Combinatorial Regularization of Descriptor Matching for Optical Flow Estimation

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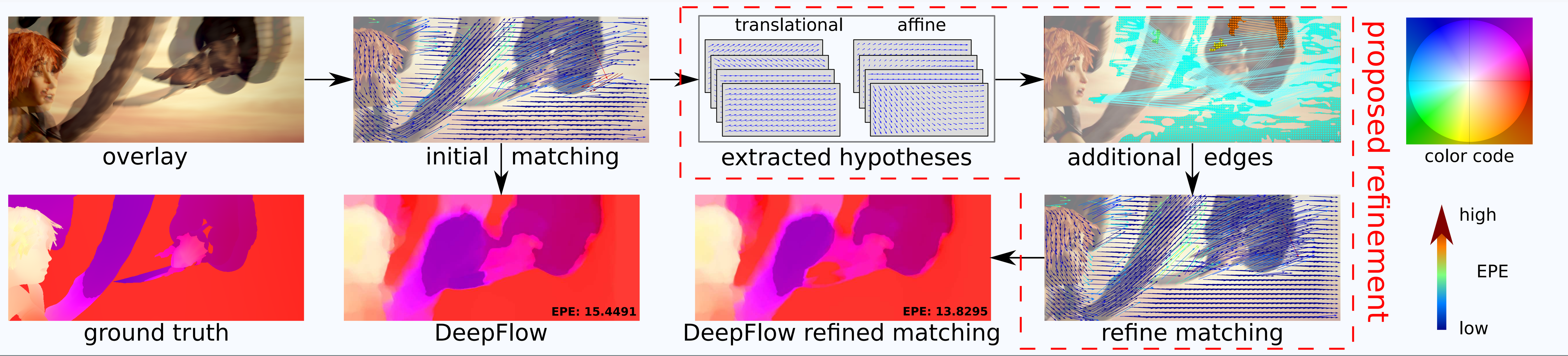
Contributions

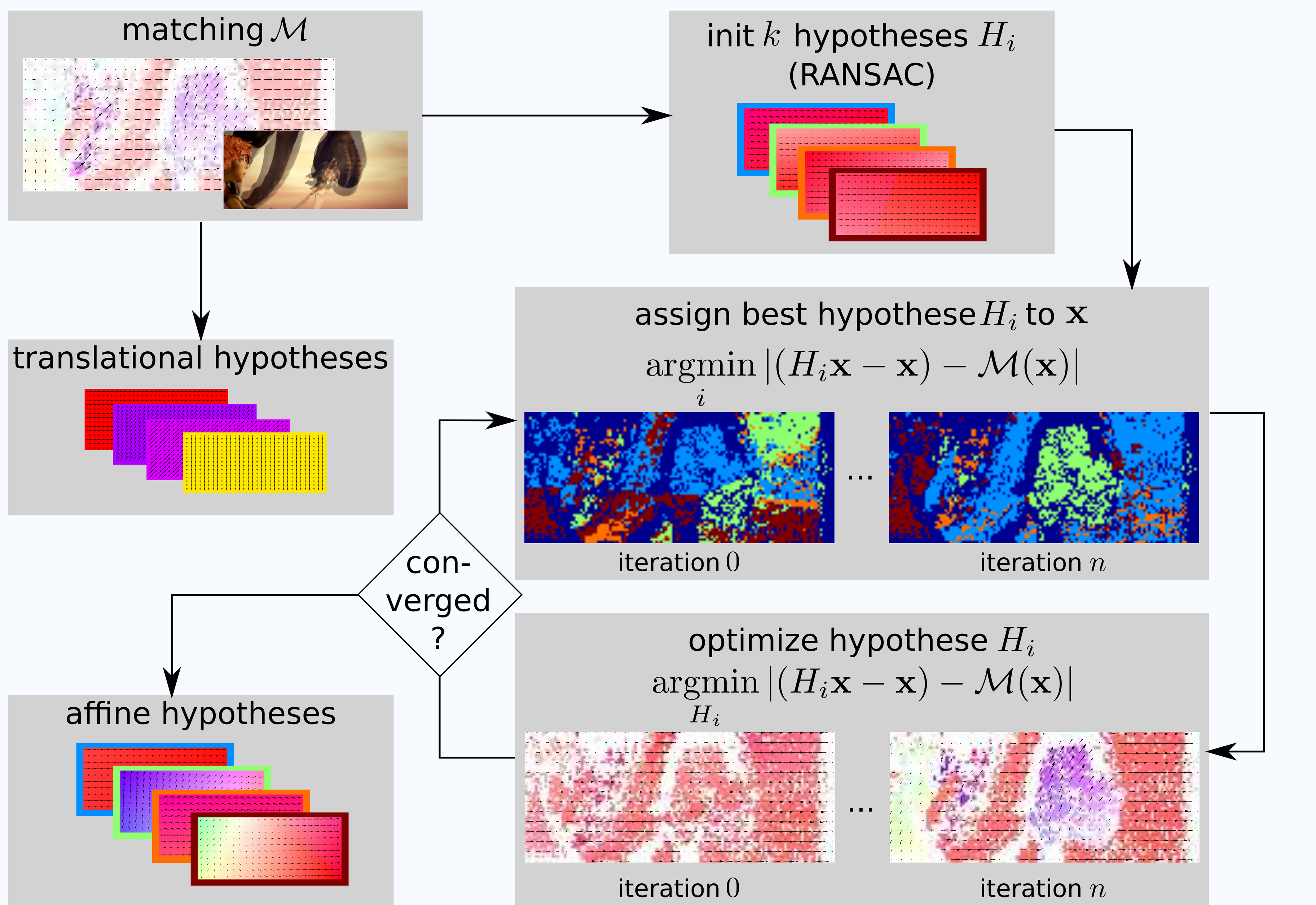
Self-contained refinement step, improving initial matchings by:

