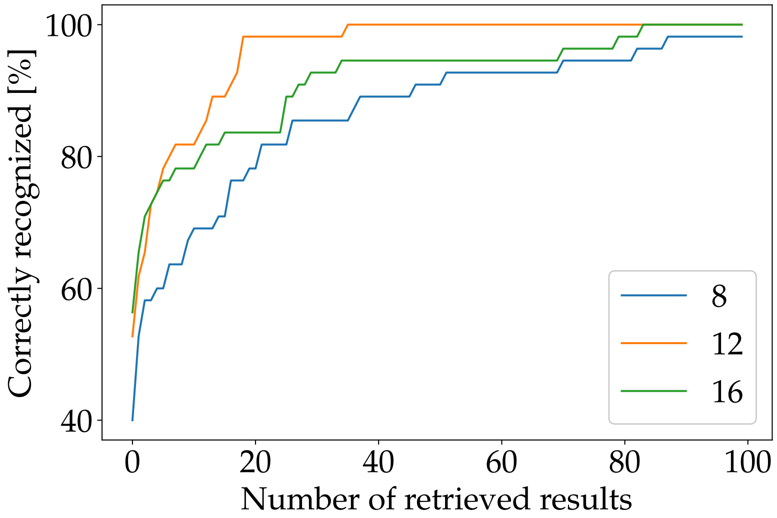




Evaluation

Training: HashBoW (Paris)





Evaluation

Influence of Feature Extractor: HashBoW