

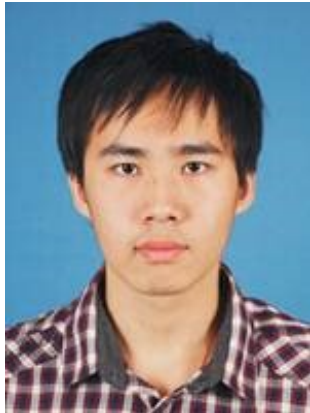


JUNE 18-22, 2023  
**CVPR**   
VANCOUVER, CANADA

# Rethinking Optical Flow from Geometric Matching Consistent Perspective



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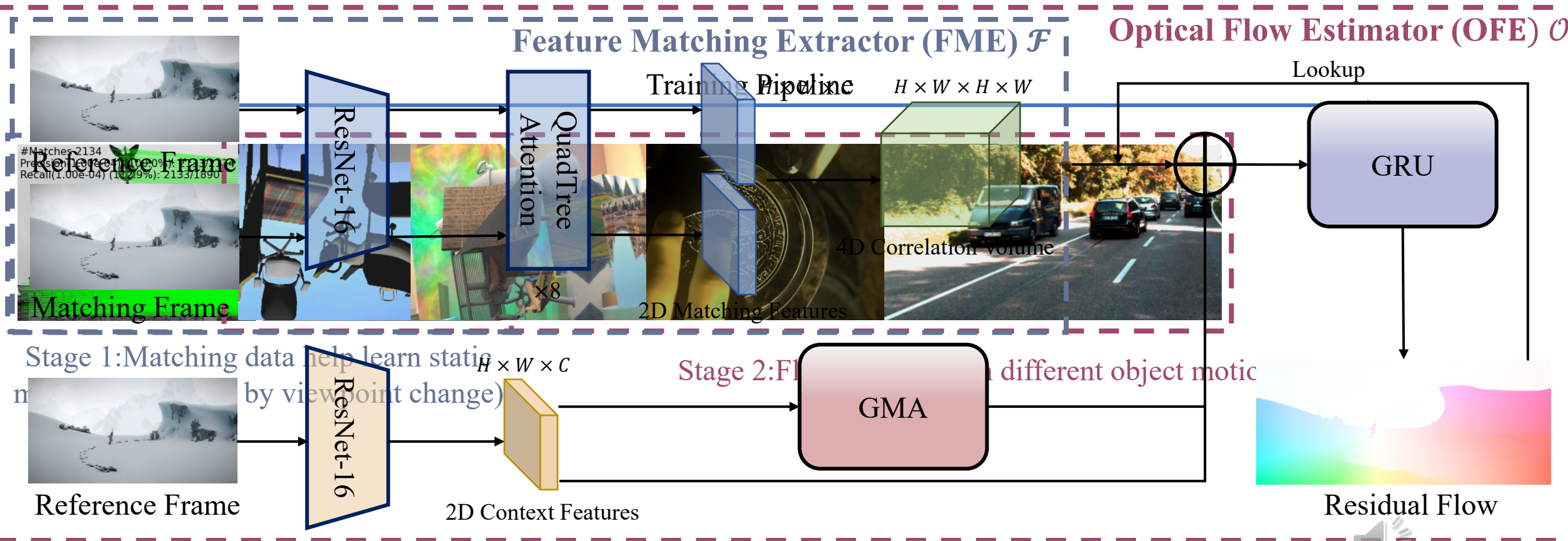
Paper Tag: **TUE-AM-127**



