# **Sparse-to-Dense Hypercolumn Matching for Long-Term Visual Localization**

### Contribution

We show that exhaustive search for keypoint correspondents (**sparse-to-dense matching**) outperforms traditional keypoint matching in challenging conditions.

### Pipeline



We consider a hierarchical localization pipeline, similar to HF-Net: Given a query image, we first identify a set of prior locations using image retrieval. We then match feature points across the 2D query image and the retrieved local 3D point cloud. This step, however, is prone to fail as it is still very difficult to detect and match sparse feature points across very different conditions.

### **Retraining NetVLAD**

We train our image-retrieval pipeline using the popular pooling layer NetVLAD.



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But in a long-term scenario, consistent detection and matching is hard.

Here make use of appropriate feature descriptors, coming from the retrieval network.

### Sparse-to-Dense Hypercolumn Matching (Ours)





### https://github.com/germain-hug/S2DHM



### Ablation Study

Method

NV (pre-train NV-r (re-train NV-r + S-S +NV-r + S-S +NV-r + S-D +NV-r + S-D +

Ablation study run on RobotCar Seasons nighttime images

### **Qualitative Results**







thresholds.

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	_		,			
	Day-All			Night-All		
l	Threshold Accuracy			Threshold Accuracy		
	0.25m	0.5m	5m	0.25m	0.5m	5m
	$2^{\circ}$	5°	10°	$2^{\circ}$	5°	10°
ned)	6.4	26.3	90.9	0.3	2.3	15.9
ned)	4.1	17.8	86.9	2.4	11.4	84.6
- SP	52.9	78.5	93.8	10.9	32.7	87.4
- H	49.0	77.9	93.6	14.8	44.5	89.7
⊦ SP	50.3	77.5	92.9	14.4	43.2	87.8
⊦ H	45.7	78.0	95.1	22.3	61.8	94.5

Sparse-to-Sparse Superpoint matching [4 inliers]

Sparse-to-Dense Hypercolumn matching [87 inliers]