

Disparate Image Matching using DUDE (Duality Descriptor)

EE604 Course Project
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Motivation

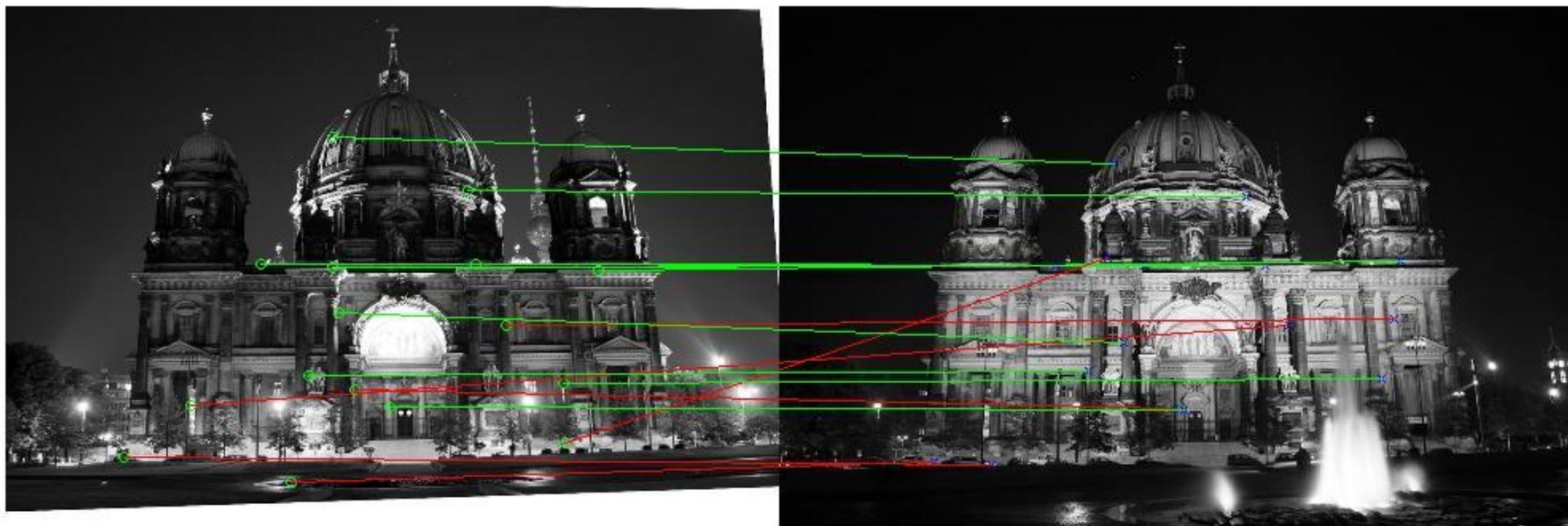


Image Correspondence

- Image matching
- 3D reconstruction
- Object Tracking
- Object Recognition
- Depth Estimation

Disparate Images

Challenging Input: Painting vs. Image, different time of day, different centuries, different image sensors etc.



Image Source: Image Source: Kwon, Youngwook P., et al. "Dude (Duality descriptor): A robust descriptor for disparate images using line segment duality." *Image Processing (ICIP), 2016 IEEE International Conference on.* IEEE, 2016.