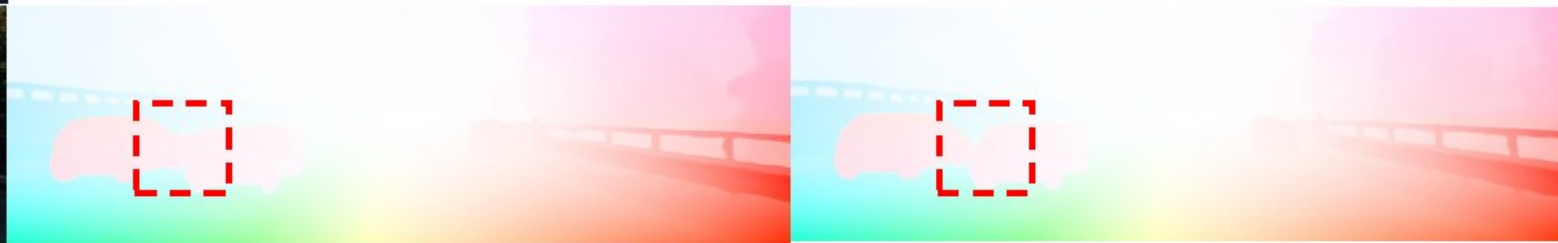
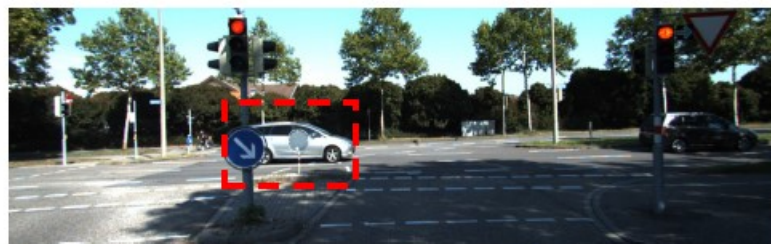
# Quick Review

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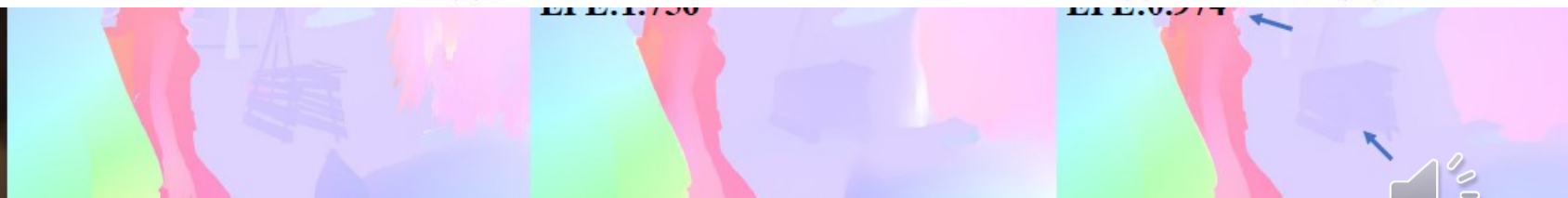
# Quick Review



(a) Reference Frame

(b) GMA

(c) MatchFlow(G)



(a) Reference Frame

(b) Ground Truth

(c) GMA

(d) MatchFlow(G)

# Quick Review



<https://github.com/DQiaole/MatchFlow>



# Introduction

## Training Pipeline



Stage 1: Matching data help learn static match (e.g. caused by viewpoint change)

