# UNIVERSITY OF CAMBRIDGE

## • Problem

• Learning robust features for long-term visual localization

## • Local features only

- Focusing mainly on *local* reliability
- Performing exhaustive detection
- Sensitive to viewpoint, illumination, season changes and dynamic objects

### • Local features + explicit semantics

- Requiring accurate semantic labels at test time
- Fragile to segmentation errors especially for night images

### • Motivation

- Implicitly embedding semantics into local features
- No need of ground-truth semantics for training
- Learning from off-the-shelf segment network in the training
- Semantic–aware and feature-aware guidance
- No explicit semantic labels required at test time



Exhaustive detection of prior local features

#### Our framework

- [1] LBR, Xue, et al., CVPR 2022
- [2] Suerpoint, DeTone et al., CVPRW 2018
- [3] R2D2, Revaud et al., NeurIPS 2019
- [4] SuperGlue, Sarlin et al, CVPR 2020
- [5] ASLFeat, Luo et al., CVPR 2020
- [6] ConvNeXt, Liu et al, CVPR 2022

# **SFD2: Semantic-guided Feature Detection and Description**

# Fei Xue, Ignas Budvytis, Roberto Cipolla

- Approach
- Semantic-aware guidance detection
- Redefined reliability = local reliability  $\otimes$  stability
- Favoring features from robust areas, e.g., buildings
- Suppressing features from unstable areas, e.g., trees, pedestrians



Semantic mask

Stability map

Reliability map

### • Semantic-aware guidance - description

- Inter-class loss features with same labels should be close, otherwise far
- Intra-class loss ranking positive/negative keypoints with same labels



- Feature-aware guidance
- Feature consistency between encoded features (ConvNeXt for supervision)
- Style transfer learning of night images
- More effective at embedding high-level semantic information



- **Results**
- Robust semantic-aware detection and matching
- 1k keypoints with reliability from high to low (red, green, blue,



Superpoint

**R2D2** 

• More accurate localization accuracy on Aachen dataset (day/night)

	2°, 0.25m/5°, 0.5m/10°, 5m		
LBR	88.3 / 95.6 / <b>98.8</b>	84.7 / 93.9 / <b>100.0</b>	<ul> <li>Better than methods with explicit labels</li> <li>Better than prior local features</li> <li>Close to advanced matchers</li> </ul>
R2D2	N/A	84.7 / 90.8 / 96.9	
ASLFeat	N/A	81.6 / 87.8 / <b>100.0</b>	
SPP+SPG	<b>89.6</b> / 95.4 / <b>98.8</b>	86.7 / 93.9 / <b>100.0</b>	
Ours	88.2 / <b>96.0</b> / 98.7	87.8 / 94.9 / 100.0	

#### • Robust to keypoint reduction and faster





Hig

Final reliability map





More on buildings Fewer on trees Robust to night images

Robust to viewpoint changes

Robust to illumination/season changes

ASLFeat

Ours

- 2.2x faster than R2D2
- 3.4x faster than ASLFeat
- 4.4x faster than SPP+SPG

LBR	39.3
R2D2	72.4
ASLFeat	112.3
SPP+SPG	146.5
Our	33.2

Localization accuracy with different number of keypoints Test time of 1024 keypoints (ms)