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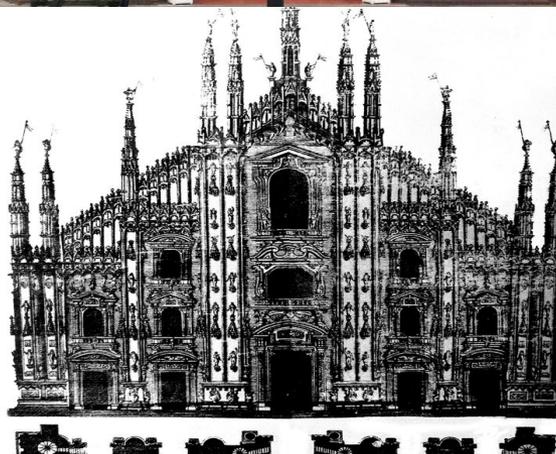
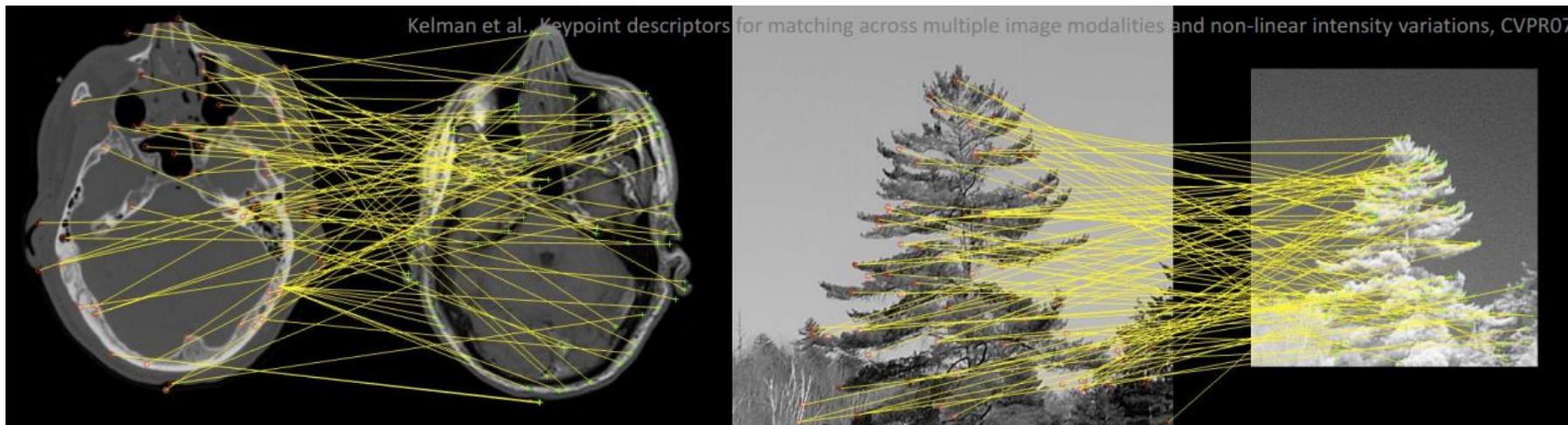


Image Source: Image Source: Kwon, Youngwook P., et al. "Dude (Duality descriptor): A robust descriptor for disparate images using line segment duality." *Image Processing (ICIP), 2016 IEEE International Conference on.* IEEE, 2016.

SIFT on difficult input



CT (Computed Tomography)

MR (Magnetic Resonance)

EO (Electro-Optics)

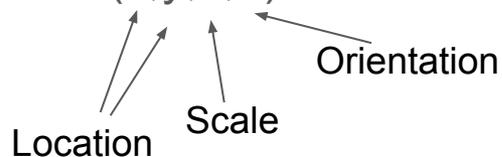
IR (Infra-Red)

Very few correct matches!

