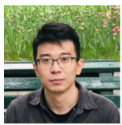
# SOSNet

## Second Order Similarity Regularization for Local Descriptor Learning

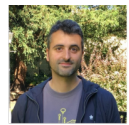


Yurun Tian


Xin Yu


Bin Fan


Fuchao Wu


Huub Heijnen


Vassileios Balntas


http://research.scape.io/sosnet

20 June 2019

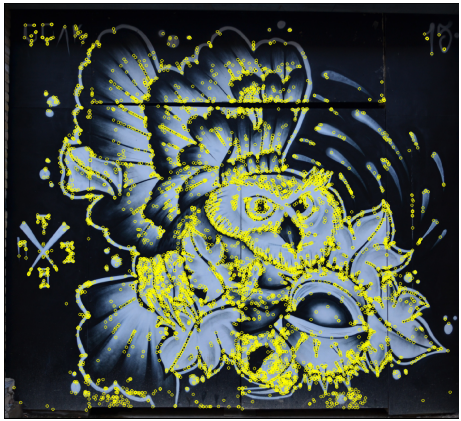
SCAPE

CASIA

Australian National University

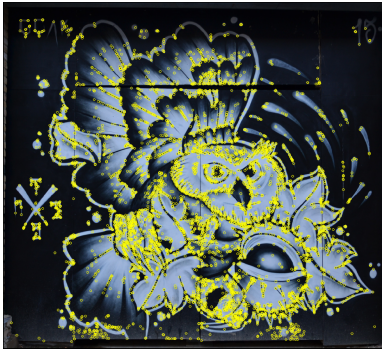
Problem: Matching two images from different viewpoints, under changing conditions.

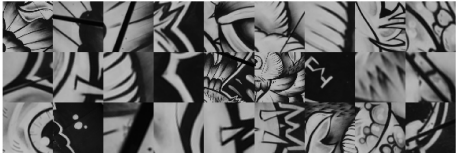
# Step 1: Extract Keypoints

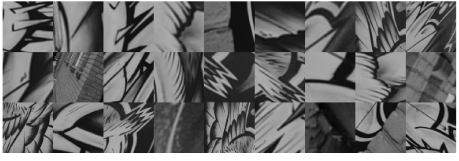


# Step 2: From Keypoints to Descriptors

Keypoints → Patches → Descriptors

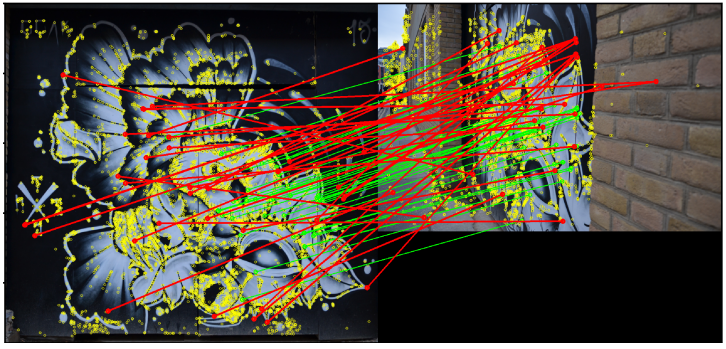






# Challenges

SIFT # Total Matches: 76 # Correct Matches: 40



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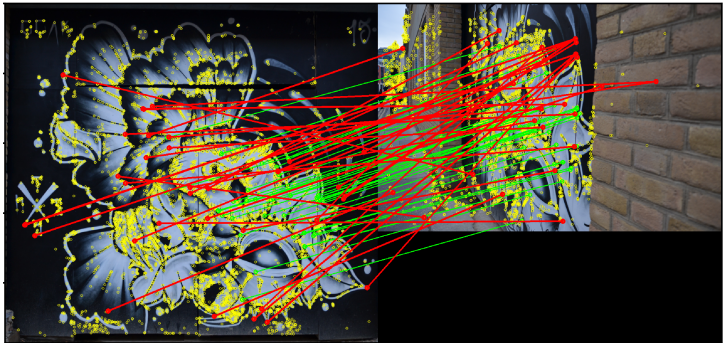

