



Adaptive Spot-Guided Transformer for Consistent Local Feature Matching

Jiahuan Yu*, Jiahao Chang*, Jianfeng He, Tianzhu Zhang⁺, Feng Wu

University of Science and Technology of China

* Equal contribution + Corresponding author



Project Homepage: https://astr2023.github.io

Introduction

- Motivation
- Novelty
- Evaluation
- Visualization
- Conclusion

Introduction

- Local feature matching serves as a fundamental task in many 3D vision tasks



Visual Localization







Structure from Motion (SfM)

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Motivation

- Local consistency is ignored in Transformer-based methods:
 - For two similar adjacent pixels in reference image (red and green), the corresponding attention maps with source image:
 - are quite different (see Vanilla Attention)
 - include too many irrelevant areas (see Linear Attention)
 - Leading to inconsistent matching results between similar adjacent pixels



(a)Reference

(b)Linear Attention (c)Vanilla Attention

(d)Ours

(e)Matching Result

Motivation

- Scale variation is not properly handled in existing coarse-to-fine methods:
 - Existing coarse-to-fine manner: refine coarse matching result in **fixed-size** fine stage windows
 - When scale variation is large, correct matching pixel may be **out of** fine stage window
 - Coarse matching: (x_i, x_j) , correct matching: (x_i, \tilde{x}_j) , fixed window size: s_i



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Novelty

- A unified coarse-to-fine architecture named Adaptive Spot-Guided Transformer (ASTR) taking local consistency and scale variation into consideration
 - **Spot-Guided Attention**: maintain local consistency
 - Adaptive Scaling: handle large scale variation



Novelty -- Spot-Guided Attention

- For each pixel *P* in reference image:
 - N(P): adjacent area of P
 - Similarity score: similarity between *P* and *N*(*P*)
 - Confidence score: matching confidence of N(P)
 - Selection score = Similarity score × Confidence score
 - Spot area: adjacent area of correspondence pixel of {P} U topk(N(P))
- Do attention between P and spot area
- Adjacent and similar pixel share similar spot area
- Filter irrelevant area



Novelty -- Adaptive Scaling

- Coarse matching (x_i, x_j) is obtained in coarse stage
- Correct matching (x_i, x_j), if window size s_i is fixed, x_j may be **out of window**
- Use coarse matching (x_i, x_j) and RANSAC algorithm to calculate **relative depth** d_i/d_j, and scale the windows:

$$\frac{s_i}{s_j} = \frac{d_j}{d_i}$$



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Evaluation

Homography Estimation (HPatches)

Catagory	Method	Homo	matches		
Calegory	Wethod	@3px	@5px	@10px	matches
	D2Net [15]+NN	23.2	35.9	53.6	0.2K
	R2D2 [42]+NN	50.6	63.9	76.8	0.5K
Detector-based	DISK [55]+NN	52.3	64.9	78.9	1.1K
	SP [14]+SuperGlue [47]	53.9	68.3	81.7	0.6K
	Patch2Pix [64]	46.4	59.2	73.1	1.0k
Detector-free	Sparse-NCNet [43]	48.9	54.2	67.1	1.0K
	COTR [24]	41.9	57.7	74.0	1.0K
	DRC-Net [27]	50.6	56.2	68.3	1.0K
	LoFTR [50]	65.9	75.6	84.6	1.0K
	PDC-Net+ [54]	66.7	76.8	85.8	1.0k
	ASTR(ours)	71.7	80.3	88.0	1.0K

Visual Localization (InLoc & Aachen)

InLoc

Method	DUC1	DUC2			
Wethod	$(0.25m,10^\circ)$ / $(0.5m,10^\circ)$ / $(1m,10^\circ)$				
Patch2Pix [64](w.SP [47]+CAPS [58])	42.4 / 62.6 / 76.3	43.5 / 61.1 / 71.0			
LoFTR [50]	47.5 / 72.2 / 84.8	54.2 / 74.8 / 85.5			
MatchFormer [57]	46.5 / 73.2 / 85.9	55.7 / 71.8 / 81.7			
ASpanFormer [9]	51.5 / 73.7 / 86.4	55.0 / 74.0 / 81.7			
ASTR(ours)	53.0 / 73.7 / 87.4	52.7 / 76.3 / 84.0			