Basics of Image Matching

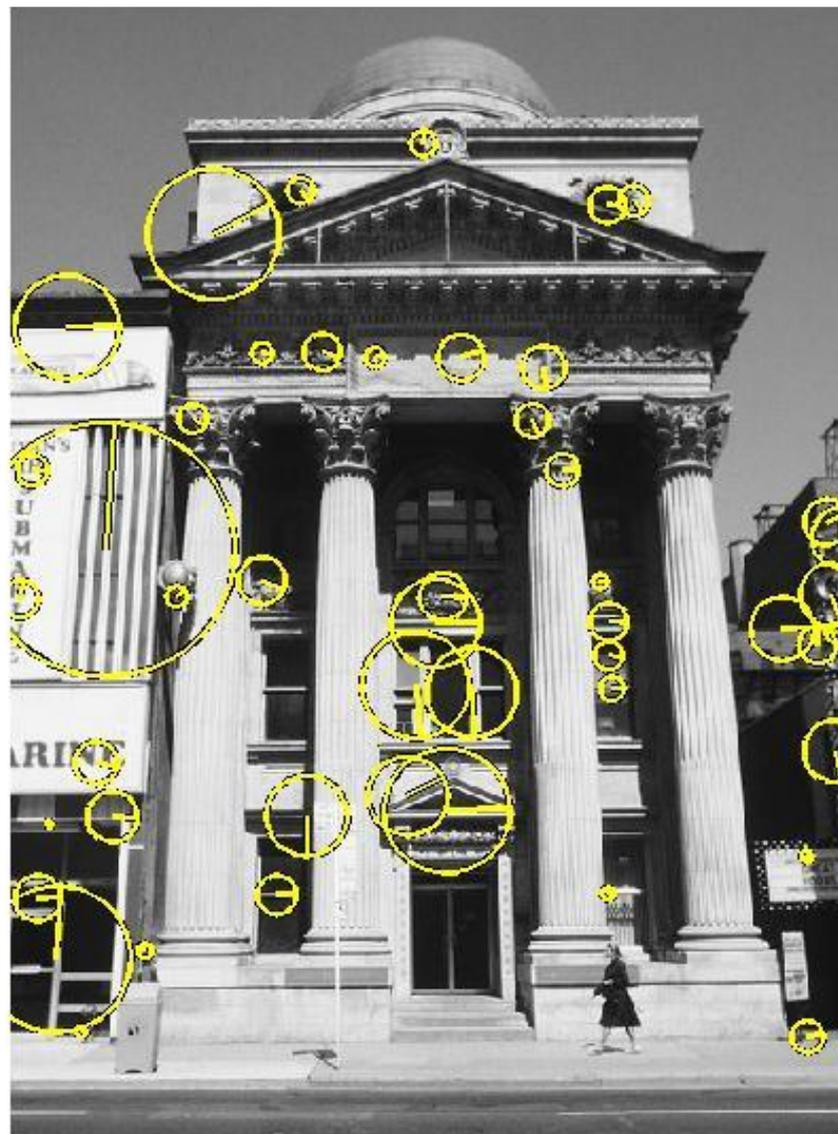
Feature detector

provides a list of (x,y,s,θ)



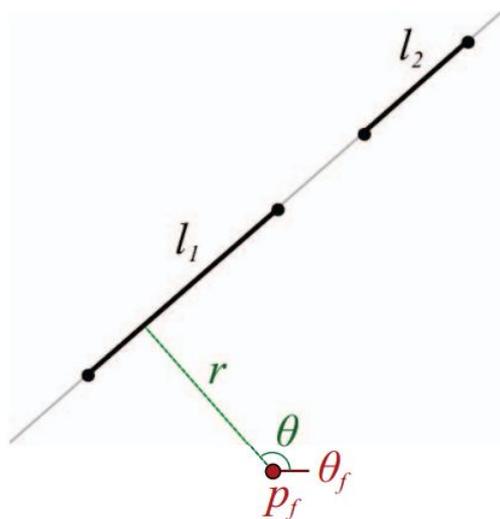
Feature descriptor

assigns each detected feature a descriptor
“how it looks”

