





Scalable and Efficient Hierarchical Visual Topological Mapping



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¹ INTRODUCTION:

Compared to metric m topological maps

- Are simpler and mor
- Occupy less space
- Can map very long trajectories

To make the loop closure searche more efficient and scalable, we u

Indexing techniques

We propose:

- Hierarchical representations



Hierarchical Mapping and Localization in the global descriptor embedding space Orange Circle: Images, Outlined: Current Green Square: Locations, Outlined: Current Hatched marking: Search region for current image

² METHODOLOGY:

- We build on top of the existing HTMap technique: Garcia-Fidalgo et al. 2018
- We add optimization & improvements for **accurate** and **efficient** localization
- We adapt the framework for **learned global descriptors**



City Centre Dataset

NetVLAD (Len 4096)

Through empirical analysis, we identify and define the characteristics of an ideal global descriptor for scalable and efficient visual localization





We present a methodology for quantifying and contrasting these characteristics









distinct





Тоо

DIPVAE R128 (Len 128

- The use of have learned global descriptors to group similar images into locations
- The **characteristics** of an ideal global descriptor for use in a hierarchical setting
- The use of compact learned global descriptors that excel in continuity and distinctiveness characteristics, as an efficient and scalable means for hierarchical topological mapping.

S. Ramachandran, J. Horgan, G. Sistu and J. McDonald, "Scalable and Efficient Hierarchical Visual Topological Mapping," 2023 21st International Conference on Advanced Robotics (ICAR), 2023, pp. 113-120, doi: 10.1109/ICAR58858.2023.10406394.

³ EVALUATION:

We **compare** hierarchical topological mapping technique with stateof-the-art global descriptors

- Hand-crafted: PHOG
- Learned:
- Contrastive Supervised: **NetVLAD**
- Semantic Supervised: LoST
- VAE Unsupervised: **DIPVAE**

and perform extensive analysis on the impact of the global descriptor used



PHOG (Len 1260)

NetVLAD128 (Len 128) DIPVAE R64 (Len 128)





St Lucia Dataset (17.6 km, 21,815 images)





moves





Distance matrices of different global descriptors for *City* Centre dataset with 20-25 locations shown as lower and upper triangular distance matrices along with corresponding distance scales on the sides.

Distinctiveness

Descriptor distance between images from different regions should be significantly larger than that to images from similar regions



4 RESULTS:

Unsupervised learned VAE-based descriptor DIPVAE (both R64 and R128) variants

excels in

- Distinctiveness
- Continuity

Characteristics and achieve:

Significantly less total false positive locations

Descriptor similarity decreases

gradually as the robot/vehicle

- Significantly lower compute time
- Significantly lower total mapping runtime



- upto* **2.3x faster** than NetVLAD, less than half runtime
- upto* 9.5x faster than PHOG, close to one-tenth runtime
- *maximized gains when trajectory is **longer** and consists of more locations
- While maintaining the same recall performance

GDescriptor	n(Loc)	Runtime (s) \downarrow	GDescriptor	Length 1	Туре	Device	BSize 1	Compute Time (s) ↓
PHOG	721	27939.47	PHOG	1260	Handcrafted	CPU	16	0.005455 0.007601
LoST	654	12041.02	LoST	6144	Supervised	GPU	22	0.181668 0.231041
NetVLAD	624	6753.36	NetVLAD	4096	Supervised	GPU	22	0.027397 0.048229
NetVLAD Cropped	698	8878.51	NetVLAD Cropped	128	Supervised	GPU	22	0.027907 0.049699
DIPVAE R128	665	2967.95	DIPVAE R128	128	Unsupervised	GPU	1500	0.000008 0.000179
DIPVAE R64	609	3070.28	DIPVAE R64	128	Unsupervised	GPU	6000	0.000002 0.000040

Runtime on St Lucia for various descriptors with the number of locations produced corresponding to that run.

Global Descriptors considered for evaluation. **Compute times** (per image) are reported for the specified max batch size *Bsize*, and for a batch size of 1 separated by a vertical bar.





Hierarchical Topological Map using 6 different global descriptors. Large dots: Locations, size proportional to number of images. Small dots: Images with same color as the location they belong to



Each dot represents one run with the line showing a series of runs of the corresponding global descriptor on St Lucia *Results on other tracks (New College City Centre, KITTI 00, 05, and 06) are in the paper **Total Mapping Runtime reported does not include descriptor compute time

