Online Traversable Region Detection in Unstructured Outdoors

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Sungho Jo
School of Computing
KAIST

KAIST School of Computing

How to Long-Term Autonomy?

Following contents based on Ph.d Research by Honggu Lee

Objectives

(1) Self-supervised learning approach
- Use interaction with the world to automatically learn the traversability from sensor data.
- Recognize and predict collisions with the environment directly from sensors without human supervision

(2) Model building
- Environment representation model can adapt to changes in environment, even a region is hidden below dense vegetation.

(3) Experimental Evidence
- Implementation of environment representation terrain model learning approach on an automated vehicle in real-world application.

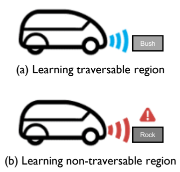


Figure.1 Self-supervised learning

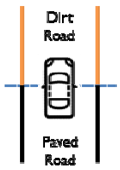


Figure.2 Adaptive learning to changes

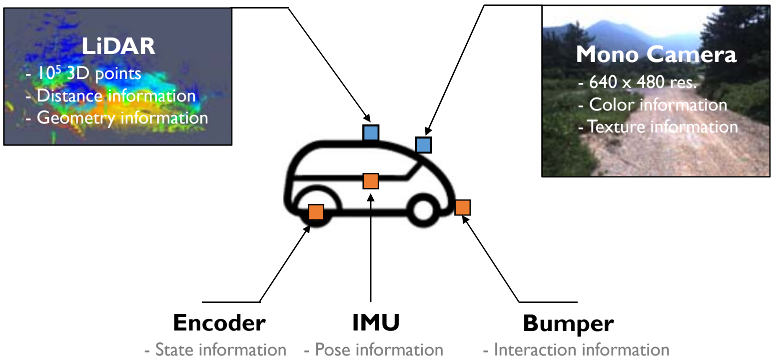

Figure.3 Example images for experiments

System Overview and Data Representation

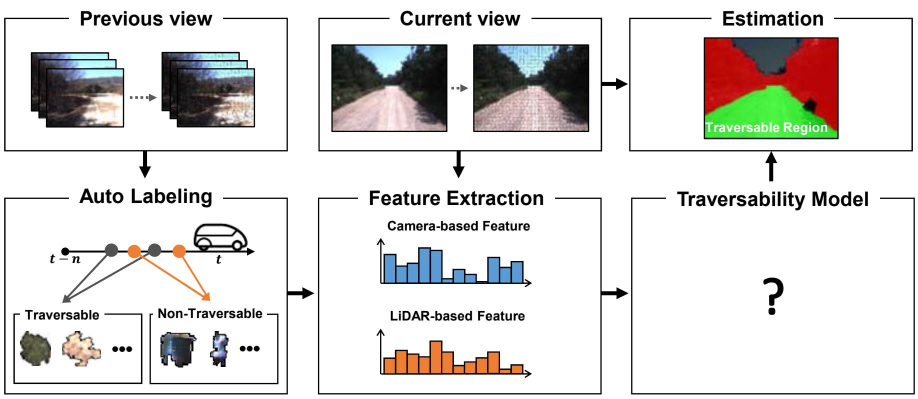
- Vehicle System Overview
- Proposed Methods Overview
- Data Representation
- Autonomous Labeling System

Vehicle System Overview

- 2 Vision sensors: Camera and LiDAR.
- 3 Positioning Sensors: IMU, Encoder and Bumper.



Proposed Methods Overview



Data Representation

- Image-based representation: Superpixels
- Visually homogeneous pixels while respecting natural scene boundaries.

(a) Grid (b) Superpixels (c) Superpixels with corresponding 3D points

Figure. Basic unit of our terrain model approach

Automatic Labeling System

- Robot interacts with its environment.
- Autonomously collect and label training data.