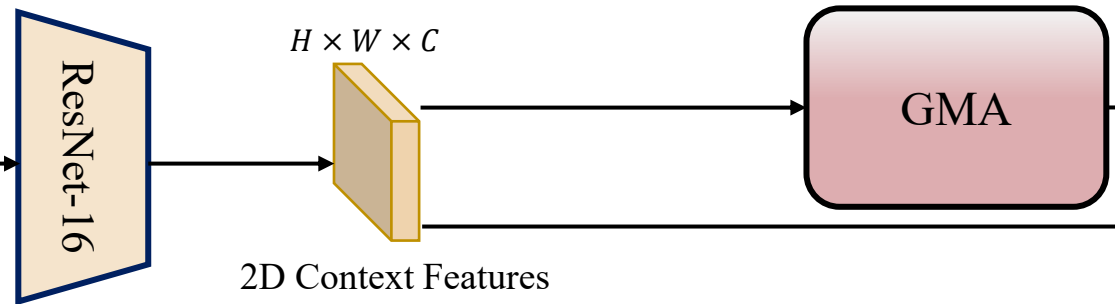
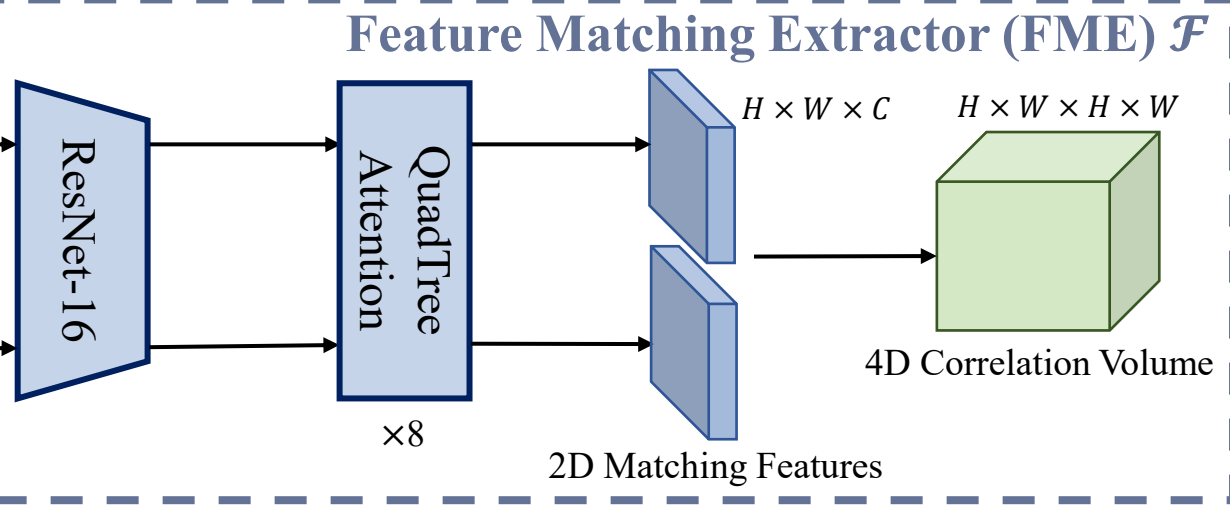
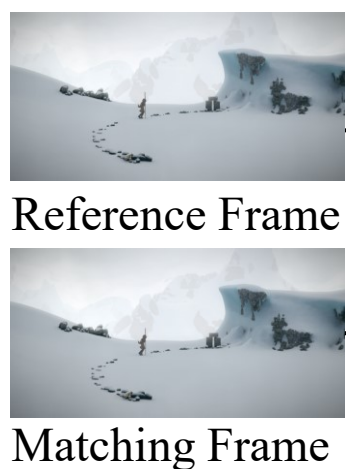
Stage 2: Flow data to learn different object motion within scene

