

Computer Vision Lab #9

Implement Visual Place Recognition using Bag of Visual Words

Objective:

To implement a visual place recognition system that identifies the top 10 most similar images to a given query image from a database using the **Bag of Visual Words model**.

Required Tools:

- Python 3.x
- OpenCV library for Python
- scikit-learn library for Python
- NumPy library
- A dataset of images (e.g., Freiburg dataset)

Task 1: Implement a visual place recognition system following these steps

Part 1: Preparation and Setup

1. Download and Setup Dataset:

- Download the Freiburg dataset from the provided link. <https://uni-bonn.sciebo.de/s/c2d0a1ebbe575fdb2a35a8033f1e2ab>
- Unzip and store the images in a directory accessible to your Python script.

Data Examples



```

1337850707.108278
1337850707.558294
1337850708.058266
1337850708.508274
1337850709.008243
1337850709.458249
1337850709.958227
1337850710.408230
1337850710.908209
1337850711.358219
1337850711.858189
1337850712.358196

```

```

-0.103 GPS_RAM gps time=1337850706.695046, utctime=[3x1]
(9, 11, 23), lat=48.014315, lon=7.832350, qual=1, sats=0, hdop=1.3
0.798 GPS_RAM gps time=1337850707.596094, utctime=[3x1]
(9, 11, 24), lat=48.014315, lon=7.832350, qual=1, sats=0, hdop=1.3
1.700 GPS_RAM gps time=1337850708.498274, utctime=[3x1]
(9, 11, 25), lat=48.014315, lon=7.832350, qual=1, sats=0, hdop=1.3
2.982 GPS_RAM gps time=1337850709.700428, utctime=[3x1]
(9, 11, 26), lat=48.014315, lon=7.832350, qual=1, sats=0, hdop=1.3
3.784 GPS_RAM gps time=1337850710.502017, utctime=[3x1]
(9, 11, 27), lat=48.014315, lon=7.832350, qual=1, sats=0, hdop=1.3
4.586 GPS_RAM gps time=1337850711.303706, utctime=[3x1]
(9, 11, 28), lat=48.014315, lon=7.832350, qual=1, sats=0, hdop=1.3
5.908 GPS_RAM gps time=1337850712.706173, utctime=[3x1]
(9, 11, 29), lat=48.014315, lon=7.832350, qual=1, sats=0, hdop=1.3
6.718 GPS_RAM gps time=1337850713.507768, utctime=[3x1]
(9, 11, 30), lat=48.014315, lon=7.832350, qual=1, sats=0, hdop=1.3
7.514 GPS_RAM gps time=1337850714.312165, utctime=[3x1]
(9, 11, 31), lat=48.014315, lon=7.832350, qual=1, sats=0, hdop=1.3
8.608 GPS_RAM gps time=1337850715.718731, utctime=[3x1]
(9, 11, 32), lat=48.014315, lon=7.832350, qual=1, sats=0, hdop=1.3
9.723 GPS_RAM gps time=1337850716.520946, utctime=[3x1]
(9, 11, 33), lat=48.014315, lon=7.832350, qual=1, sats=0, hdop=1.3
10.524 GPS_RAM gps time=1337850717.322499, utctime=[3x1]
(9, 11, 34), lat=48.014315, lon=7.832350, qual=1, sats=0, hdop=1.3
11.927 GPS_RAM gps time=1337850718.724799, utctime=[3x1]
(9, 11, 35), lat=48.014315, lon=7.832350, qual=1, sats=0, hdop=1.3

```

2. Software Installation:

- Ensure Python 3.x is installed on your system.
- Install necessary Python libraries using pip:

`pip install numpy opencv-python-headless scikit-learn`

Part 2: Image Loading and Preprocessing

1. Load Images:

- Write a function to read all images from the dataset directory.
- Convert images to grayscale to simplify processing and improve computation speed.

2. Feature Extraction:

- Use SIFT (Scale-Invariant Feature Transform) to extract keypoints and descriptors from each image.

Part 3: Building the Visual Dictionary

1. Feature Aggregation:

- Combine descriptors from all images into a single matrix.

2. K-Means Clustering:

- Apply k-means clustering to the aggregated descriptors to form **k** clusters; start with **k=1000**.

`Import the kmeans from
from sklearn.cluster import KMeans`

- Each cluster center represents a "visual word" in the BoVW dictionary.

Part 4: Encoding Images

1. Histogram Encoding:

- For each image, create a histogram that counts how many descriptors belong to each visual word.
- Normalize histograms to account for varying image sizes and descriptor counts.

Part 5: Query Processing

1. Query Image:

- Extract features from the query image(s).
- Encode these features using the same visual dictionary to get a histogram.

2. Similarity Search:

- Use Nearest Neighbors to find the 10 closest histograms in the dataset. Import it from `from sklearn.neighbors import NearestNeighbors`
- Use the `Euclidean distance` as a measure of similarity.

Part 6: Visualization of Results

1. Output and Visualization:

- Display the top 10 similar images.
- Optionally, generate an HTML file to present these images in a browser for easy viewing.

Example Code Snippets:

```
import cv2
import numpy as np
import os
from sklearn.cluster import KMeans
from sklearn.neighbors import NearestNeighbors
import matplotlib.pyplot as plt
import webbrowser
import tempfile

def load_images(image_folder):
    images = []
    for filename in os.listdir(image_folder):
        path = os.path.join(image_folder, filename)
        img = cv2.imread(path, cv2.IMREAD_GRAYSCALE)
        if img is not None:
            images.append(img)
    return images

def extract_features(images):
    sift = cv2.SIFT_create()
    descriptors_list = []
    keypoints_list = []
    for img in images:
```

```

        keypoints, descriptors = sift.detectAndCompute(img, None)
        if descriptors is not None:
            descriptors_list.append(descriptors)
            keypoints_list.append(keypoints)
    return keypoints_list, descriptors_list

def build_codebook(descriptors_list, codebook_size=1000):
    #your code here
    return kmeans

def encode_features(descriptors_list, kmeans):
    histograms = []
    for descriptors in descriptors_list:
        #your code here
    return histograms

def find_similar_images(query_histogram, histograms):
    #your code here
    return indices[0]

def visualize_results(image_paths, indices):
    #your code here

def main():
    image_folder = 'your image path'
    images = load_images(image_folder)
    _, descriptors_list = extract_features(images)
    kmeans = build_codebook(descriptors_list)
    histograms = encode_features(descriptors_list, kmeans)
    query_histogram = histograms[0] # Assuming first image is the query
    indices = find_similar_images(query_histogram, histograms)
    image_paths = [os.path.join(image_folder, f) for f in
os.listdir(image_folder)]
    visualize_results(image_paths, indices)

if __name__ == '__main__':
    main()

```

Task 2: Parameter Optimization:

- Explore the effect of **varying the number of visual words** (i.e., the k in k -means) on the recognition performance. Start with small values and gradually increase to see the impact on accuracy and computation time.
- Experiment with different feature detectors such as ORB or SURF, and compare their effectiveness and efficiency against SIFT.

Task 3: Weighting Visual Words:

- Investigate the use of **Term Frequency-Inverse Document Frequency (TF-IDF) weighting** to give more importance to less frequent visual words that might be more distinctive.