Aachen

Method	Day	Night						
Meulou	$(0.25m,2^\circ)$ / $(0.5m,5^\circ)$ / $(1m,10^\circ)$							
Localization with matching pairs provided in dataset								
R2D2 [42]+NN	-	71.2 / 86.9 / 98.9						
ASLFeat [36]+NN	-	72.3 / 86.4 / 97.9						
SP [14]+SuperGlue [47]	-	73.3 / 88.0 / 98.4						
SP [14]+SGMNet [8]	-	72.3 / 85.3 / 97.9						
Localization with matching pairs generated by HLoc								
LoFTR [50]	88.7 / 95.6 / 99.0	78.5 / 90.6 / 99.0						
ASpanFormer [9]	89.4 / 95.6 / 99.0	77.5 / 91.6 / 99.0						
AdaMatcher [22]	89.2 / 95.9 / 99.2	79.1 / 92.1 / 99.5						
ASTR(ours)	89.9 / 95.6 / 99.2	76.4 / 92.1 / 99.5						

Relative Pose Estimation (MegaDepth & ScanNet)

MegaDepth				ScanNet (* train on MegaDepth)					
Catagory	Mathad	Pose estimation AUC		Catagomy	Mathad	Pose estimation AUC			
Category	Method	$@5^{\circ}$	$@10^{\circ}$	$@20^{\circ}$	- Calegory Method		$@5^{\circ}$	$@10^{\circ}$	$@20^{\circ}$
Detector based	SP [14]+SuperGlue [47]	42.2	59.0	73.6		D2-Net [15]+NN	5.3	14.5	28.0
Detector-based	SP [14]+SGMNet [8]	40.5	59.0	73.6	Detector-based	SP [14]+OANet [61]	11.8	26.9	43.9
Detector-free	DRC-Net [27]	27.0	42.9	58.3		SP [14]+SuperGlue [47]	16.2	33.8	51.8
	PDC-Net+(H) [54]	43.1	61.9	76.1		DRC-Net [27]*	7.7	17.9	30.5
	LoFTR [50]	52.8	69.2	81.2		MatchFormer [57]*	15.8	32.0	48.0
	MatchFormer [57]	53.3	69.7	81.8	Detector-free	LoFTR-OT [50]*	16.9	33.6	50.6
	QuadTree [52]	54.6	70.5	82.2		Quadtree [52]*	19.0	37.3	53.5
	ASpanFormer [9]	55.3	71.5	83.1		ASTR(ours)*	19.4	37.6	54.4
	ASTR(ours)	58.4	73.1	83.8		· · · · · ·			

Evaluation

Ablation study on MegaDepth

Index	Multi-Level	Spot-Guided	Scaling	Pose estimation AUC			
		(l = 5, k = 4)	Scalling	$@5^{\circ}$	$@10^{\circ}$	$@20^{\circ}$	
1				45.6	62.2	75.3	
2	\checkmark			46.7	63.1	76.3	
3	\checkmark	\checkmark		47.7	64.5	77.4	
4	\checkmark	\checkmark	\checkmark	48.3	65.0	77.7	

Different Adjacent Area Size *l* and top-*k*

	Pose estimation AUC							
k(l = 5)	$@5^{\circ}$	$@10^{\circ}$ $@20^{\circ}$		l(k-4)	Pose estimation AUC			
1	46.0	62.7	76.2	l(n = 4)	$@5^{\circ}$	$@10^{\circ}$	$@20^{\circ}$	
2	47.5	64.0	77.1	3	46.7	63.2	76.1	
3	47.3	63.8	76.7	5	47.7	64.5	77.4	
4	47.7	64.5	77.4	7	47.2	63.4	76.8	
5	47.1	63.7	77.0	9	43.0	60.5	74 8	
6	46.9	63.6	76.6		.5.0	0010	, 110	

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Visualization

Fine Stage Window Scaling and Depth Estimation



Qualitative Comparison



(b)Vanilla Attention

(a)Reference

(c)Ours

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Conclusion

- A novel Adaptive Spot-Guided Transformer (ASTR) for local feature matching
- Two novel module:
 - **Spot-Guided Attention**: maintain local consistency, filter irrelevant attention areas
 - Adaptive Scaling: scale fine stage window to handle large scale variation
- SOTA performance in extensive experimental





Thanks!

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