





## • Problem

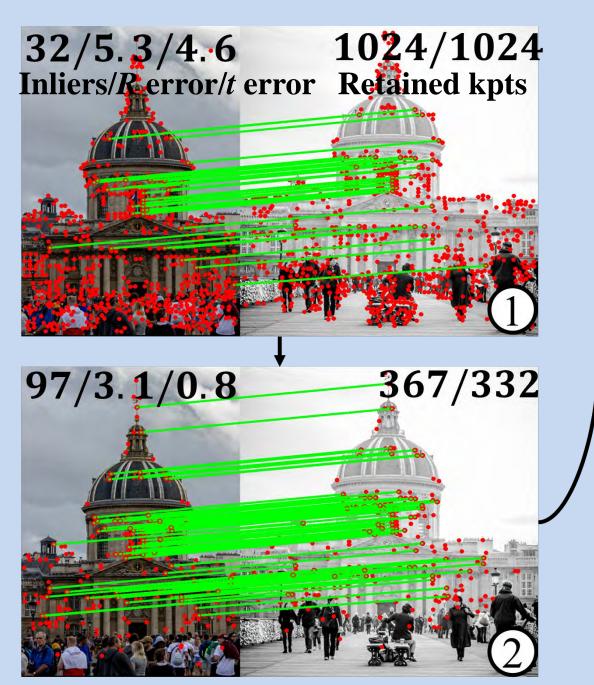
• Relative pose estimation via keypoints matching

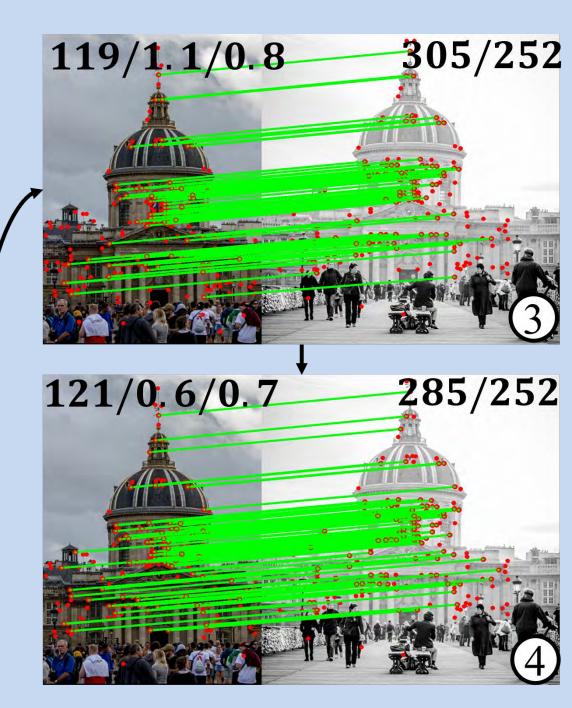
## • Limitations of prior methods

- Matching and pose estimation are independent
- Geometric information is ignored
- Graph-based matchers have good performance but suffer from high computational cost

## • Motivation

- Iterative matching and pose estimation
- Adaptively discarding keypoints without correspondences
- Robust pose-guided pooling





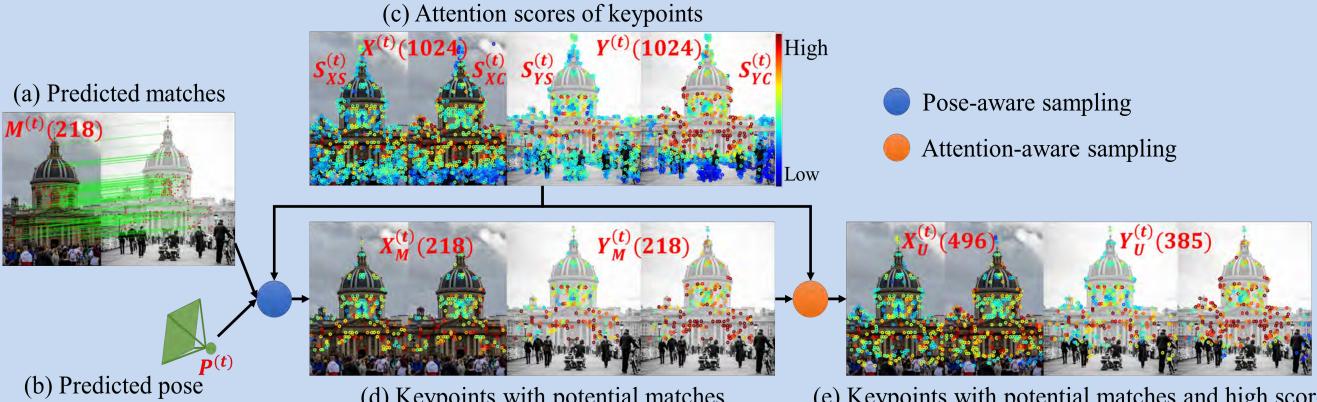
**Iterative matching and pose estimation** (more matches, more precise poses, fewer keypoints)

- [1] SuperGlue, Sarlin et al, CVPR 2020
- [2] SGMNet, Chen et al., ICCV 2021
- [3] CLNet, Zhao et al., ICCV 2021
- [4] YFCC, Thomee et al., Communications of the ACM, 2016
- [5] Suerpoint, DeTone et al., CVPRW 2018

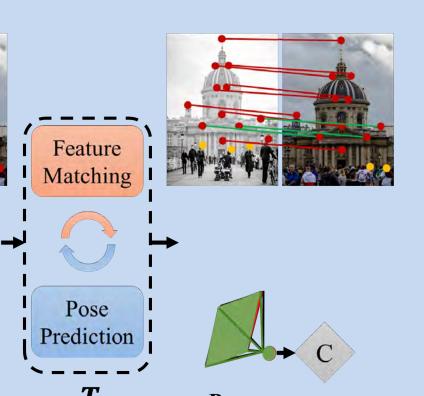
# **IMP: Iterative Matching and Pose Estimation with Adaptive Pooling**