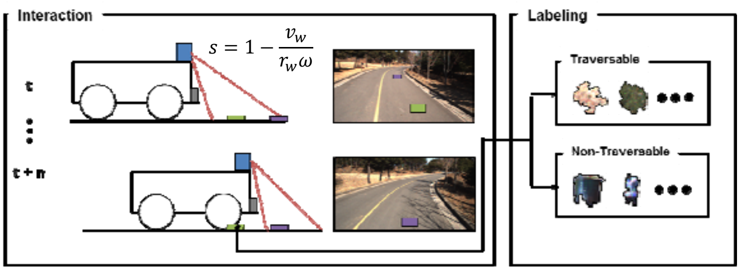


Figure. Illustration of automatic labeling system from interaction

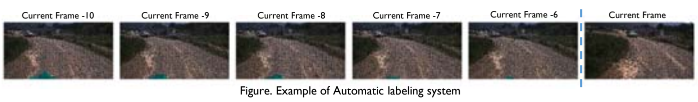
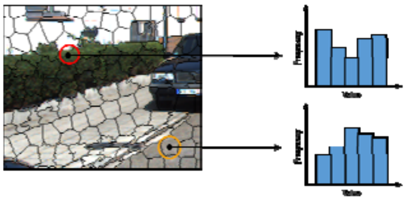


Figure. Example of Automatic labeling system

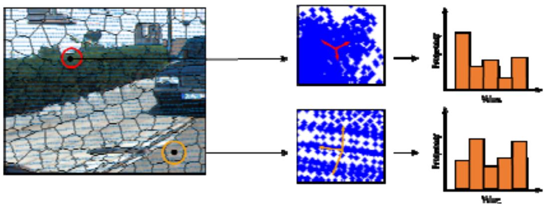
Feature Extraction

- Multi-sensor feature extraction.
- Color and Geometry histogram.

a) Color histogram.



b) Geometry histogram.

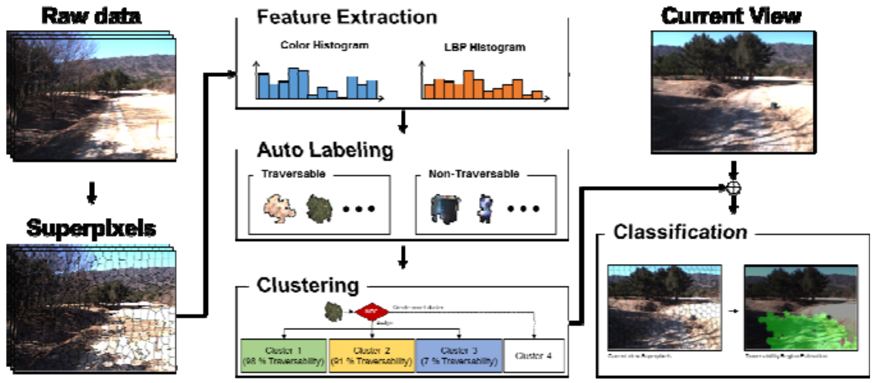


Proposed Method I:

An Incremental Nonparametric Bayesian Clustering Based Traversable Region Estimation

- Proposed Method Overview
- Traversability estimation with clustering
- Incremental Nonparametric Clustering
- Experimental Results
- Conclusion

An Incremental Nonparametric Bayesian Clustering Based Traversable Region Estimation[1]



An Incremental Nonparametric Bayesian Clustering Based Traversable Region Estimation[1]

- Traversability estimation with clustering result

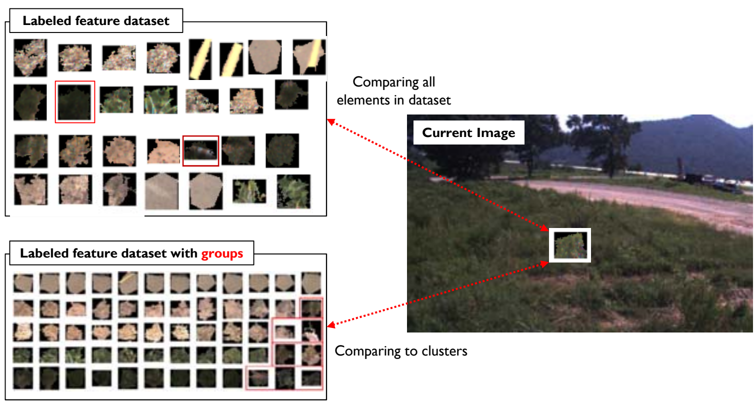
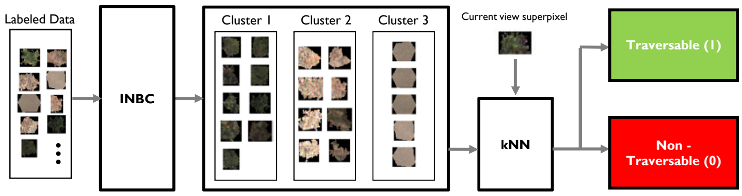