## Motivations

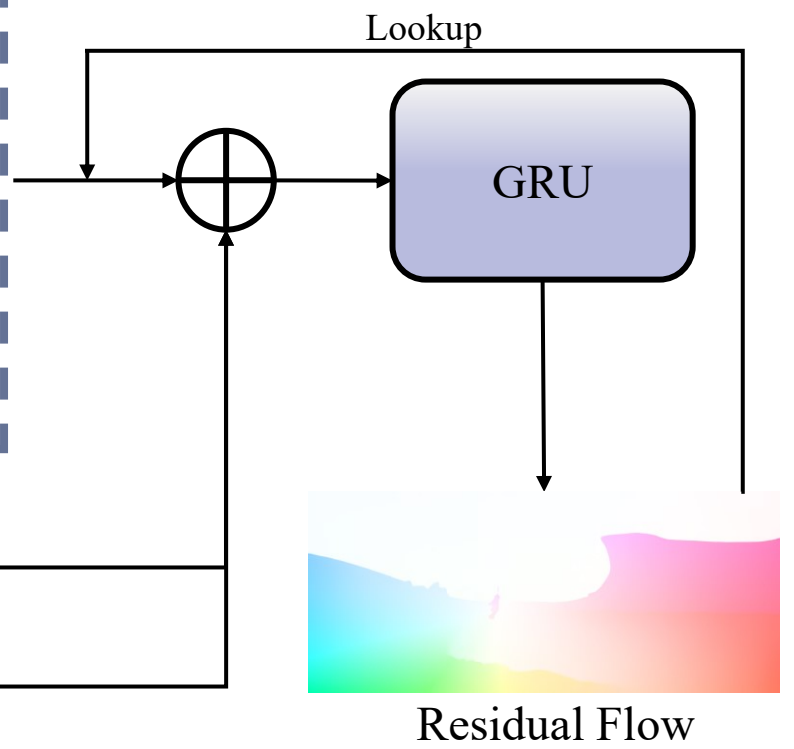
- Geometric Image Matching (GIM) shares some common challenges with optical flow estimation.
- It is much easier and simple to collect the real-world GIM data.
- Rethinking of the general training pipeline of optical flow.



# Methodology



## Optical Flow Estimator (OFE) $\mathcal{O}$



$$C(i, j) = \langle F_1(i), F_2(j) \rangle \in \mathbb{R}^{H \times W \times H \times W}$$



# Methodology

Pre-training Loss:

$$C(i, j) = \langle F_1(i), F_2(j) \rangle \in \mathbb{R}^{H \times W \times H \times W}$$

$$\mathcal{P}_c(i, j) = \text{softmax}(C(i, \cdot) / \tau)_j \cdot \text{softmax}(C(\cdot, j) / \tau)_i$$

$$\mathcal{L}_c = -\frac{1}{|\mathcal{M}_c^{gt}|} \sum_{(i, j) \in \mathcal{M}_c^{gt}} \log \mathcal{P}_c(i, j)$$

Optical Flow Loss:

$$\mathcal{L} = \sum_{i=1}^N \gamma^{N-i} \|f_{gt} - f_i\|_1$$



# Experiments



## Datasets:

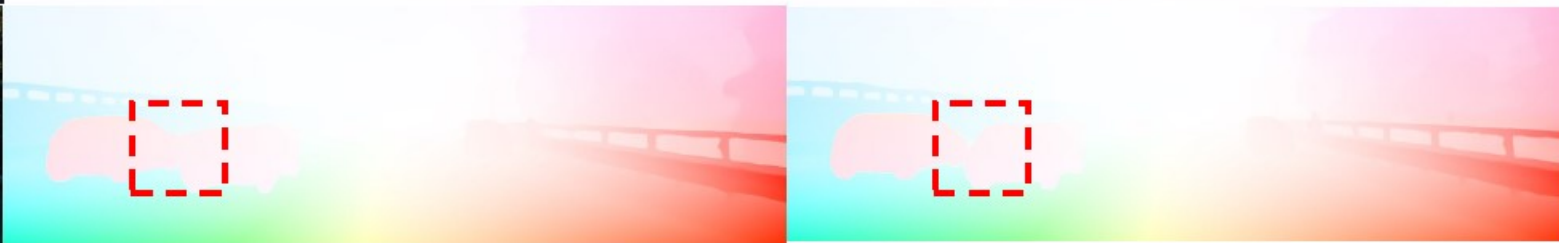
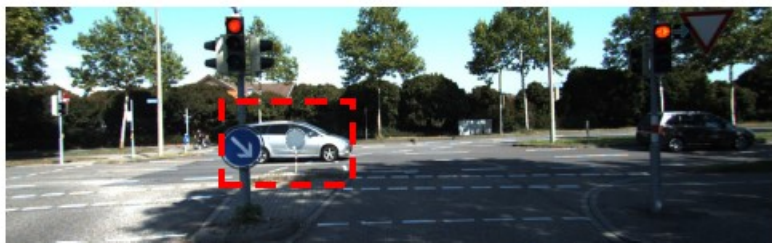
- MegaDepth
- FlyingChair (C) + FlyingThings3D (T)
- Sintel (S) + KITTI (K) + HD1K (H)