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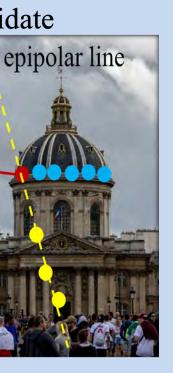
- Approach **Iterative matching and pose estimation** Transformer-based recurrent module • Pose-aware loss in the training process Pose-guided matching in the testing process \_\_\_\_\_ Feature I Feature I Matching 111-20-47 Groundtruth pose  $P^{gt}$  — Newly predicted match — Discarded keypoint [] Iterative block  $X^{(t)} \in R^{m(t) \times d} \quad X^{(t+1)} \in R^{m(t+1) \times d}$ descriptor candidate  $Y^{(t)} \in \mathbb{R}^{n(t) \times d} \quad Y^{(t+1)} \in \mathbb{R}^{n(t+1) \times d}$ Descriptor Geometry-aware Augmentation Pooling Geometry-aware Matching  $M^{(t)}$ Pose Estimation I Pose-guided • true match • geometry candidate Matching M **Transformer-based recurrent module Pose-guided matching**
- **Adaptive pooling of keypoints (Efficient IMP EIMP)**
- Pooling with attention scores and matching matrix to remove outliers
- Pose-guide pooling to avoid over pooling when matches are not good



(e) Keypoints with potential matches and high scores (d) Keypoints with potential matches **Percentage of pose errors within 5/10/20 deg on YFCC dataset Attention scores show possibilities of keypoints being inliers** (best and second-best) Uncertainty of pose shows the quality of matches

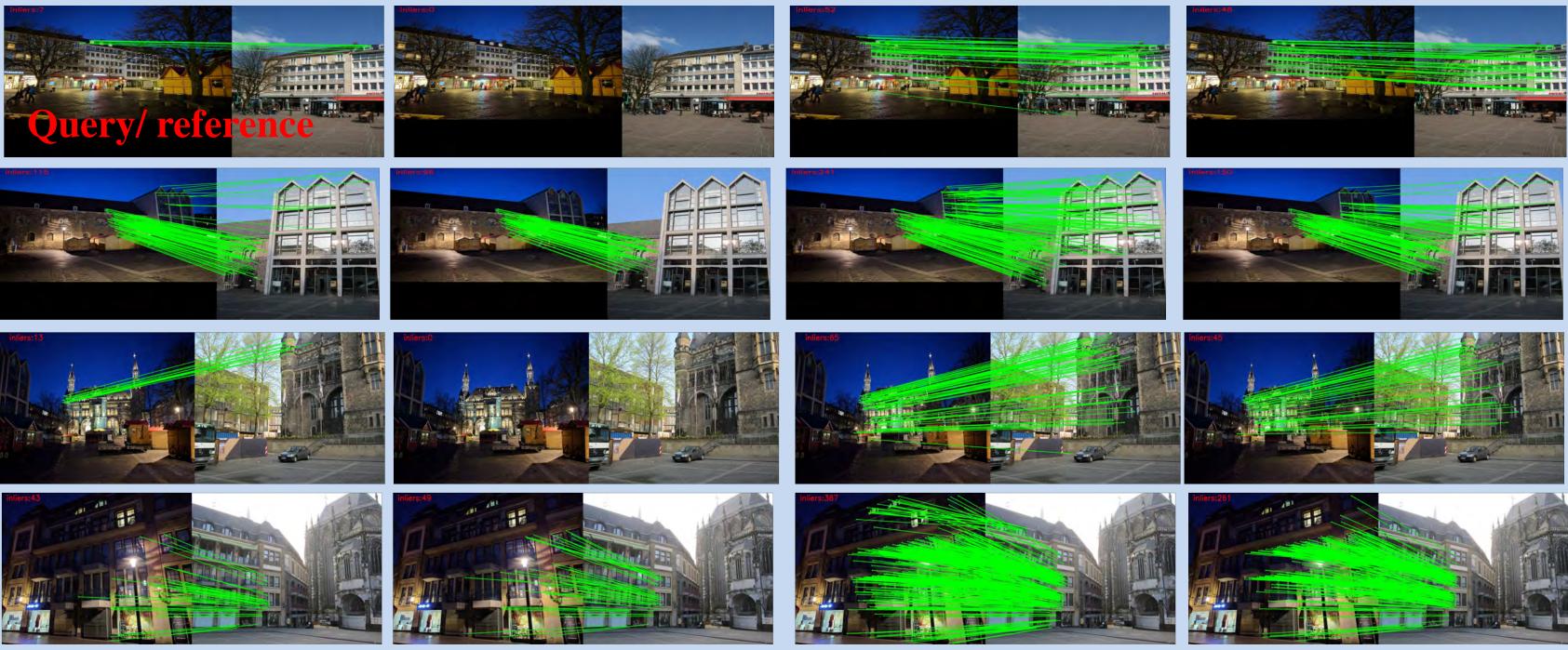


Pose convergences



- **Results**





SuperGlue

SGMNet

• More accurate poses and higher efficiency

NN	6.5	15.4	28.5
CLNet	27.8	46.4	63.8
SuperGlue	37.1	57.2	73.6
SGMNet	33.0	53.0	70.0
IMP	39.4	59.4	75.2
EIMP	37.9	57.9	74.0



### • More inliers and accurate poses (matches / inliers / R error / t error)

#### • More robust (inliers) to viewpoint, illumination, and seasonal changes



EIMP