Figure. Two different methods for comparing similarity

An Incremental Nonparametric Bayesian Clustering Based Traversable Region Estimation[1]

- Traversability estimation with clustering result
  - Obtain the object class for the features extracted from the image patches by classifying them using the *knn.*
  - Obtain the traversability property associated with each object class.



An Incremental Nonparametric Bayesian Clustering Based Traversable Region Estimation[1]

- Incremental Nonparametric Bayesian Clustering (INBC)
  - Infer the number of clusters without explicitly performing expensive model comparisons
  - Computationally efficient, adaptive and incremental.

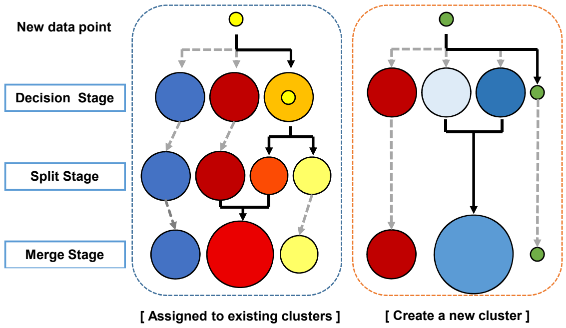


Figure. Illustration of Incremental Nonparametric Bayesian Clustering (INBC)

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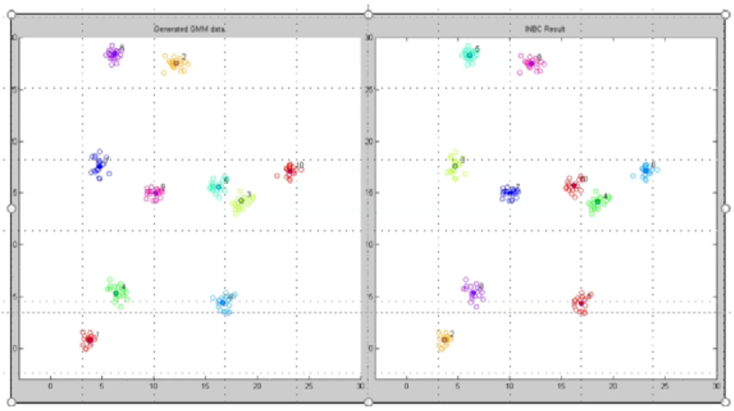
An Incremental Nonparametric Bayesian Clustering Based Traversable Region Estimation[1]

- Incremental Nonparametric Bayesian Clustering (INBC) Results



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An Incremental Nonparametric Bayesian Clustering Based Traversable Region Estimation[1]

- Incremental Nonparametric Bayesian Clustering (INBC) Results

b) Traversable Region Clustering Results

- Generate 10,000 superpixels with 5 different objects.
- Randomly select 3,000 superpixels including at least all classes to measure the clustering accuracy and add into the INBC.

Table. Purity and ARI on 3,000 superpixels dataset.