# Experiments

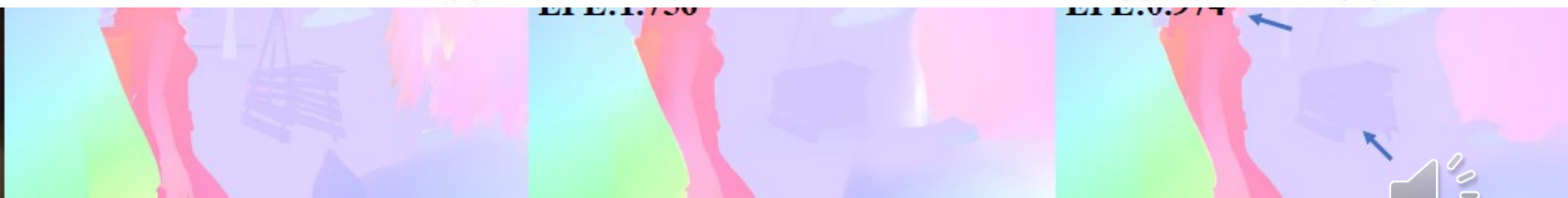
## Qualitative results:



(a) Reference Frame

(b) GMA

(c) MatchFlow(G)



(a) Reference Frame

(b) Ground Truth

(c) GMA

(d) MatchFlow(G)

# Experiments

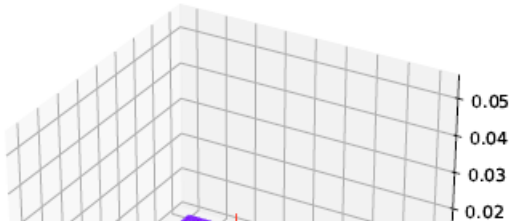
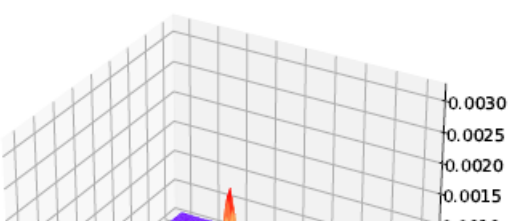
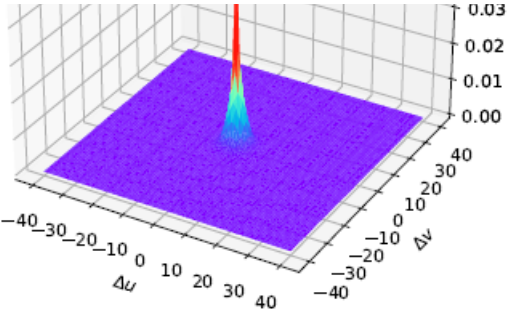
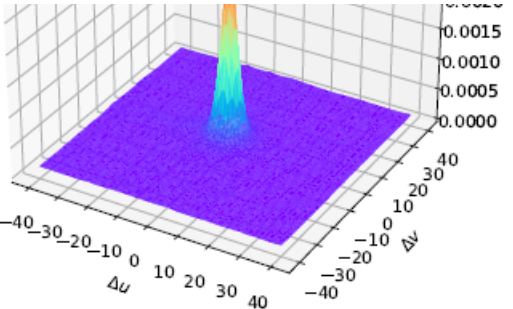
## Quantitative results:

