RAFT - Recurrent All-Pairs Field Transforms

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RAFT: Recurrent All-Pairs Field Transforms for Optical Flow

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Abstract. We introduce Recurrent All-Pairs Field Transforms (RAFT), a new deep network architecture for optical flow. RAFT extracts per-pixel features, builds multi-scale 4D correlation volumes for all pairs of pixels, and iteratively updates a flow field through a recurrent unit that performs lookups on the correlation volumes. RAFT achieves state-of-the-art performance. On KITTI, RAFT achieves an F1-all error of 5.10%, a 16% error reduction from the best published result (6.10%). On Sintel (final pass), RAFT obtains an end-point-error of 2.855 pixels, a 30% error reduction from the best published result (4.098 pixels). In addition, RAFT has strong cross-dataset generalization as well as high efficiency in inference time, training speed, and parameter count. Code is available at `https://github.com/princeton-vl/RAFT`.

1 Introduction

Optical flow is the task of estimating per-pixel motion between video frames. It is a long-standing vision problem that remains unsolved. The best systems are limited by difficulties including fast-moving objects, occlusions, motion blur, and textureless surfaces.

Optical flow has traditionally been approached as a hand-crafted optimization problem over the space of dense displacement fields between a pair of images [21,51,13]. Generally, the optimization objective defines a trade-off between a *data* term which encourages the alignment of visually similar image regions and a *regularization* term which imposes priors on the plausibility of motion. Such an approach has achieved considerable success, but further progress has appeared challenging, due to the difficulties in hand-designing an optimization objective that is robust to a variety of corner cases.

Recently, deep learning has been shown as a promising alternative to traditional methods. Deep learning can side-step formulating an optimization problem and train a network to directly predict flow. Current deep learning methods [25,42,22,49,20] have achieved performance comparable to the best traditional methods while being significantly faster at inference time. A key question for further research is designing effective architectures that perform better, train more easily and generalize well to novel scenes.

We introduce Recurrent All-Pairs Field Transforms (RAFT), a new deep network architecture for optical flow. RAFT enjoys the following strengths:

- Published in 2020 by Zachary Teed and Jia Deng (Princeton University)
- Optical Flow Problem
- Not to be confused with the distributed consensus algorithm

Table of Contents

What is Optical Flow?

What is Optical Flow?

Goal: Estimate motion field between two consecutive frames ie get a velocity vector for every pixel

Where is Optical Flow used?

- Sports Analytics: Motion Analysis for performance improvement and injury prevention
- Computer Graphics: Stable Rendering and Scene Reconstruction
- Robotics and Autonomous Driving: Obstacle motion and collision detection

Problem Statement

Definition

Given two frames I1 and I2, predict a flow field $F(x, y) = (u(x, y), v(x, y))$, where (u, v) is the horizontal and vertical displacement of pixel (x,y).

Side Notes:

- Feature Matching vs Optical Flow
- Sparse vs Dense Optical Flow Methods

Problem Statement

Assumptions

- **Brightness Constancy**: Pixel intensity doesn't change from one frame to the next

$$I(x, y, t) = I(x + dx, y + dy, t + dt)$$

- **Spatial Smoothness**: Neighboring pixel have the same motion

$$I(x + dx, y + dy, t + dt) \approx I(x, y, t) + I_x u + I_y v + I_t$$

Problem Statement

Optical Flow Constraint

$$I_x u + I_y v + I_t = 0$$

where:

$$\boxed{I_x = \frac{\partial I}{\partial x} \quad I_y = \frac{\partial I}{\partial y}}$$

Spatial Derivatives

$$\boxed{u = \frac{dx}{dt} \quad v = \frac{dy}{dt}}$$

Optical Flow

$$\boxed{I_t = \frac{\partial I}{\partial t}}$$

Temporal Derivative

The spatial and temporal derivatives I_x, I_y and I_t are known, so the goal of the classical models is to solve for u and v (aperture problem)

Taxonomy

Classical Methods (Early 1980s - Mid 2010s)

Horn-Schunk (1981)

