25th INTERNATIONAL CONFERENCE ON PATTERN RECOGNITION
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Deep Next-Best-View Planner for Cross-Season Visual Route Classification

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Abstract -This paper addresses the problem of active visual place recognition (VPR) from a novel perspective of long-term autonomy. In our approach, a next-best-view (NBV) planner plans an optimal action-observation-sequence to maximize the expected cost-performance for a visual route classification task. A difficulty arises from the fact that the NBV planner is trained and tested in different domains (times of day, weather conditions, and seasons). Existing NBV methods may be confused and deteriorated by the domain-shifts, and require significant efforts for adapting them to a new domain. We address this issue by a novel deep convolutional neural network (DNN) -based NBV planner that does not require the adaptation step.

Research Goal

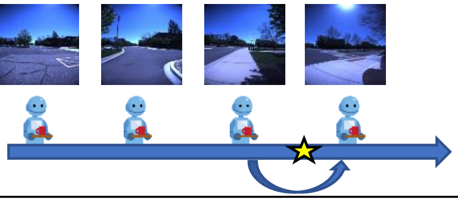
Background : VPR (Long-term visual place recognition)

Goal : classify ego-centric view images into pre-defined place classes

Standard solution : passive setting
the robot's action is determined by a predefined control rule, such as a constant speed motion rule.

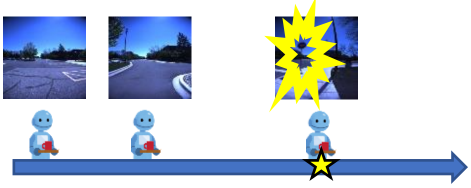
Limitations :

i. viewpoints are not necessarily optimized for the VPR task.
ii. produce an unnecessarily large number of redundant observations.



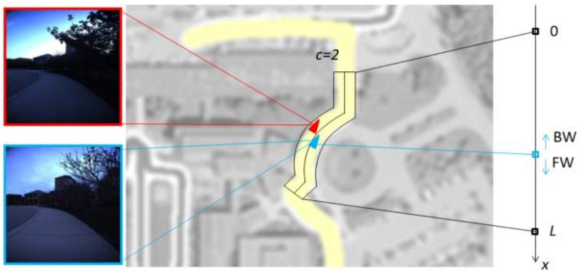
Our approach :

i. active VPR in visual route classification
ii. domain-invariant NBV planner



Proposal: NBV as POMDP (partially observable decision process)

State: s=(x,c)
c: hidden place class
x: viewpoint wrt the place c



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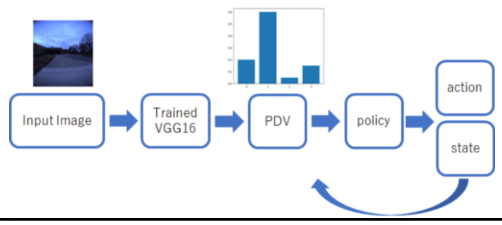
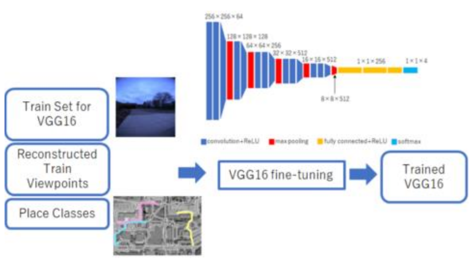
Proposed approach

The goal of an NBV planner is to plan an optimal action-observation-sequence that is expected to maximally improve the cost performance of VPR.

Training VPR

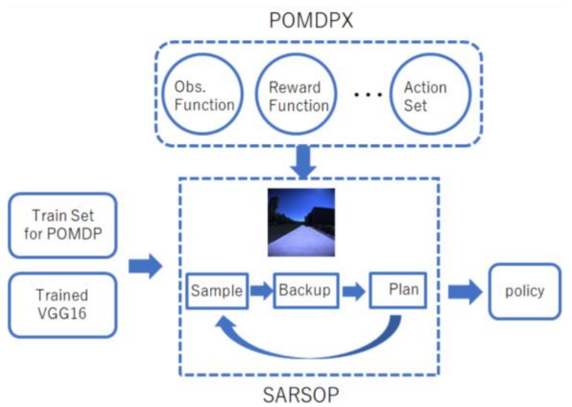


Training planner



Planning NBV

Following the definition by Kaelbling, we define POMDP as a six-tuple (S,A,T,R,W,O)



Result

a. the conventional passive single-view VPR
b. a multi-view VPR
c. the proposed multi-view VPR method

(a) success rate [%]

	ws1	ws2	ws3
single-view	86.7	64.5	77.1
multi-view	84.5	64.5	77.2
proposed	87.8	66.7	82.8

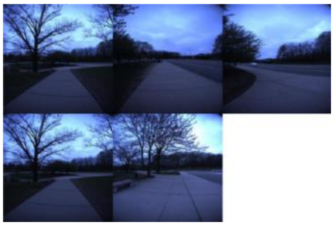
(b) average number of observations

	ws1	ws2	ws3
single-view	1.00	1.00	1.00
multi-view	2.57	2.67	2.66
proposed	2.14	1.99	2.51

(c) average travel distance

	ws1	ws2	ws3
single-view	0.0	0.0	0.0
multi-view	79.2	89.3	78.1
proposed	34.3	34.4	40.0

The figure below shows examples of the image sequences acquired at the planned viewpoints.


Example 1


Example 2

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