- Keypoint repeatability

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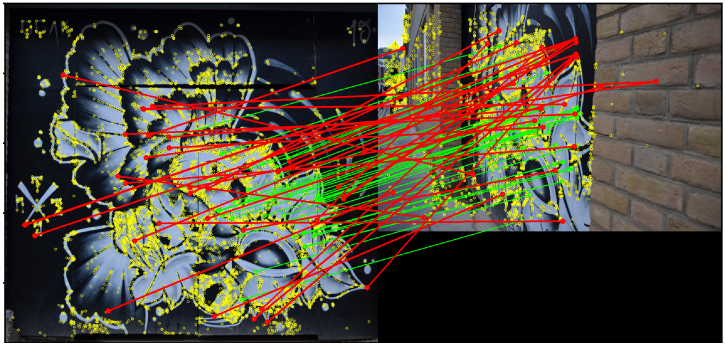

- Keypoint repeatability
  - Design more robust keypoint detection methods

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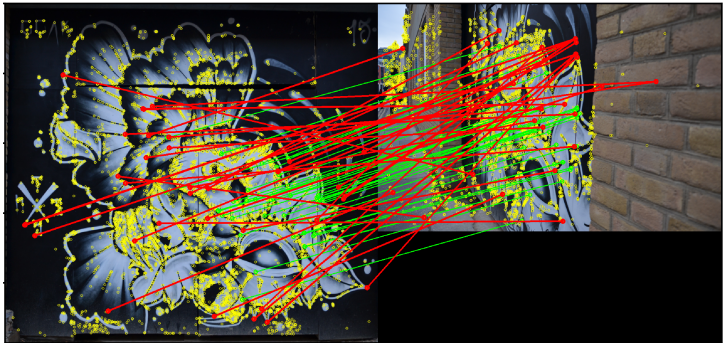

- Keypoint repeatability
  - Design more robust keypoint detection methods
- Descriptor robustness

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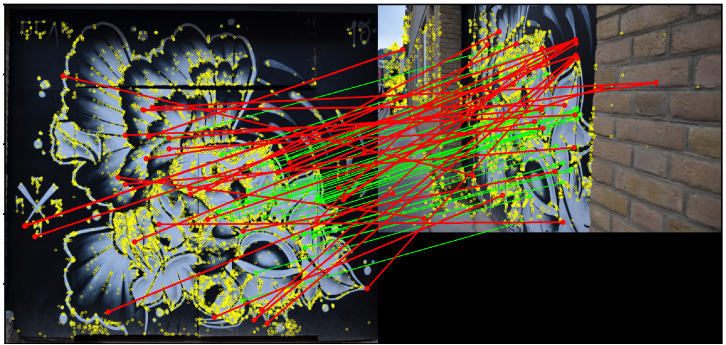

- Keypoint repeatability
  - Design more robust keypoint detection methods
- Descriptor robustness
  - Design more robust patch description methods

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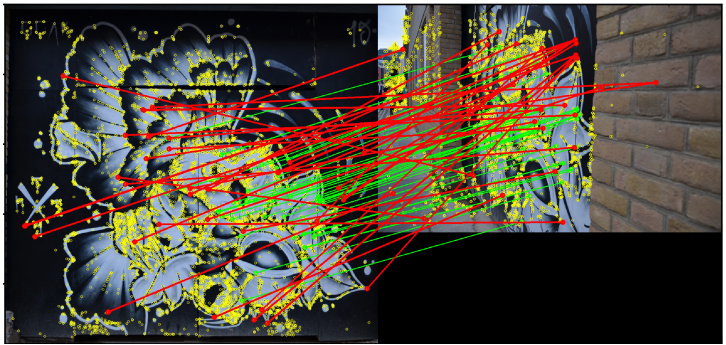


- Keypoint repeatability
  - Design more robust keypoint detection methods
- Descriptor robustness

> - Design more robust patch description methods [SOSNet]

# SOSNet: Methodology

We explore the potential of Second Order Similarity (SOS) in descriptor learning

- Previous work: optimise First Order Similarity (FOS)
  - Distances between descriptors
- This Work: Besides FOS, we can utilise Second Order Similarity (SOS) information to improve matching.
  - Distances between FOS distances
- FOS and SOS can be jointly optimized.

$$\mathcal{L} = \mathcal{L}_{\text{FOS}} + \mathcal{R}_{\text{SOS}}$$

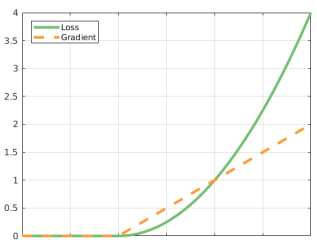
# Optimization of First Order Similarity (FOS)