Training	Method	<u>Sintel (train)</u>		<u>KITTI-15 (train)</u>		<u>Sintel (test)</u>		<u>KITTI-15 (test)</u>
		Clean	Final	Fl-epe	Fl-all	Clean	Final	Fl-all
C+T+S+K+H	PWC-Net+ [45] <sup>†</sup>	1.01 <sup>†</sup> (1.71)	2.42 <sup>†</sup> (2.34)	1.00 <sup>†</sup> (1.50)	(5.3)	3.45	4.60	7.72
	RAFT [50]	(0.76)	(1.22)	(0.63)	(1.5)	1.61*	2.86*	5.10
	RAFT-A [43]	-	-	-	-	2.01	3.14	4.78
	Separable Flow [56]	(0.69)	(1.10)	(0.69)	(1.60)	1.50	2.67	4.64
	GMA [25]	(0.62)	(1.06)	(0.57)	(1.2)	1.39*	2.47*	5.15
	AGFlow [30]	(0.65)	(1.07)	(0.58)	(1.2)	1.43*	2.47*	4.89
	KPA-Flow [29]	(0.60)	(1.02)	(0.52)	(1.1)	1.35*	2.36*	4.60
	DIP [58]	-	-	-	-	1.44*	2.83*	<b>4.21</b>
	GMFlowNet [57]	(0.59)	(0.91)	(0.64)	(1.51)	1.39	2.65	4.79
	GMFlow [54]	-	-	-	-	1.74	2.90	9.32
	CRAFT [42]	(0.60)	(1.06)	(0.58)	(1.34)	1.45*	2.42*	4.79
	FlowFormer [20]	(0.48)	(0.74)	(0.53)	(1.11)	<u>1.20</u>	<b>2.12</b>	4.68 <sup>†</sup>
	SKFlow [47]	(0.52)	(0.78)	(0.51)	(0.94)	1.28*	<u>2.23*</u>	4.84
	<b>MatchFlow(R) (Ours)</b>	(0.51)	(0.81)	(0.59)	(1.3)	1.33*	2.64*	4.72 <sup>†</sup>
	<b>MatchFlow(G) (Ours)</b>	(0.49)	(0.78)	(0.55)	(1.1)	<b>1.16*</b>	2.37*	4.63 <sup>†</sup>
<b>MatchFlow(K) (Ours)</b>	1.14	2.61	4.19 <sup>†</sup>	<b>15.6<sup>†</sup></b>	-	-	-	
<b>MatchFlow(G) (Ours)</b>	1.03	2.45	<b>4.08<sup>†</sup></b>	15.6 <sup>†</sup>	-	-	-	



# Experiments

## Ablation Study:

Experiment	 		 		<b>I-15 (train)</b> <b>Fl-all</b>		Parameters
	Method	Dataset	Sintel Clean	Sintel Final	KITTI-15 Fl-epe	KITTI-15 Fl-all	
Baseline	Baseline	C+T	1.27	2.84	4.12	14.4	5.9M
Local Matching Pre-train	Depthstill	C+T+dMegaDepth	2.10	3.47	<b>3.41</b>	<b>10.9</b>	17.0M
	DINO	ImageNet+C+T	1.52	3.08	5.50	19.2	15.4M
Number of Attention Blocks	Twins-SVT	ImageNet+C+T	1.15	2.73	4.98	16.8	5.9M
	Ours	MegaDepth+C+T	<b>1.03</b>	<b>2.45</b>	4.08	15.6	9.1M
Attention Type							15.4M
							14.3M
Global Matching							15.6
							15.4M
							<b>15.0</b>
							18.7M
							17.4
							15.4M
							16.1
							<b>15.6</b>
							15.4M

(a) Noc

(b) Occ



# Experiments

## Parameters, Timing, and GPU Memory:

Model	Para.	Infer.	Train.	Memory
GMA [25]	5.9M	74 ms	30 h	11.7 G
FlowFormer [20]	18.2 M	149 ms	107 h	43.7 G
MatchFlow(R)	14.8 M	110 ms	53 h	22.1 G
MatchFlow(G)	15.4M	126 ms	58 h	23.6 G



# Conclusion

- Employing GIM as the
  - A novel matching-based
  - Massive real-world mat
- 
- optical flow.  
flow model – MatchFlow.  
our model.

<https://github.com/DQiaole/MatchFlow>

