Robust Place Recognition of Robot in Urban Canyon Using Neural Network

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Abstract

Query (Sep. 2018)



Trained (Nov. 2014)





Motivation

Visual Place Recognition in Urban Environment



Observed Scene



Find where I am

Challenges in Revisiting the Same Place



1. Short-term Appearance Change



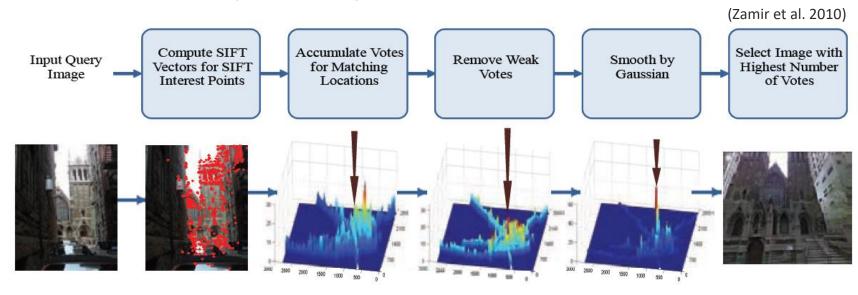
2. Long-term Appearance Change



(Kim et al. 2017)

Related Works

- 1. Using global feature
 - GIST (Murillo 09, Singh 10)
- 2. Using local feature
 - Bag-of-Words (Cummins 08)
 - Hierarchical manner (Zamir 10)



→ Not suitable for the long-term place recognition... How to overcome spatio-temporal differences?



Related Works

- 1. Ilumination-invariant imaging
 - ZNCC (Maddern 14, McManus 14)
- 2. The first place recognition based on a CNN model
 - Feature & Sequential matching (Chen 14)



→ Combine and take advantage of both methods to overcome long-term (seasons and years) changes



Find the match between a query and a corresponding image

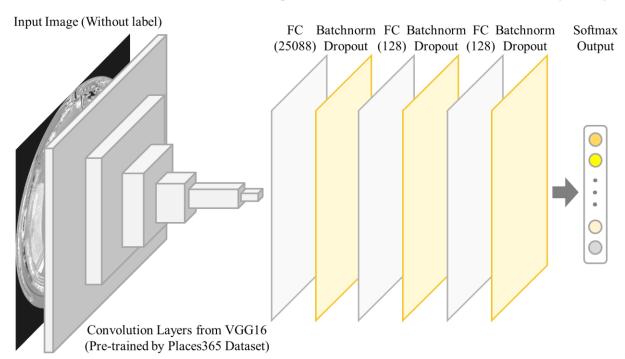
→ Feature matching is done by <u>end-to-end supervised learning</u>





Neural Network Design

- A. Convolution layers
 - Based on VGG16, pre-trained by Places365 Dataset
- B. Dense layers
 - Optimal depth and width are found by heuristic approach
- C. Prediction
 - Print out five predicted scenes which might be matched with the query image





Use *fisheye image* instead of generic image taken in urban environment

- 1. Independent to the direction
- 2. Wide field of view → Contains less-variant visual contexts (e.g. skylines, buildings...)







Generic images (Temporally variant)



Fisheye image (Temporally invariant)



Data Acquisition

Three different paths in an urban area (Daejeon, Korea)

B. Training images

Download panorama images from Google Streetview and convert them into spherical form (2014.11)

C. Test images

■ Taken by an omni-directional camera (2018.09)



Sequence type	Length [km]	Number of images
Sequence 1	1.64	137
Sequence 2	1.47	136
Sequence 3	1.61	132



Image Augmentation*

A. Illumination-invariant imaging

- Project RGB channel of original image onto single illumination invariant channel
- Robust to color and illumination variance of image dataset
- $I = \log R_2 \alpha \log R_1 (1 \alpha) \log R_3$ where R_1, R_2 , and R_3 are three color channels
- α ranges from 0.1 to 0.9 at 0.1 intervals in training, and set to be 0.5 in test