Quadratic Hinge Triplet (QHT) Loss + hard sample mining as in HardNet[1]

$$\mathcal{L}_{\text{FOS}} = \frac{1}{N}\sum_{i=1}^{N} \max \boxed{\left(0, t + d_i^{\text{pos}} - d_i^{\text{neg}}\right)^2}, \quad \text{(QHT)}$$

$$d_i^{\text{pos}} = d(\boldsymbol{x}_i, \boldsymbol{x}_i^+),$$

$$d_i^{\text{neg}} = \min_{\forall j, j \neq i} \left(d(\boldsymbol{x}_i, \boldsymbol{x}_j), d(\boldsymbol{x}_i, \boldsymbol{x}_j^+), d(\boldsymbol{x}_i^+, \boldsymbol{x}_j), d(\boldsymbol{x}_i^+, \boldsymbol{x}_j^+)\right)$$




[1] Mishchuk et al., "Working hard to know your neighbor's margins: Local descriptor learning loss".

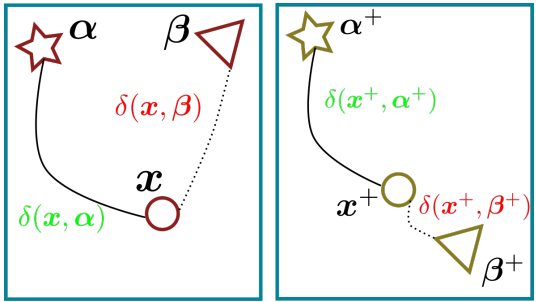
# Optimization of Second Order Similarity(SOS)

- Matching descriptors should have high SOS.

$$\mathcal{R}_{\text{SOS}} = \frac{1}{N} \sum_{i=1}^{N} d^{(2)}(\boldsymbol{x}_i, \boldsymbol{x}_i^+).$$

- We optimise second-order similarity by optimising the distance between distances.

# Optimization of Second Order Similarity(SOS)




$$y = [\delta(x, \alpha), \delta(x, \beta)]$$
$$y^+ = [\delta(x^+, \alpha^+), \delta(x^+, \beta^+)]$$
$$d^{(2)}(x, x^+) = ||y - y^+||$$
$$\downarrow$$
$$d^{(2)}(x, x^+) = \sqrt{\{\delta(x, \alpha) - \delta(x^+, \alpha^+)\}^2 + \{\delta(x, \beta) - \delta(x^+, \beta^+)\}^2}$$

# kNN search strategy for the selection of reference descriptors

$$\mathcal{R}_{\text{SOS}} = \frac{1}{N}\sum_{i=1}^{N} d^{(2)}(\boldsymbol{x}_i, \boldsymbol{x}_i^+).$$

$$d^{(2)}(\boldsymbol{x}_i, \boldsymbol{x}_i^+) = \sqrt{\sum_{j\neq i}^{N} (d(\boldsymbol{x}_i, \boldsymbol{x}_j) - d(\boldsymbol{x}_i^+, \boldsymbol{x}_j^+))^2}$$

$$\boldsymbol{c}_i = \{z_j : \boldsymbol{x}_i \in \mathit{KNN}(\boldsymbol{x}_j) \vee \boldsymbol{x}_i^+ \in \mathit{KNN}(\boldsymbol{x}_j^+)\},$$
$$\forall j \in 1 \ldots N, j \neq i$$

# Implementation

We use the network architecture of L2-Net[2]. The network is trained with Adam optimizer.


[2]Tian, Fan, and Wu, "L2-Net: Deep Learning of Discriminative Patch Descriptor in Euclidean Space".