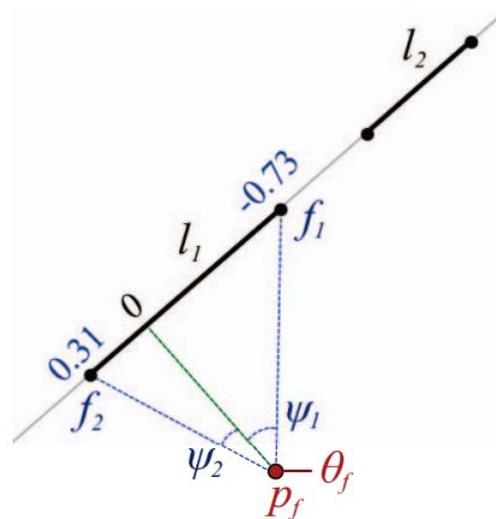


Dual Representation of Line Segments

- DUDE uses a line segment distribution
 - Less parameter sensitive, more information than pixels
 - Mathematically and geometrically easier
- A line represented as (r, θ) in dual space
- f -dimension indicates location of line segment on that infinite line
- Line segment represented by (r, θ, f_1, f_2) in the dual space



(a) r and θ

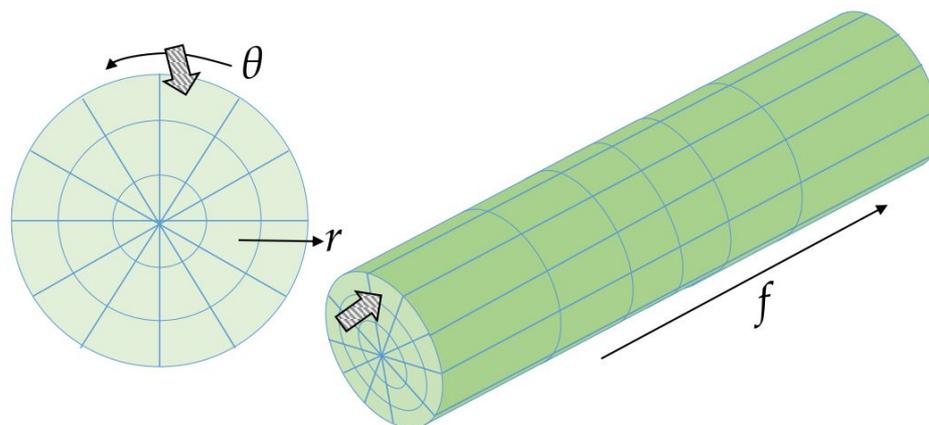
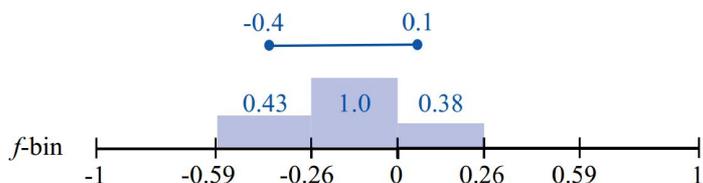


(b) f

DUDE feature descriptor

For each feature F_i we do the following:

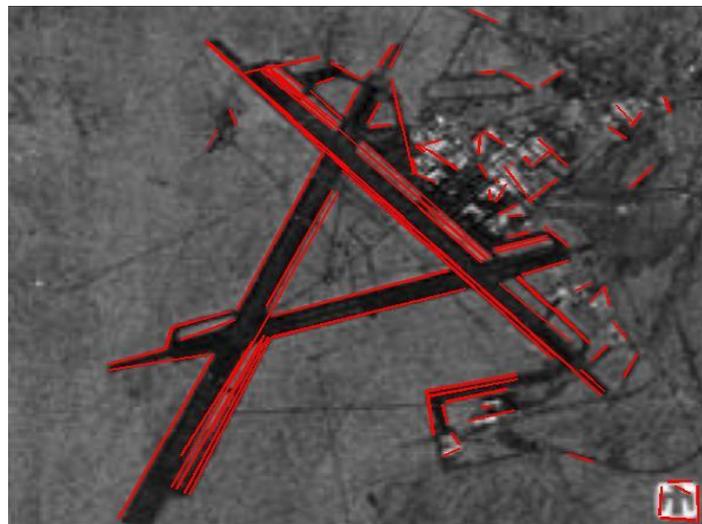
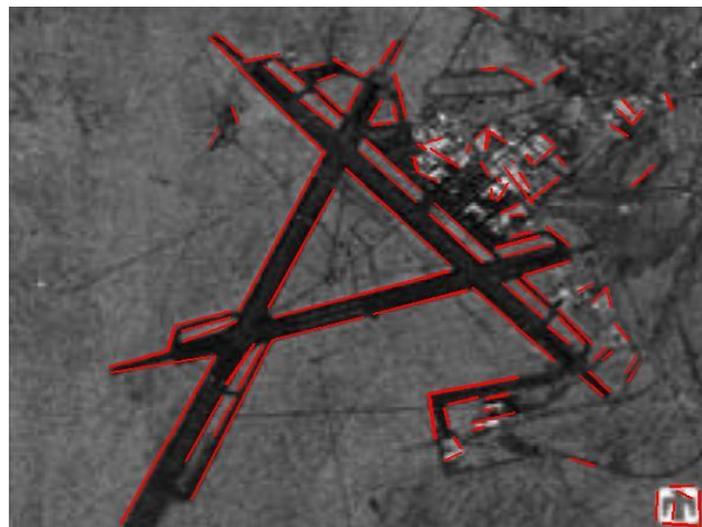
1. Identify the set of line segments 'near' F_i
2. Convert that set into the dual space
3. Perform binning in (r, θ, f) to get a 3D histogram
 - a. r and theta axis divided uniformly into n_r and n_θ bins, respectively
 - b. f_1 and f_2 denote endpoints of line segment, so segments are binned as a range, contributing to bins by coverage percentage
4. We get a $(n_r \times n_\theta \times n_f)$ -dimension descriptor



MMID (Multi-Modal Image Detector)

Target: Generate a set of repeatable features across disparate images which are more suited for the DUDE descriptor

- Because DUDE descriptors use line segments, MMID derives a feature per line segment: (x_i, y_i) at its midpoint, s_i as half length, and θ_i its orientation
- For greater consistency of feature detection, MMID generates multiple groupings of line segments from the initial proposals (by existing techniques like LSD) by randomly merging them incrementally
- The merged line segments are then used for extracting features

