ProbDiffFlow: An Efficient Learning-Free Framework for Probabilistic Single-Image Optical Flow Estimation

Mo ZHOU, Jianwei WANG, Xuanmeng ZHANG, Dylan CAMPBELL, Kai WANG, Long YUAN, Wenjie ZHANG, Xuemin LIN

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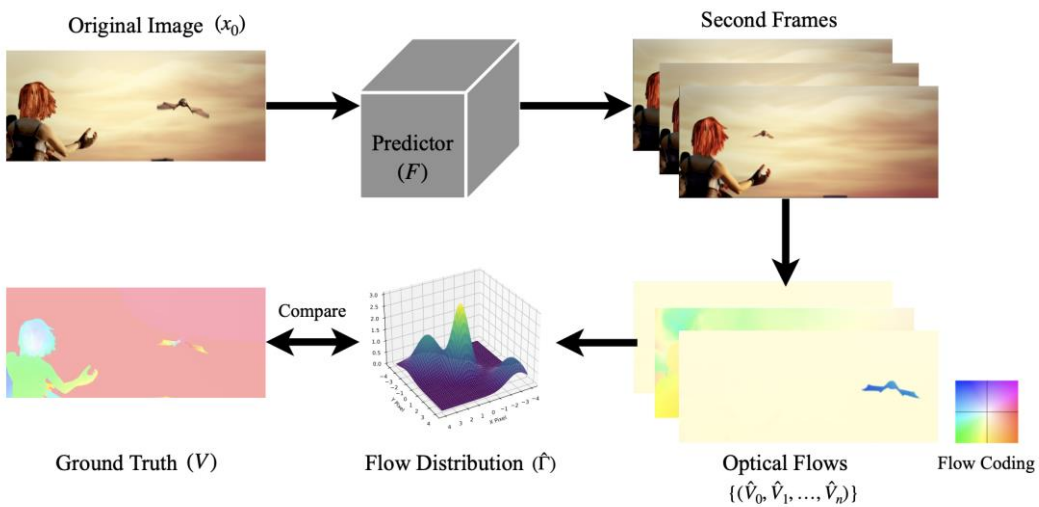
Problems & Ideas

- Problems of existing approaches:
  - Two-frame Dependency: Traditional methods require consecutive frames. Consecutive frames often unavailable in practice.
  - Supervised Training Limitation: Existing single-image methods depend heavily on labeled data. Obtaining labeled optical flow data is expensive and labor-intensive.
  - Deterministic Predictions: Current methods produce fixed outputs, unable to model motion uncertainties.
- Ideas: Leverage a training-free diffusion model to generate diverse future frames from a single image and aggregate flow predictions into a probabilistic distribution.



Overview of optical flow distribution prediction: Given an original image (x_0), the optical flow distribution predictor (F) estimates a set of plausible optical flows (Γ).

Main Contributions

- Contributions:
  - New Perspective: reformulate single-image optical flow as predicting a distribution of plausible motions rather than a single result;
  - Training-Free Framework: propose ProbDiffFlow, a diffusion-based method that requires no task-specific training to generate diverse motion estimates;
  - Strong Empirical Results: Demonstrate effectiveness across synthetic and real-world datasets, achieving high accuracy and motion diversity.

Method	Sintel.C					Sintel.F				
	EPE(px) ↓	F1-bg(%) ↓	F1-fg(%) ↓	F1-all(%) ↓	AE(°) ↓	EPE(px) ↓	F1-bg(%) ↓	F1-fg(%) ↓	F1-all(%) ↓	AE(°) ↓
RAFT [1]	7.14	12.15	24.30	21.80	81.85	8.32	13.42	26.85	24.97	95.35
PWC-Net [2]	8.13	14.28	28.56	25.62	93.17	10.07	15.19	30.38	28.25	115.4
RPK-Net [3]	3.73	10.28	20.56	18.44	42.75	6.76	10.82	21.63	20.12	77.47
RAPID-Flow [4]	3.63	9.91	19.81	17.77	41.60	6.52	10.74	21.48	19.98	74.72
U-Net [5]	10.99	19.35	38.71	34.72	115.95	13.58	20.0	40.0	37.20	115.63
Motion-Blurred [6]	4.27	11.80	23.58	20.19	42.91	7.16	12.40	24.80	20.98	77.69
ProbDiffFlow (Ours)	**3.43**	**9.64**	**19.28**	**17.29**	**39.31**	**6.18**	**10.34**	**20.69**	**19.24**	**70.82**
	5.51%	2.72%	2.68%	2.70%	5.50%	5.21%	3.72%	3.68%	3.79%	5.22%

Method	KITTI 2015					Spring				
	EPE(px) ↓	F1-bg(%) ↓	F1-fg(%) ↓	F1-all(%) ↓	AE(°) ↓	EPE(px) ↓	F1-bg(%) ↓	F1-fg(%) ↓	F1-all(%) ↓	AE(°) ↓
RAFT [1]	24.04	22.11	44.22	28.44	108.92	6.29	13.76	27.52	18.92	72.08
PWC-Net [2]	32.76	26.2	52.4	33.70	114.43	7.44	16.51	33.02	22.70	85.26
RPK-Net [3]	16.65	17.94	35.81	23.03	95.29	3.06	11.56	23.13	15.90	45.07
RAPID-Flow [4]	16.80	20.0	39.90	25.72	96.90	3.04	11.35	22.69	15.60	44.84
U-Net [5]	43.67	39.77	79.53	51.15	126.33	9.91	21.64	43.28	29.75	113.57
Motion-Blurred [6]	17.80	21.27	43.52	28.50	98.50	3.64	12.14	29.30	16.31	46.50
ProbDiffFlow (Ours)	**15.90**	**17.90**	**35.79**	**23.02**	**82.87**	**3.02**	**11.25**	**22.5**	**15.47**	**44.61**
	4.50%	0.22%	0.06%	0.04%	13.03%	0.66%	0.88%	0.84%	0.83%	0.51%

Quantitative Comparison of Optical Flow Methods: Performance comparison on multiple datasets using EPE, AE, and F1 metrics — ProbDiffFlow achieves top accuracy and diversity across all benchmarks.