Formulate optical flow as energy minimization problem solved with iterative relaxation

$$E(u, v) = \iint \underbrace{(I_x u + I_y v + I_t)^2}_{\text{Brightness Constancy}} + \underbrace{\alpha^2 \left(\|\nabla u\|^2 + \|\nabla v\|^2\right)}_{\text{Smoothness Term}} dx\, dy$$

which can be solved with the Euler-Lagrange equations:

$$I_x(I_x u + I_y v + I_t) + \alpha^2 \nabla^2 u = 0$$
$$I_y(I_x u + I_y v + I_t) + \alpha^2 \nabla^2 v = 0$$

Classical Methods (Early 1980s - Mid 2010s)

Horn-Schunk (cont.)

The previous PDEs can be solved with iterative relaxation until convergence

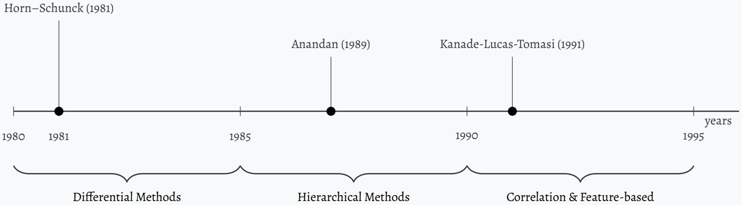
$$u^{k+1} = \bar{u}^k - \frac{I_x \left(I_x \bar{u}^k + I_y \bar{v}^k + I_t \right)}{\alpha^2 + I_x^2 + I_y^2}$$

$$v^{k+1} = \bar{v}^k - \frac{I_y \left(I_x \bar{u}^k + I_y \bar{v}^k + I_t \right)}{\alpha^2 + I_x^2 + I_y^2}$$

Classical Methods (Early 1980s - Mid 2010s)

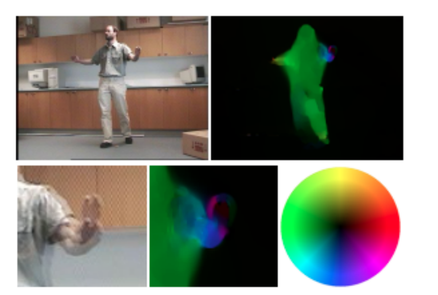
Classical Methods Improvements

1. Feature Extraction
2. Pixel Similarity
3. Iterative Relaxation

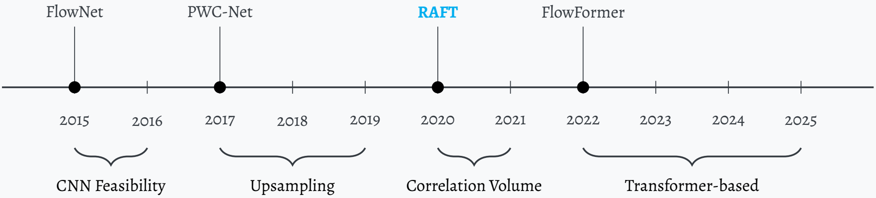


Classical Methods Challenges

- Accuracy: Large Displacement, Occlusions, Illumination & appearance changes
- Slow: no training phase, iteration has to be made at inference time



Deep Learning Methods (Mid 2010s-Present)



- FlowNet (162M): Showed that supervised learning could outperform classical methods, but heavy and struggled with large displacement
- PWC-Net (8.8M): Introduce pyramid, warping and cost volume ideas for upsampling (U-Net)
- RAFT (4.8M): All-pairs correlation volume
- FlowFormer (18.2M): Transformer-based model

Recurrent All-Pairs Field Transfoms (RAFT)