# Performance

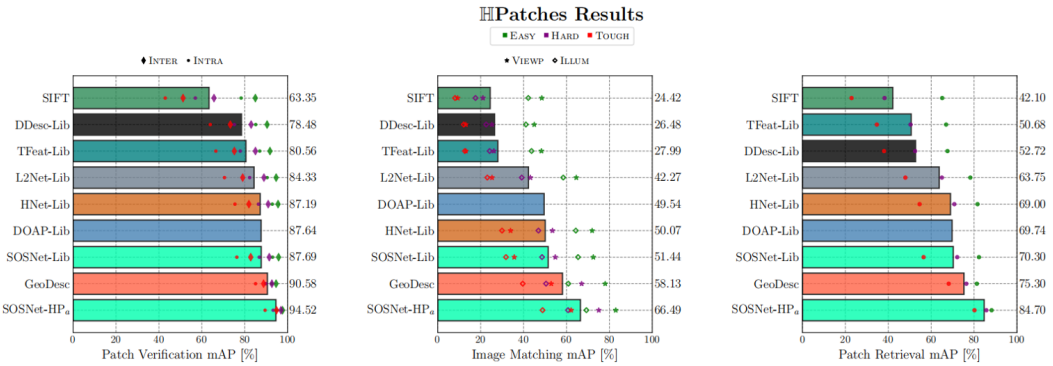
Performance of SOSNet on UBC dataset[3].

| Train | Notredame | Yosemite | Liberty | Yosemite | Liberty | Notredame | Mean |
|---|---|---|---|---|---|---|---|
| Test | Liberty | | Notredame | | Yosemite | | |
| SIFT [20] | 29.84 | | 22.53 | | 27.29 | | 26.55 |
| DeepDesc [32] | 10.9 | | 4.40 | | 5.69 | | 6.99 |
| MatchNet [2] | 7.04 | 11.47 | 3.82 | 5.65 | 11.6 | 8.70 | 8.05 |
| L2Net [34] | 3.64 | 5.29 | 1.15 | 1.62 | 4.43 | 3.30 | 3.24 |
| CS L2Net [34] | 2.55 | 4.24 | 0.87 | 1.39 | 3.81 | 2.84 | 2.61 |
| HardNet [25] | 1.47 | **2.67** | 0.62 | 0.88 | 2.14 | 1.65 | 1.57 |
| HardNet-GOR [25, 39] | 1.72 | 2.89 | 0.63 | 0.91 | 2.10 | 1.59 | 1.64 |
| Michel *et al.* [16] | 1.79 | 2.96 | 0.68 | 1.02 | 2.51 | 1.64 | 1.77 |
| SOSNet | **1.25** | 2.84 | **0.58** | **0.87** | **1.95** | **1.25** | **1.46** |
| TFeat+ [2] | 7.39 | 10.13 | 3.06 | 3.80 | 8.06 | 7.24 | 6.64 |
| L2Net+ [34] | 2.36 | 4.70 | 0.72 | 1.29 | 2.57 | 1.71 | 2.23 |
| CS L2Net+ [34] | 1.71 | 3.87 | 0.56 | 1.09 | 2.07 | 1.3 | 1.76 |
| HardNet+ [25] | 1.49 | 2.51 | 0.53 | 0.78 | 1.96 | 1.84 | 1.51 |
| HardNet-GOR+ [25, 39] | 1.48 | 2.43 | 0.51 | 0.78 | 1.76 | 1.53 | 1.41 |
| DOAP+ [14] | 1.54 | 2.62 | 0.43 | 0.87 | 2.00 | 1.21 | 1.45 |
| DOAP-ST+ [14] [15] | 1.47 | 2.29 | 0.39 | 0.78 | 1.98 | 1.35 | 1.38 |
| SOSNet+ | **1.08** | **2.12** | **0.35** | **0.67** | **1.03** | **0.95** | **1.03** |
| GeoDesc+ [21] | 5.47 | | 1.94 | | 4.72 | | 4.05 |
| SOSNet-HP+ | 2.10 | | 0.79 | | 1.39 | | 1.42 |

[3]Winder, Hua, and Brown, "Picking the best daisy".

# Performance

Performance of SOSNet on HPatches dataset[4].




[4] Balntas et al., "HPatches: A Benchmark and Evaluation of Handcrafted and Learned Local Descriptors".

# Performance

Performance of SOSNet on ETH dataset[5].