Superpixel size	$s = 20$	$s = 30$	$s = 50$	$s = 100$	$s = 150$
Paved road purity	0.941(±0.020)	0.986(±0.012)	0.931(±0.018)	0.927(±0.022)	0.901(±0.025)
Dirt road purity	0.891(±0.027)	0.914(±0.033)	0.909(±0.021)	0.887(±0.031)	0.872(±0.039)
Yellow short grass purity	0.889(±0.041)	0.920(±0.038)	0.911(±0.024)	0.871(±0.040)	0.866(±0.043)
Green short grass purity	0.822(±0.048)	0.852(±0.057)	0.849(±0.031)	0.810(±0.041)	0.801(±0.047)
Green tall grass purity	0.818(±0.074)	0.838(±0.079)	0.823(±0.088)	0.807(±0.077)	0.784(±0.091)
Number of Clusters	6.41(±0.387)	5.32(±0.118)	5.74(±0.223)	6.77(±0.499)	7.22(±0.581)
ARI on Clustering	0.878(±0.082)	0.908(±0.040)	0.897(±0.069)	0.861(±0.108)	0.843(±0.120)

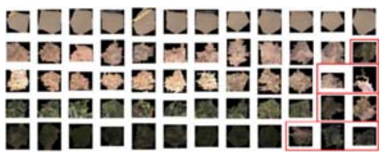

Figure. A clustering result on unstructured outdoor scene

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An Incremental Nonparametric Bayesian Clustering Based Traversable Region Estimation[1]

- Traversability Experiments

a) Traversable Region Estimation Results

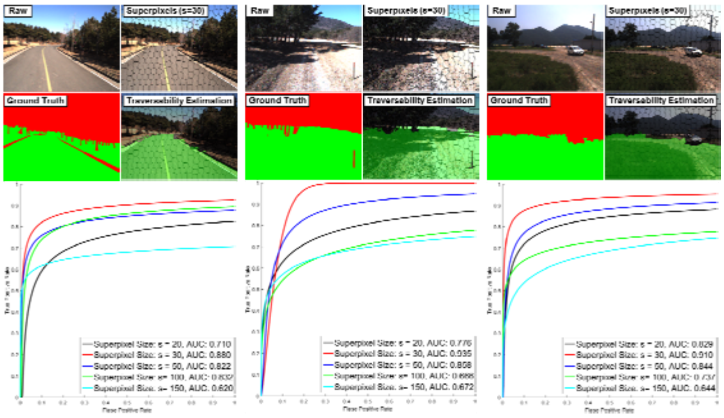

Figure. Qualitative examples of the success of the traversable region classifier

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An Incremental Nonparametric Bayesian Clustering Based Traversable Region Estimation[1]

- Traversability Experiments

b) Computation times

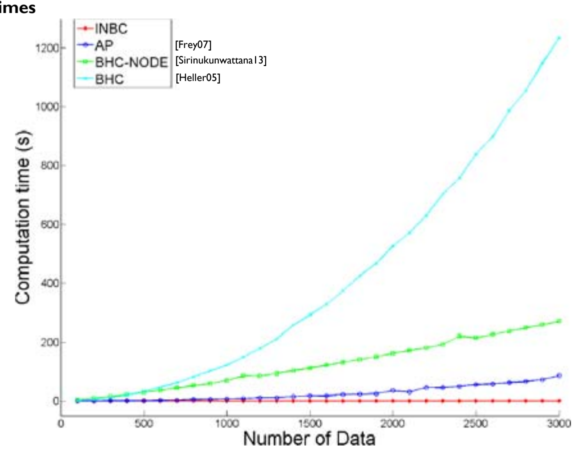

Figure. Computational times (s) of the state-of-the-art nonparametric clustering algorithm

[Frey07] BJ. Frey and D. Dueck, "Clustering by passing messages between data points", **SCIENCE**, 2007
[Heller05] KA. Heller and Z. Ghahramani "Bayesian hierarchical clustering", **ICML**, 2005
[Sirinukunwattana13] K. Sirinukunwattana, et al., "Bayesian hierarchical clustering for studying cancer gene expression data with unknown statistics", **PloS one**, 2013

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An Incremental Nonparametric Bayesian Clustering Based Traversable Region Estimation[1]