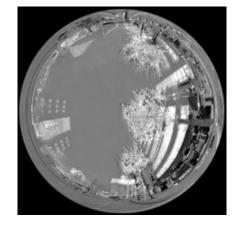
B. Rotation

- Reduce directional variance
- Rotated at 30 degrees from 0 to 360 degrees



ii-imaging





rotation





Top-1 and Top-5 Accuracies*

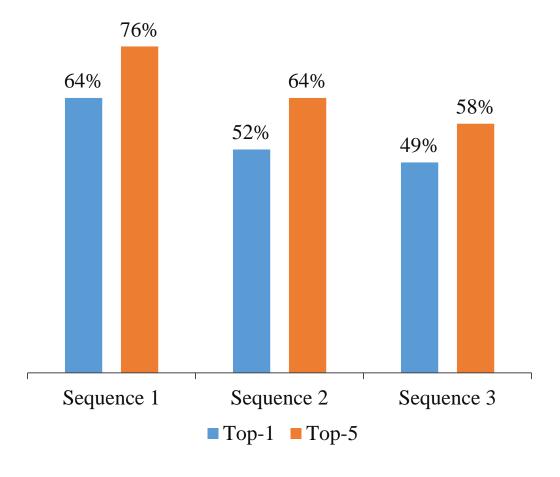
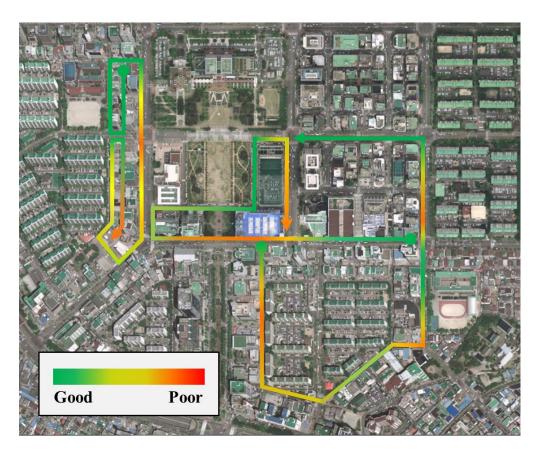


