BRISKS: Binary Features for Spherical Images on a Geodesic Grid Hao Guan and William A. P. Smith **Department of Computer Science** {hq607,william.smith}@york.ac.uk



Motivation

360 video and spherical/omnidirectional images now widely used:

- Virtual reality
- Omnidirectional SLAM/structure-from-motion
- Autonomous vehicles

Standard image processing/vision techniques adapted heuristically from planar images to spherical images

We extend a binary feature (BRISK) to spherical images in a way that respects spherical geometry



Problems with planar image representation

Standard spherical image representation is equirectangular projection:

Flattened planar images unsuitable for processing directly:

- Rotation-dependent distortion particularly near the poles
- Introduces artificial boundaries
- Uneven sampling

Multiscale geodesic grid representation

- We represent and store spherical images using a triangular subdivision mesh
- Subdivision scheme provides multiresolution representation
- Mesh stored in half-edge for constant time adjacency queries

Possible image resolutions restricted to small set of possibilities:

No. subdivisions (s)	No. pixels $(=V_s)$	F_s
0	12	20
1	42	80
2	162	320
3	642	1,280
4	2,562	5,120
5	10,242	20,480
6	40,962	81,920
7	163,842	327,680
8	655,362	1,310,720
9	2,621,442	5,242,880



Local charts



The log map enables us to build a local chart in the tangent space around an interest point Geodesic distances of pixels from interest point are preserved



Interest point detection

- We detect FAST corners at octaves and intra-octaves Sub-pixel position
- refinement
- Continuous scale estimate

Subdivision scheme does not provide intra-octaves

Detect by using AST pattern with 1.5x scale difference



Rotation-invariant descriptor extraction

From the 9-ring neighbourhood around an interest point:

- Approximate gradient direction using average from all "long range" pairs
- This defines characteristic direction
- Sampling pattern in tangent space rotated to characteristic direction
- Different sized sampling pattern for octave and intra-octave features

Experimental Results

Synthetic (rendered) image dataset provides ground truth correspondence and

controllable lighting:

Varying translation (ground truth depth on right)

	Rotation and Translation	
Ours	0.93 (419)	Γ
SSIFT [2]	0.65 (412)	
SIFT [3], [4]	0.57 (392)	

Repeatability (average number of detected features in brackets)



[1] J. Xiao, K. A. Ehinger, A. Oliva, and A. Torralba, "Recognizing scene viewpoint using panoramic place representation," in Proc. CVPR, 2012, pp. 2695–2702. [2] J. Cruz-Mota, I. Bogdanova, B. Paquier, M. Bierlaire, and J.-P. Thiran, "Scale invariant feature transform on the sphere: Theory and applications," Int. J. Comput. Vis., vol. 98, no. 2, pp. 217–241, 2012. [3] T. Goedeme, T. Tuytelaars, L. Van Gool, G. Vanacker, and M. Nuttin, "Omnidirectional sparse visual path following with occlusion-robust feature tracking," in Proc. OMNIVIS, 2005. [4] D. Scaramuzza and R. Siegwart, "Appearance-guided monocular omni- directional visual odometry for outdoor ground vehicles," IEEE Trans. Robotic. Autom., vol. 24, no. 5, pp. 1015–1026, 2008.

Summary

- Lightweight, binary feature for spherical images
- All steps of the BRISK pipeline extended to sphere in natural way

Varying illumination

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0.64 (414)

0.49 (414)

0.41 (396)

- SSIFT [20]

Performance exceeds naïve features on planar flattened images and SIFT on the sphere



(a) Characteristic orientation



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Example of a corner passing the spherical AST



(b) Sampled intensities





Real image dataset (SUN 360 [1]) used to test performance under rotation and noise

	Rotation	Noise			
		10dB	15dB	20dB	
Ours	0.94 (384)	0.90 (379)	0.93 (383)	0.93 (385)	
SSIFT [2]	0.86 (391)	0.76 (389)	0.79 (379)	0.83 (374)	
SIFT [3], [4]	0.70 (391)	0.65 (371)	0.67 (378)	0.66 (384)	