- adding new matches
- resolve ambiguities in homogenous regions
- correction of wrongly estimated outliers

Overview



Hypotheses



Additional Edges

- extend 4 / 8 neighborhood
- identify homogenous regions
- remove small regions
- connect similar regions (HSV-color-histogram)

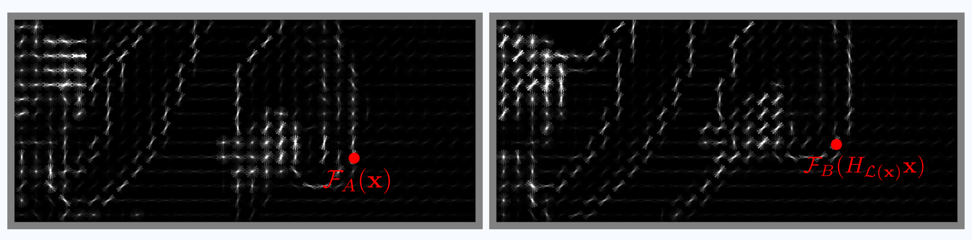
Combinatorial Refinement

$$E(\mathcal{L}) = \underbrace{E_A(\mathcal{L}) + E_M(\mathcal{L})}_{\text{Data terms}} + \underbrace{E_S(\mathcal{L})}_{\text{Smoothness}}$$

Appearance term:

$$E_A(\mathcal{L}) = \sum_{\mathbf{x}} -\max\left(\frac{\langle \mathcal{F}_A(\mathbf{x}), \mathcal{F}_B(H_{\mathcal{L}(\mathbf{x})}\mathbf{x})\rangle}{\|\mathcal{F}_A(\mathbf{x})\|_2 \cdot \|\mathcal{F}_B(H_{\mathcal{L}(\mathbf{x})}\mathbf{x})\|_2}, \alpha\right) \cdot \sigma(\mathbf{x})$$

$\sigma(\mathbf{x})$ = structureness



Matching term:

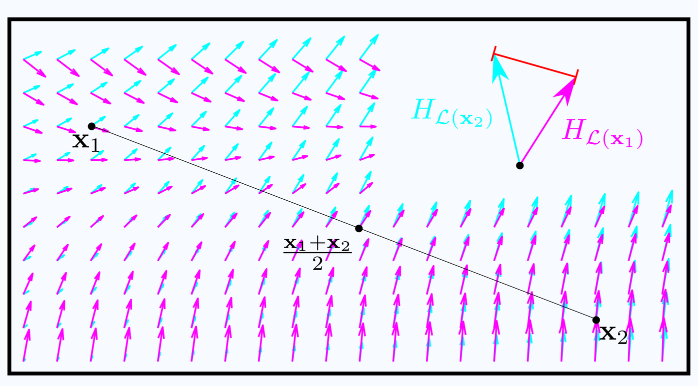
$$E_M(\mathcal{L}) = \sum_{\mathbf{x}} \min(\|(H_{\mathcal{L}(\mathbf{x})}\mathbf{x} - \mathbf{x}) - \mathcal{M}(\mathbf{x})\|_2, \theta) \cdot C(\mathbf{x})$$

$C(\mathbf{x})$ = confidence/indicator of matching

Smoothness term [4] **:**

$$E_S(\mathcal{L}) = \sum_{(\mathbf{x}_1,\mathbf{x}_2)\in\mathcal{E}} \omega(\mathbf{x}_1,\mathbf{x}_2) \cdot \min\left(\left|H_{\mathcal{L}(\mathbf{x}_1)}\frac{\mathbf{x}_1+\mathbf{x}_2}{2} - H_{\mathcal{L}(\mathbf{x}_2)}\frac{\mathbf{x}_1+\mathbf{x}_2}{2}\right|_1, \beta\right)$$

$$\omega(\mathbf{x}_1,\mathbf{x}_2) = \lambda \cdot \exp -\frac{\|\mathcal{F}_A(\mathbf{x}_1)-\mathcal{F}_A(\mathbf{x}_2)\|_2}{\nu}$$



