

Efficient Part-Graph Hashes for Object Categorization

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Motivation

In this work we present a part-graph-based classification method for classifying objects using an additive feature (GRSD-). The method allows for easy addition of new training data, without re-creating the complete model, classification time is low due to hashing, and is flexible enough to work with partial occlusions. We compared the proposed classification method on laser point clouds to SVM. We used an additive version of the GRSD feature [1],which is a histogram of neighborhoods of surfaces of different type. We exploited the additive property to efficiently compute the features for different groupings of the parts.



We used the roughly 1000 Hokuyo laser scans of objects from [1] for training and 200 scans of objects for evaluation. The scans are smoothed and segmented based on the criteria defined in [2]: grown until the angle between the seed and added normals is below 45° . The resulting parts are then used to create a part-graph by finding the touching parts, and all possible part groupings are enumerated up to a given number of parts.



Object Categories

Used common categories found in public household object datasets [1]:

- TUM Organizational Principles Database: http://ias.in.tum.de/kb/ wiki/index.php/Example_images_of_kitchens
- Household Objects for Robotic Retrieval: published by Choi et al.[3].
- KIT Object Models Web Database: http://i61p109.ira.uka.de/ ObjectModelsWebUI/
- Semantic 3D Database: http://ias.cs.tum.edu/download/ semantic-3d
- Household Objects Database from Willow Garage: http://www.ros. org/wiki/household_objects_database

Category	OPD	ALS	KIT	SemDB	WG	TOTAL
short cylinder	93	3	26	9	68	199
flat box	23	5	28	4	3	63
tetrapak	4	0	1	4	1	10
box	42	4	23	4	2	75
tall cylinder	12	1	6	3	18	40
other	145	12	26	11	40	234

References

- Zoltan Csaba Marton, Dejan Pangercic, Nico Blodow, Michael Beetz. Combined 2D-3D Categorization and Classification for Multimodal Perception Systems. In The International Journal of Robotics Research, Sage Publications, 2011.
- [2] Oscar Martinez Mozos and Zoltan Csaba Marton and Michael Beetz, "Furniture Models Learned from the WWW – Using Web Catalogs to Locate and Categorize Unknown Furniture Pieces in 3D Laser Scans", in Robotics & Automation Magazine, volume 18, number 2, pages 22–32,2011,IEEE
- [3] Young Sang Choi, Travis Deyle, and Charles C. Kemp. A List of Household Objects for Robotic Retrieval Prioritized by People with ALS (Version 092008). CoRR, abs/0902.2186, 2009
- [4] Ajmal S. Mian, Mohammed Bennamoun, and Robyn Owens. Three-Dimensional Model-Based Object Recognition and Segmentation in Cluttered Scenes. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 10, October 2006.

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Hashing Based Classification

Each grouping can be represented as a graph, and a unique arrangement key computed for it. We used the grad order, but spectral analysis is also possible. We then computed features for all part groupings for training and test data. For each arrangement key a classifier can be defined (nearest neighbors in our case) and used for identifying new instances. The classification results (distribution of class probabilities) of each grouping is accumulated for the constituent parts, and a final grouping step is needed to identify the complete objects. For now, we evaluated the method for known part gropings, making a final classification by considering the sizeweighted results for all grouped parts. Future work will focus on finding the optimal part grouping into objects in a cluttered scene, for example through model fitting aided by the per-part probabilities.

The hashing procedure over the isomorphic graph features enables faster and more discriminative training (as exemplified by NN outperforming SVM) and facilitates fast lookups. A related idea was explored in [4], but with a hash table built on local 3D features for CAD fitting, while we have feature independent hashing.



Evaluation



Confusion matrix using Euclidean distance for the GRSD- feature with five random segmentations of each scan added as training data.

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