Architecture

Evaluation

Results

Input, Output and Flavors

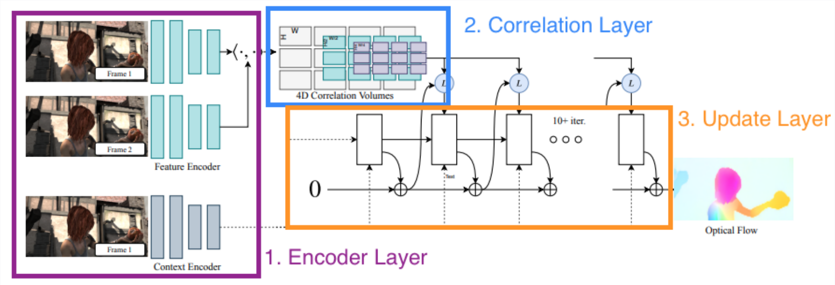
- Input: H x W x 2C; C=3
- Output: H x W x 2

Flavors:

- RAFT (4.8 M)
- RAFT-S (1M)

Architecture

Overview



Architecture

Novel Ideas

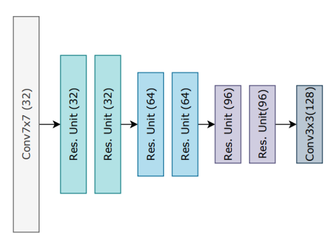
Limitations	**RAFT Improvements**
Fine details lost due to UNet architecture	Feature Encoder store and update a single flow field
Fixed number of iterations during training and inference	GRU-based opdate operator with shared weights
Large displacement missed because correlation performed locally	4D correlation volume

Architecture

Encoder Layer

The encoder layer is made of:

- Feature Encoder g_θ: extract per-pixel feature from I1 and I2
- Context Encoder h_θ: extract edges feature from I1



$$g_\theta : \mathbb{R}^{H\times W\times 3} \mapsto \mathbb{R}^{H/8\times W/8\times D}$$

Differences:

- Feature encoder uses instance normalization
- Context encoder uses batch normalization

Why RAFT add additional context encoder?

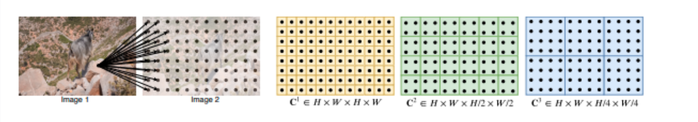
Architecture

Correlation Layer

Compute pixel similarity about small and large displacement:

1. **Correlation Pyramid**: For each pixel in I1, compute its similarity score to every pixel in I2 by taking the dot product between all pairs of feature vectors (or with a single matrix multiplication)
   This forms a 4-Layer Pyramid C^1, C^2, C^3, C^4, where C^k has dimension $HxWxH/2^k xW/2^k$ and k is the kernel size

$$C(i,j,k,l) = \sum_h g_\theta(I_1)_{ijh} \cdot g_\theta(I_2)_{klh}$$



Architecture

Correlation Layer (cont.)

2. **Correlation Lookup**: A lookup operator L_C which maps each pixel in I1 to its estimate correspondance in I2. Given the current predicted flow $f_1(u), f_2(v)$ and the pixel (x,y), compute the tentative correspondance $x^{'} = (x + f_1(x), y + f_2(y))$ and look in its local neighborhood to find the actual correspondance

$$N(x^{'})_r = \{x^{'} + dx \| \|dx\|_1 \leqslant r\}$$

Why it's more efficient:

1. Precompute correlation volume
2. Local lookup

Architecture

Update Layer

Instead of one-shot flow estimate like earlier model, RAFT uses a recurrent update mechanism:

1. **Initialization**: Zero optical flow ie assume no motion
2. **Inputs**: concatenate correlation features + flow features + context features into a single feature map

Update Layer (cont.)

3. **Update**: ConvGRU Refine flow step by step by integration correlation and context iteratively

$$z_t = \sigma(Conv_{3\times 3}([h_{t-1}, x_t], W_z)) \quad \text{(Update gate)}$$

$$r_t = \sigma(Conv_{3\times 3}([h_{t-1}, x_t], W_r)) \quad \text{(Reset gate)}$$