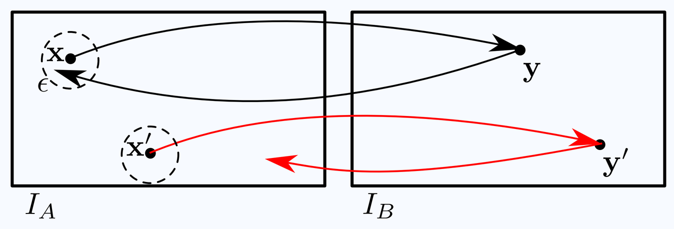
- metric regularization
  $\rightarrow$ submodular binary problems

Optimization:

MRF with Fast_PD. Parameters $(\alpha, \beta, \theta, \lambda, \nu)$ are optimized on a subset using the downhill-simplex algorithm of Nelder and Mead.

Scoring

Forward-backward checking removes inconsistent matches. Remaining matches are weighted according to their *color and structure tensor*.



Results Matching

Method	EPE	Points
LDOF	3.4627	$2.14 \cdot 10^3$
LDOF+R	**3.4537**	$\mathbf{6.19 \cdot 10^3}$
Deep	3.5073	$5.87 \cdot 10^3$
Deep+R	**3.1757**	$\mathbf{6.56 \cdot 10^3}$

(a)

Component	EPE
4-connected	5.484
affine hypotheses	5.397
add edges	5.4127
affine & edges	**5.303**

(b)

Part	LDOF	DeepFlow	EpicFlow
matching	22.4	126.7	
refinement	13.1	11.9	
optical flow	26	40.7	4.3
total	61.5	179.3	142.8

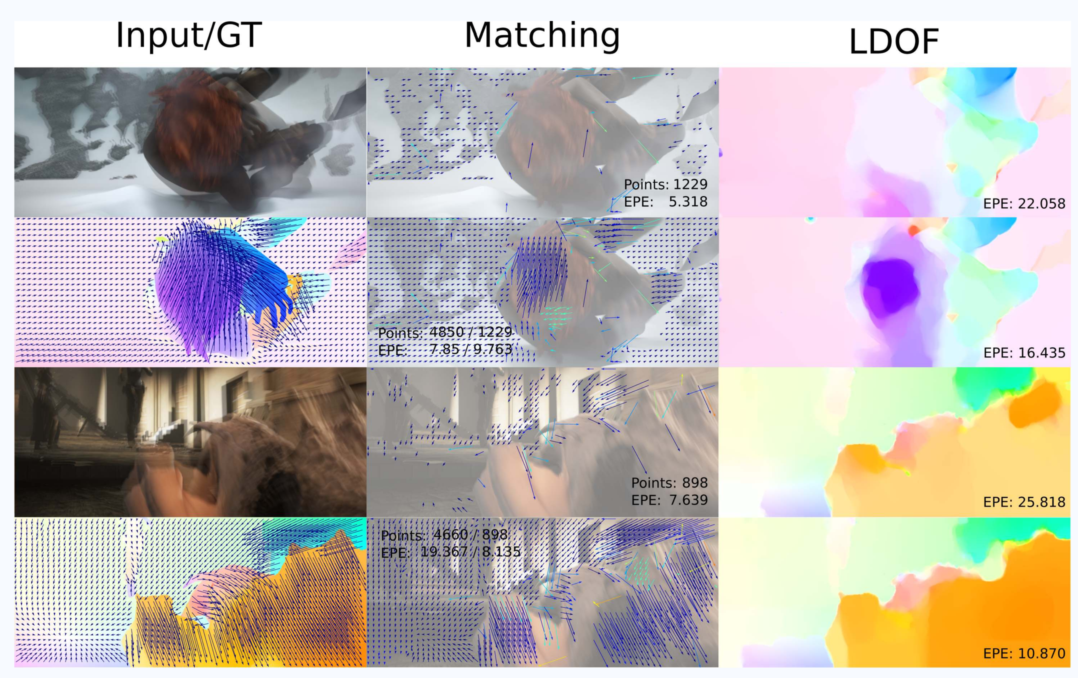
(c)

(a): EPE on matches (same points) and the number of (confident) points, before and after refinement. **(b)**: Evaluation of the different steps. **(c)**: Runtime in sec.