| | | # Image | # Registered | # Sparse Points | # Observations | Track Length | Reproj. Error |
|---|---|---|---|---|---|---|---|
| **Fountain** | SIFT | 11 | 11 | 14K | 70K | 4.79 | 0.39px |
| | DSP-SIFT | | 11 | 14K | 71K | 4.78 | 0.37px |
| | L2Net | | 11 | 17K | 83K | 4.88 | 0.47px |
| | GeoDesc | | 11 | 16K | 83K | 5.00 | 0.47px |
| | SOSNet | | 11 | 17K | 85K | 4.92 | 0.43px |
| **Herzjesu** | SIFT | 8 | 8 | 7.5K | 31K | 4.22 | 0.43px |
| | DSP-SIFT | | 8 | 7.7K | 32K | 4.22 | 0.45px |
| | L2Net | | 8 | 9.5K | 40K | 4.24 | 0.51px |
| | Geodesc | | 8 | 9.2K | 40K | 4.35 | 0.51px |
| | SOSNet | | 8 | 9.7K | 41K | 4.26 | 0.53px |
| **South Building** | SIFT | 128 | 128 | 108K | 653K | 6.04 | 0.54px |
| | DSP-SIFT | | 128 | 112K | 666K | 5.91 | 0.58px |
| | L2Net | | 128 | 170K | 863K | 5.07 | 0.63px |
| | GeoDesc | | 128 | 170K | 887K | 5.21 | 0.64px |
| | SOSNet | | 128 | 178K | 913K | 5.11 | 0.67px |
| **Madrid Metropolis** | SIFT | 1344 | 500 | 116K | 733K | 6.32 | 0.60px |
| | DSP-SIFT | | 467 | 99K | 649K | 6.52 | 0.66px |
| | L2Net | | 692 | 254k | 1067K | 4.20 | 0.69px |
| | GeoDesc | | 809 | 306K | 1200K | 3.91 | 0.66px |
| | SOSNet | | 844 | 335K | 1411K | 4.21 | 0.70px |
| **Gendarmenmarkt** | SIFT | 1463 | 1035 | 338K | 1872K | 5.523 | 0.69px |
| | DSP-SIFT | | 979 | 293K | 1577K | 5.381 | 0.74px |
| | L2Net | | 1168 | 667k | 2611K | 3.91 | 0.73px |
| | GeoDesc | | 1208 | 779K | 2903K | 3.72 | 0.74px |
| | SOSNet | | 1201 | 816K | 3255K | 3.984 | 0.77px |

[5]Schönberger et al., "Comparative Evaluation of Hand-Crafted and Learned Local Features".

# Analysis

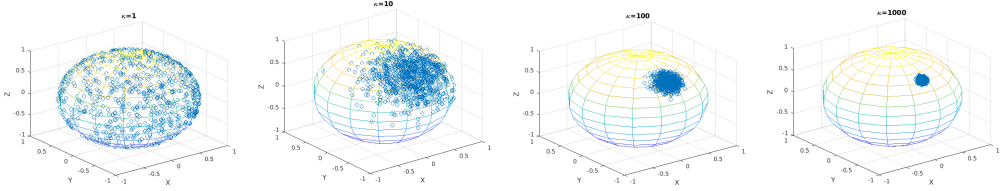
We define a von Mises-Fisher distribution performance measure ($\rho$)

Unit vector

$$f(\mathbf{x}|\boldsymbol{\mu},\kappa) = c_q(\kappa)e^{\kappa\,\boldsymbol{\mu}^T\mathbf{x}}$$

Concentration Parameter
Small value indicates a scattered distribution.
Large value indicates a concentrated distribution

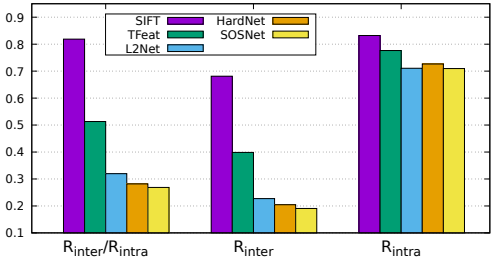
Mean Direction




| Distribution of class centers | Distribution of elements inside a class |
|---|---|
| $k_{inter}$ | $k_{intra}$ |
| ⇓ | ⇑ |

$$\rho = \frac{\kappa_{\text{inter}}}{\kappa_{\text{intra}}} \propto \frac{R_{\text{inter}}}{R_{\text{intra}}}$$

# Performance




- Observations
  - As performance increases, ratio $\rho$ and $R_{\text{inter}}$ drop monotonically;
  - SOSR helps to exploit more space of the hypersphere, Intra-class distribution may also become more scattered;
  - SIFT descriptors(normalized) tend to gather together in a small region of the hypersphere.
- Our SOS regularisation term, might potentially be useful in other metric learning problems

# The End

- Please visit our poster at 3.2 150 (15:20-18:00)
- Pre-trained network & code available

`http://research.scape.io/sosnet`

Thank You