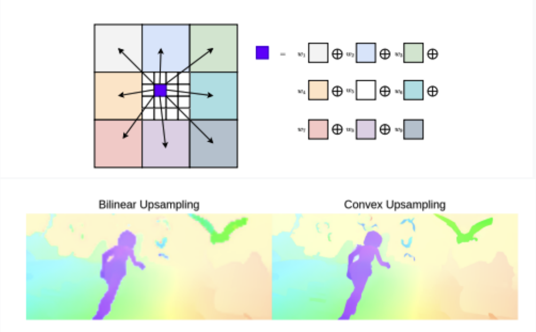
$$\tilde{h}_t = \tanh(Conv_{3\times 3}([r_t \odot h_{t-1}, x_t], W_h)) \quad \text{(Candidate hidden state)}$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad \text{(New hidden state)}$$

4. **Flow Prediction**: Flow prediction is updated $f^{k+1} = f_k + \Delta f$ and prediction are made at 1/8 resolution for image efficiency

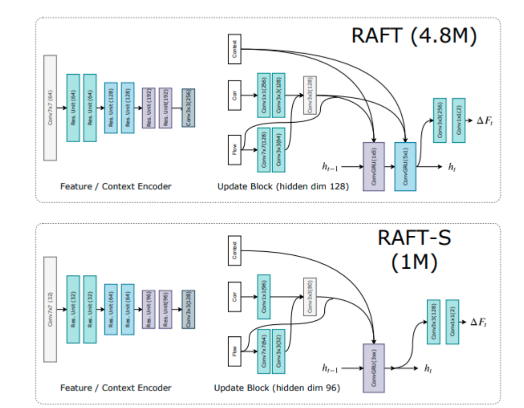
Update Layer (cont.)

5. **Upsampling**: Use a learn convex mask over 3x3 neighborhood instead of bilinear upsampling



RAFT Flavors

Differences



Differences:

- RAFT-S uses bottleneck residual units and 3x3 convolution in GRU
- Full model uses GRU updates blocks with 1x5 and 5x1 filters to increase receptive field

Evaluation

Datasets

- Hardware: 2x 2080Ti GPU
- Datasets:
  - FlyingThings: Synthetic dataset with large displacement and complex occlusions
  - KITTI: Real driving scene images with sparse ground truth from LiDAR. Involves rigid motion
  - Sintel: Synthetic animated movie with non-rigid motion

Sintel Example

FlyingThings Example

Evaluation

Training

1. Pretrained on FlyingThings for 100K iterations
2. Trained on FlyingThings3D for 100K iterations
3. Fine-tuned on Sintel and KITTI for 100K iterations

Intuition:

- Use FlyingThings to learn priors because is diverse
- Evaluate using both synthetic dataset and real dataset

Evaluation

Metrics

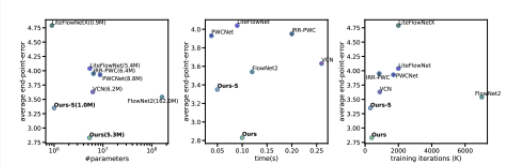
- Loss Function: L1 distance with exponentially increasing weight

$$\mathcal{L} = \sum_{i}^{N} \gamma^{N-i} \|f_{gt} - f_i\|_1; \gamma = 0.8$$

- Optimizer: AdamW with gradient clip $[-1, 1]$
- Metric: End-Point-Error (EPE)

Results

- Training Iterations
  - Surpass PWC-Net after 6 updates
  - Surpass FlowNet after 3 updates
- EPE on Sintel: 5.04 vs 8.36 (40% reduction)
- EPE on KITTI: 2.855 vs 4.098 (16% reduction)
- Inference Time: Doesn't beat PWC-Net (0.034s)
  - RAFT-S: (0.043s)
  - RAFT: (0.097s)



Perspective

Limitations

- Non-rigid motion and occlusions not handled well
- Still requires O(MN) to compute correlation volume
- Large displacement bottlenecked by higher pyramid-level
- Model is still large

Future Directions

- SEA-RAFT: reduce runtime, faster convergence, better generalization
- FlowFormer: uses transformers to improve upon non-repetitive larger displacement and non-rigid motion
- \ours: occlusion mask with forward-backward consistency check
- GMFlow: reduce dependence on many iterations

Questions?

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