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

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

Source: Cummins and Newman [2]
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

<table>
<thead>
<tr>
<th>Bits</th>
<th>Add</th>
<th>Query</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>0.12 s</td>
<td>0.19 s</td>
</tr>
<tr>
<td>8</td>
<td>0.15 s</td>
<td>1.23 s</td>
</tr>
<tr>
<td>12</td>
<td>0.27 s</td>
<td>3.19 s</td>
</tr>
<tr>
<td>16</td>
<td>0.56 s</td>
<td>2.09 s</td>
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<tr>
<td>20</td>
<td>0.84 s</td>
<td>1.11 s</td>
</tr>
<tr>
<td>24</td>
<td>1.19 s</td>
<td>0.71 s</td>
</tr>
</tbody>
</table>
Evaluation

Influence of Training Dataset (DBoW)
Evaluation

Influence of Feature Extractor: DBoW & HBST

![DBoW Graph](image)

![HBST Graph](image)
Evaluation

Final Method Comparison

<table>
<thead>
<tr>
<th>Method</th>
<th>Add</th>
<th>Query</th>
</tr>
</thead>
<tbody>
<tr>
<td>DBoW</td>
<td>14.15</td>
<td>10.27 s</td>
</tr>
<tr>
<td>HBST</td>
<td>5.09</td>
<td>2.67 s</td>
</tr>
<tr>
<td>HashBoW-random</td>
<td>0.15</td>
<td>1.23 s</td>
</tr>
<tr>
<td>HashBoW-trained</td>
<td>0.32</td>
<td>3.74 s</td>
</tr>
</tbody>
</table>

→ 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: L₁, L₂, 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

<table>
<thead>
<tr>
<th>Method</th>
<th>Train</th>
<th>Add</th>
<th>Query</th>
</tr>
</thead>
<tbody>
<tr>
<td>DBoW3</td>
<td>74 m 12 s</td>
<td>14.22 s</td>
<td>10.42 s</td>
</tr>
<tr>
<td>VPRL DBoW (ours)</td>
<td>14 m 41 s</td>
<td>3.12 s</td>
<td>1.98 s</td>
</tr>
</tbody>
</table>
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.

Tim Stricker

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Literature


Bonus Slides
Evaluation

Parameter Analysis: Vocabulary Tree Size / Structure (DBoW)
Evaluation

Parameter Analysis: Vocabulary Tree Size / Structure (DBoW)

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Training time</th>
<th>Parameters</th>
<th>Training time</th>
</tr>
</thead>
<tbody>
<tr>
<td>k = 4, L = 10</td>
<td>74 m 23 s</td>
<td>k = 10, L = 5</td>
<td>64 m 41 s</td>
</tr>
<tr>
<td>k = 7, L = 7</td>
<td>65 m 35 s</td>
<td>k = 10, L = 6</td>
<td>74 m 12 s</td>
</tr>
<tr>
<td>k = 32, L = 4</td>
<td>83 m 6 s</td>
<td>k = 10, L = 7</td>
<td>78 m 35 s</td>
</tr>
</tbody>
</table>
Evaluation

Parameter Analysis: Vocabulary Tree Size / Structure (DBoW)

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Add</th>
<th>Query</th>
</tr>
</thead>
<tbody>
<tr>
<td>k = 4, L = 10</td>
<td>12.88 s</td>
<td>10.40 s</td>
</tr>
<tr>
<td>k = 7, L = 7</td>
<td>13.04 s</td>
<td>10.39 s</td>
</tr>
<tr>
<td>k = 32, L = 4</td>
<td>20.88 s</td>
<td>13.35 s</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Add</th>
<th>Query</th>
</tr>
</thead>
<tbody>
<tr>
<td>k = 4, L = 10</td>
<td>9.95 s</td>
<td>19.00 s</td>
</tr>
<tr>
<td>k = 7, L = 7</td>
<td>14.33 s</td>
<td>10.42 s</td>
</tr>
<tr>
<td>k = 32, L = 4</td>
<td>17.74 s</td>
<td>10.80 s</td>
</tr>
</tbody>
</table>
Evaluation

Parameter Analysis: Maximum Leaf Size (HBST)

<table>
<thead>
<tr>
<th>Max. Leaf Size</th>
<th>Add</th>
<th>Query</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>9.69 s</td>
<td>2.10 s</td>
</tr>
<tr>
<td>10</td>
<td>4.58 s</td>
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<tr>
<td>30</td>
<td>5.15 s</td>
<td>2.71 s</td>
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<tr>
<td>50</td>
<td>6.20 s</td>
<td>3.22 s</td>
</tr>
<tr>
<td>100</td>
<td>8.85 s</td>
<td>4.61 s</td>
</tr>
</tbody>
</table>
Evaluation

Tree Construction Strategy (HBST)

<table>
<thead>
<tr>
<th>Construction</th>
<th>Add</th>
<th>Train</th>
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</thead>
<tbody>
<tr>
<td>Incremental</td>
<td>5.17 s</td>
<td>-</td>
</tr>
<tr>
<td>Complete</td>
<td>0.02 s</td>
<td>103.27 s</td>
</tr>
</tbody>
</table>
Evaluation

Training: HashBoW (Holidays)
Evaluation

Training: HashBoW (Paris)

![Graph 1: Correctly recognized results vs. Number of retrieved results](image1)

![Graph 2: Correctly recognized results vs. Number of retrieved results](image2)
Evaluation

Influence of Feature Extractor: HashBoW

![Graph showing the evaluation of different feature extractors.](image-url)