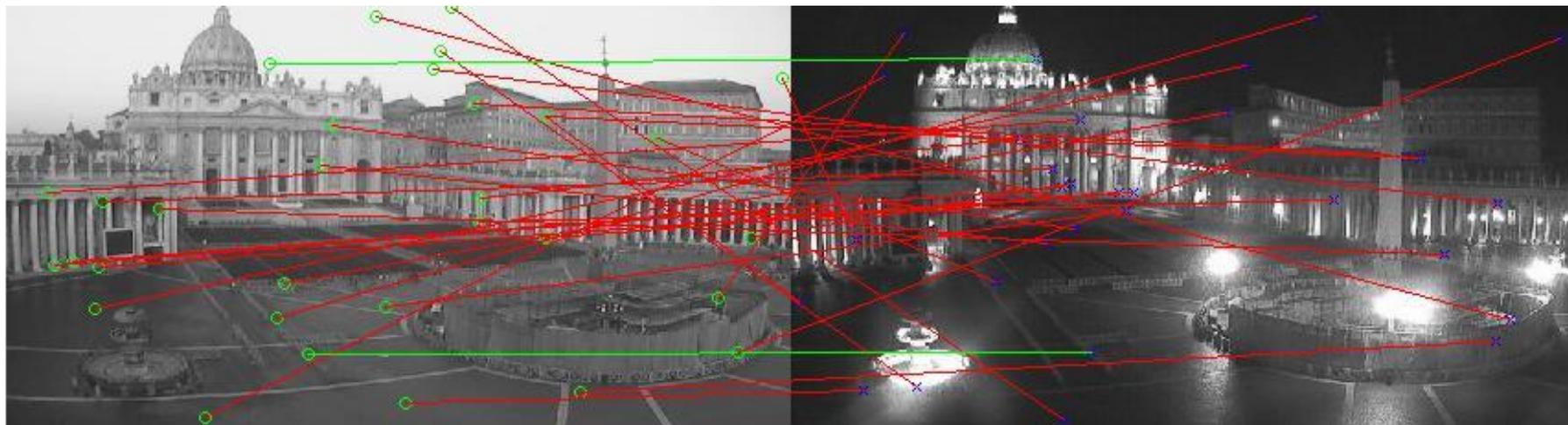


Contribution

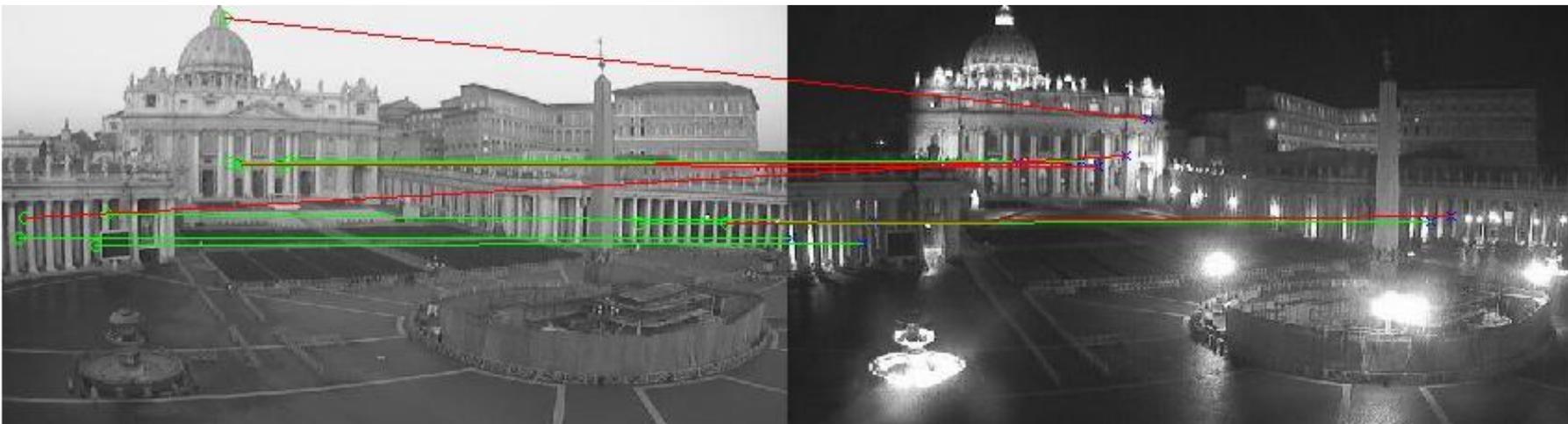
- No implementation of DUDE descriptor or MMID detector available, we implemented both of them ourselves in MATLAB
- Code will be cleaned and released soon on Github
- Used other existing feature descriptors like SIFT, SURF, MSER, SYM-I and SYM-G to compare against our implementation of DUDE

Qualitative Results

SIFT



DUDE



Qualitative Results

SIFT



DUDE



Quantitative Results

mAP on an image pair

Detectors

Descriptors	SIFT	SYM-I	SYM-G	JSPEC	MMID
SIFT	0.1878	0.28	0.25	0.61	0.1
SYMD	0.22	0.20	0.25	-	0.26
SIFT-SYMD	0.28	0.35	0.36	-	-
DUDE	0.1121	0.1741	0.2009	-	0.5343



Quantitative Results

Repeatability on an image pair from dataset

Features

	SIFT	MMID
k = 50	0.0327	0.0979
k = 100	0.0524	0.1264
k = 200	0.11	0.18
k = 300	0.14	0.1825



Conclusion

- We implemented a novel feature detection and description system for disparate image matching
- DUDE outperforms existing descriptors like SIFT, MSER on disparate image dataset
- Combined with the MMID detector, DUDE achieves results close to state-of-the-art with significantly more efficient computation

Thank You