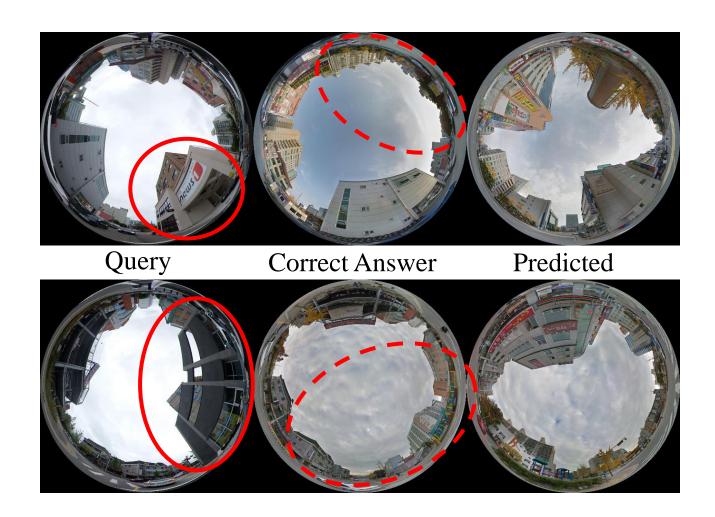
Illustration of test results





Unmatched Cases

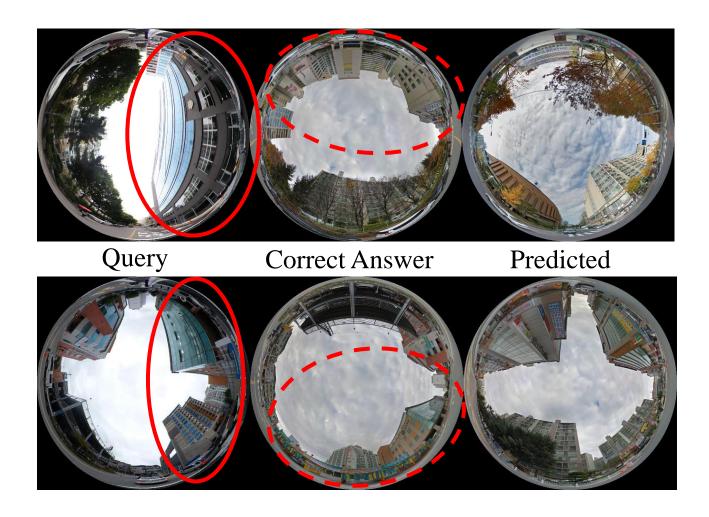
A. Newly-built building





Unmatched Cases

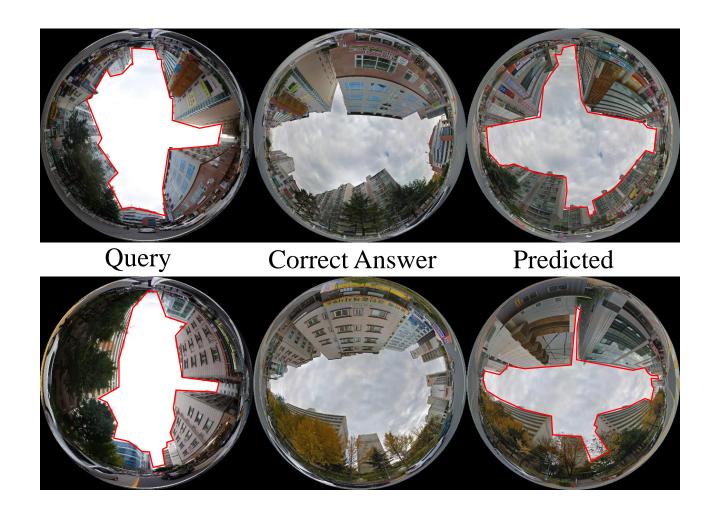
A. Newly-built building





Unmatched Cases

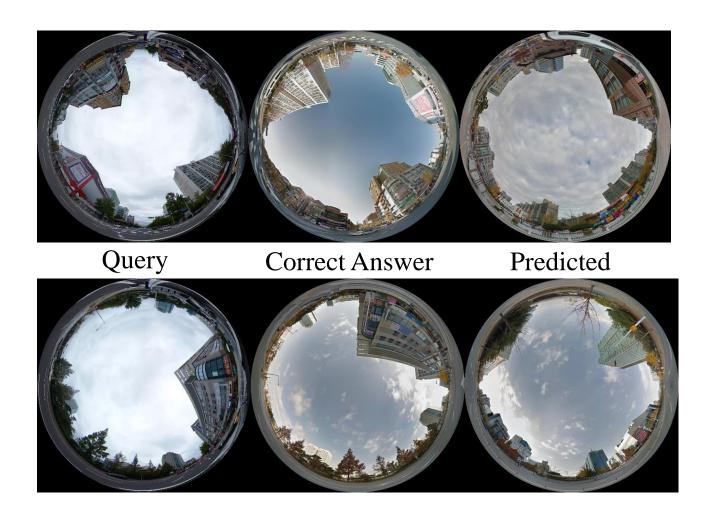
B. Similar structure





Unmatched Cases

C. Lack of features





Discussion

- The suggested method classifies urban scenes well in spite of seasonal, illuminant, and viewpoint changes cause by the four-year gap.
- However, severe change of landscape during four years makes the task hard.
- Follow-up study on a proper far-long-term localization by spherical image should be conducted.

Acknowledgement

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Questions



Video by omnidirectional camera, mounted on vehicle (2018.09)