- Traversability Experiments

c) Traversable Region Estimation (Adaptation Evaluation) Results

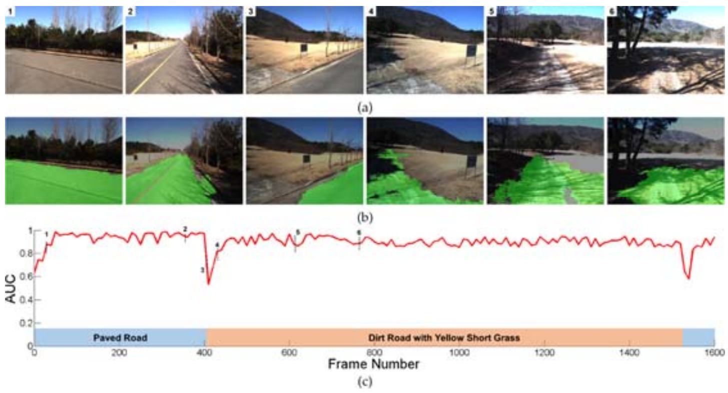

Figure. Incremental Learning Experiment In T1 and T2.
(a) Some challenging exemplary original scenes,
(b) Classifier results (Green is traversable),
(c) AUC changing when the robot is exploring in environment T1 and T2.

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An Incremental Nonparametric Bayesian Clustering Based Traversable Region Estimation[1]

- Conclusion

a) Self-supervised learning approach
- The system of our proposed approach automatically learn the traversability from sensor data to the terrain properties in unknown and unstructured environment.

b) Model building
- We show the method [2] for adapting to changes in environment. It allows handling of large data streams in real time on board a robot while maintaining good clustering performance.

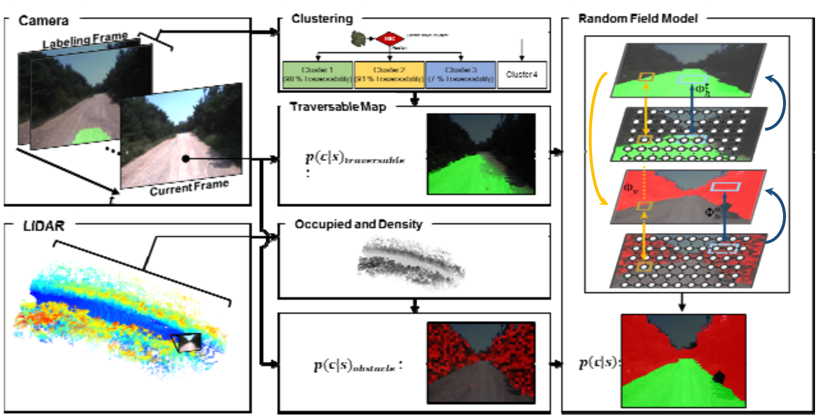
c) Questions for the future work
- Is non-traversable region always non-traversable?
- What if robot try to go shortest path?

Proposed Method 2:

Unsupervised Class Estimation for Autonomous Vehicle

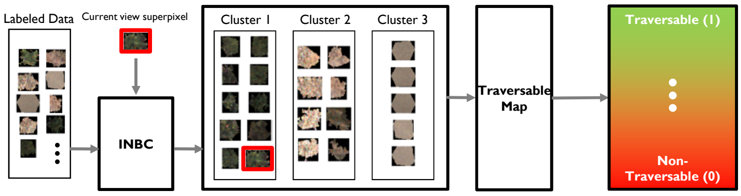
- Proposed Method Overview
- Probabilistic Traversable Map
- Probabilistic Obstacle Map
- Random Field Approach
- Experimental Results
- Conclusion

Unsupervised Class Estimation for Autonomous Vehicle[2]