Optical Flow on Sintel Dataset

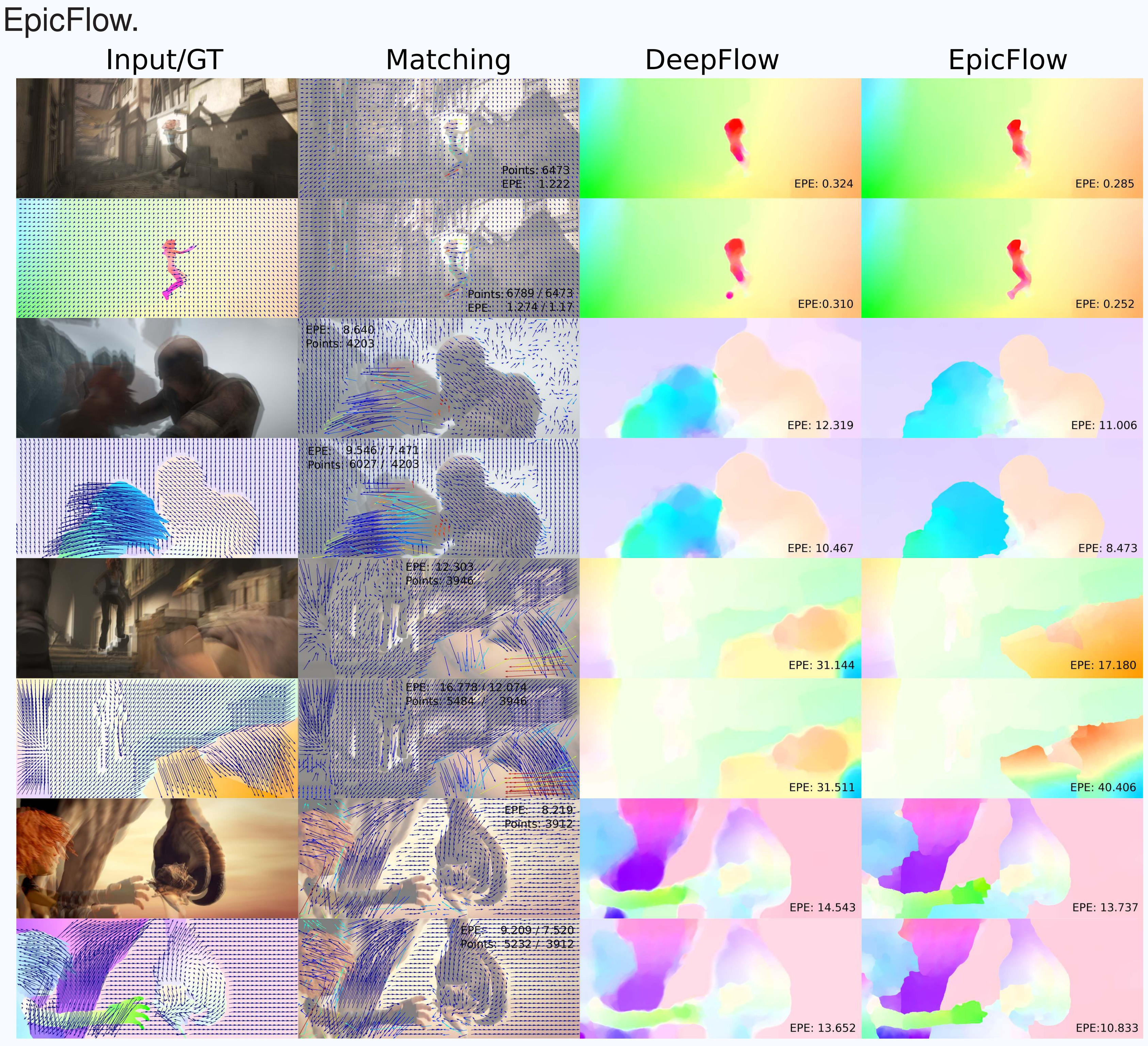
	Method	EPE
Training	Ldof [1]	6.026
	Ldof+R	**5.616**
	Deep [2]	4.022
	Deep+R	**3.852**
	Epic [3]	3.566
	Epic+R	**3.497**
Test	Deep [2]	7.212
	Deep+R	**6.769**

(a)



(b)

(a) Evaluation on the final pass of the Sintel (training/test) dataset. The refinement improves all methods. **(b)** & **(c)**: Qualitative results for LDOF, DeepFlow and EpicFlow.



(c)

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[3] J. Revaud, P. Weinzaepfel, Z. Harchaoui, and C. Schmid. EpicFlow: Edge-Preserving Interpolation of Correspondences for Optical Flow. CVPR 2015.

[4] Y. Jiaolong and L. Hongdong. Dense, accurate optical flow estimation with piecewise parametric model. CVPR 2015.

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