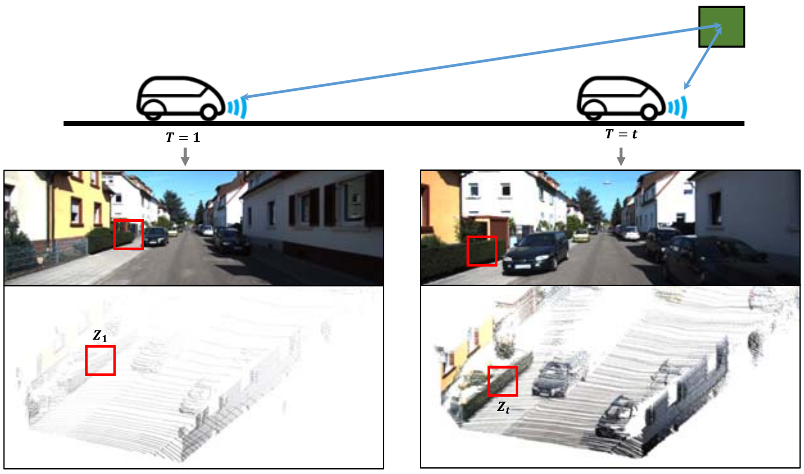
Unsupervised Class Estimation for Autonomous Vehicle[2]

- Probabilistic Traversable Map
  - Based on INBC.



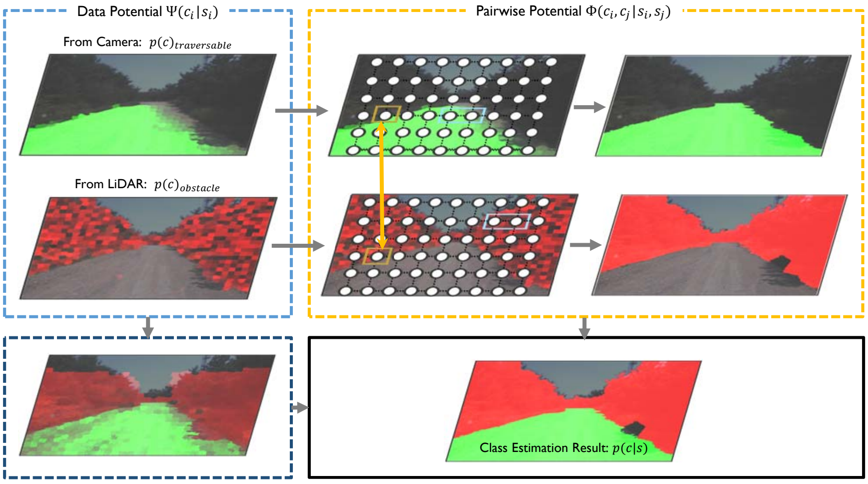
Unsupervised Class Estimation for Autonomous Vehicle[2]

- Probabilistic Obstacle Map
  - Based on the method of standard probabilistic occupancy map
  - Update from sensors readings with different location, orientations and time.



Unsupervised Class Estimation for Autonomous Vehicle[2]

- Class estimation with Random Field Approach



Unsupervised Class Estimation for Autonomous Vehicle[2]

- Experimental Results

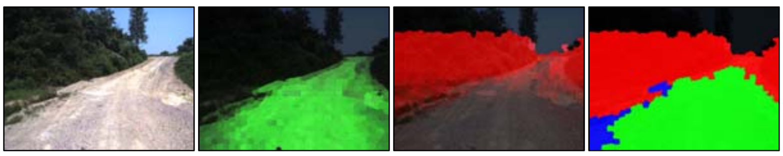


Figure. a) Dirt road class estimation results, raw, traversable map, obstacle map, and final result

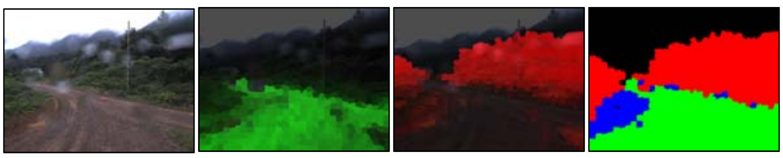


Figure. b) Dirt road in rainy day class estimation results, raw, traversable map, obstacle map, and final result

Conclusion

Summary

- Traversability Estimation for Autonomous Robot

- The Problems are,

- The Solutions are,
  - Method [1]: An Incremental Nonparametric Bayesian Clustering Based Traversable Region Detection.
  - Method [2]: Unsupervised Class Segmentation for Autonomous Vehicle.

Thank You