Optical Flow of Moving Objects

Madhupriya Pulletikurthi
Information Science and Engineering
Dayananda Sagar College of Engineering, Bangalore, India

Donthireddy Bharathi
Information Science and Engineering
Dayananda Sagar College of Engineering, Bangalore, India

B Lohitha
Information Science and Engineering
Dayananda Sagar College of Engineering, Bangalore, India

Basavakeerthi B
Information Science and Engineering
Dayananda Sagar College of Engineering, Bangalore, India

Mr Suresh Kumar M
Assistant Professor
Information Science and Engineering
Dayananda Sagar College of Engineering, Bangalore, India
sureshkumar-

Abstract— This work introduces a novel approach to optical flow estimation. RAFT employs new deep network architecture to iteratively refine pixel-wise motion predictions. It excels in handling challenging scenarios like traffic analysis, vehicle tracking, object movement with large displacements and occlusions. Experimental results demonstrate RAFT's superior accuracy and robustness compared to state-of-the-art methods, making it a valuable tool for computer vision applications.

Keywords-- Optical flow, Recurrent All-Pairs Field Transforms, Multi-scale 4D Correlation volumes, GRU block

I. INTRODUCTION

As we are aware of congested roads which lead to huge number of accidents from day to day. The victims of these accident require immediate attention which is possible only through constant monitoring of the traffic flow and analysis the motion of the vehicles.

To develop a deep network model using optical flow of moving objects which is a crucial part of traffic analysis. This model can be used by the traffic monitoring unit to identify congestion, accidents and to track vehicles. In case of any accidents the traffic monitoring unit can immediately detect the collusion and take necessary actions.

II. OPTICAL FLOW OF MOVING OBJECTS USING DIFFERENT ML APPROACHES

Optical flow, especially when applied to tracking moving objects, can leverage various machine learning (ML) approaches to analyze and predict motion in a video sequence. Each approach has its advantages and limitations, depending on factors such as the complexity of the scene, computational efficiency, dataset availability, and the specific requirements of the application. Table 1 presents a comparison of different methods used in optical flow by researchers.

Di Jia, Kai Wang et. al [1] is an innovative approach for optical flow estimation built upon correlation blocks. BRAFT leverages recurrent neural networks (RNNs) to generate all-pairs field transforms, enhancing the accuracy and efficiency of optical flow estimation. BRAFT presents a promising advancement in optical flow estimation by integrating correlation blocks and recurrent all-pairs field transforms, offering enhanced accuracy and robustness in capturing complex motion patterns while maintaining computational efficiency. However, its practical applicability might depend on factors such as implementation complexity and data requirements.

Ms. Rajashree Revaji Shinde et. al [2] This paper presents a novel approach to designing and analyzing an algorithm for the unsupervised recurrent all-pairs field transform of optical flow.The proposed method combines two-frame optical flow estimation with recurrent all-pairs field transform to produce an accurate and efficient solution. Results demonstrate that the proposed algorithm is capable of providing accurate estimations of optical flow in a number of video sequence datasets.

Maximilian Luz et. al [3] The focus of this thesis lies not in the applications of motion cues, but in estimating the motion itself from 2D image sequences as a vector field in the image plane. This field of motion is referred to as *optical flow*. In particular, we investigate a specific class of methods for this problem, combining two concepts that have both individually lead to significant performance improvements over previous approaches: RAFT and DICL.

Philippe Weinzaepfel et. al [4] This approach uses matching algorithm with a variational approach for optical flow. This outperforms current algorithms, especially for s40+. Matching algorithm does not improve the motion estimation in the context of small displacements. DeepFlow efficiently handles large displacements occurring in realistic videos, and shows competitive performance on optical flow benchmarks. Furthermore, it sets a new state-of-the-art on the MPI-Sintel dataset.

Nelson Monz ́on et. al [5] This paper demonstrates exponential function together with a TV process. Small constant that ensures a minimum isotropic smoothing. Exponential functions that mitigate the regularization at image edges, which usually provide precise flow boundaries. Nevertheless, if the smoothing is not well controlled, it may produce instabilities in the computed motion fields. Two alternatives are aimed at reducing the effect of instabilities. We observe that the pure exponential function is highly unstable while the other strategies preserve accurate motion contours for a large range of parameters.

Philipp Fischer et.al [6]: This thesis explores CNN: FlowNetSimple (top) ;FlowNetCorr (bottom) methods for learning optical flow with convolution networks. It generates a synthetic Flying Chairs dataset. The results are to generalize very well to existing datasets such as Sintel and KITTI, achieving competitive accuracy at frame rates of 5 to 10 fps.

Xuezhi Xiang et. al [7]: The paper explores PWC-Net [2]-unsupervised and CNN with transformer architecture. The delves into occlusion compensation loss, Rectify the occlusion map and assist the network in learning how to predict the flow in the occluded regions. This experiment increased the accuracy of the optical flow and improving the flow in the occluded regions.

III. OPTICAL FLOW OF MOVING IN DIFFERENT USE CASES

Table 2 presents the different use cases in optical flow by researchers.

Karen Simonyan Andrew Zisserman et. al [8]: uses Deep Convolutional Networks (ConvNets) for action recognition in video. The methods used are Two-stream ConvNet architecture. Multitask learning, applied to two different action classification datasets, are used to increase the amount of training data and improve the performance on both. Trained and evaluated on the standard video actions benchmarks of UCF-101 and HMDB-51, where it is competitive with the state of the art.

Joel Janai et. al [9]: examines Semantic Instance Segmentation, Epipolar Flow, Sparse Matches, High-Speed Flow. It surveys on problems, datasets, and methods in computer vision for autonomous vehicles. Modular pipelines offer the advantage of parallelization, interpretability, and ease of introducing prior knowledge.

Jun Wu et. al [10]: evaluates The Gray code algorithm, speckle projector and block matching methods. The Gray code reconstruction with disparity image pixels within 0.6 pixels and absolute error within 0.025 pixels. The average accuracy error was 0.35 mm, which met the light field depth estimation requirements. This paper provided a better view finding the depth of the moving object.

Yahya Moshaei-Nezhad et. al [11]: tackles Occlusion detection algorithm and then the CNN occlusion masking. Demonstrates that the proposed method is able to handle motion (global and local), outliers, and occlusions in IRT images during brain surgery. It increases the accuracy of the results for motion of outliers.

Zoltan Rozsa et. al [12]: presents Optical Flow Estimation along-side Motion-in-Depth Estimation, Ground Model Estimation to calculate 3D Scene Flow and generating Virtual Point Cloud. It demonstrates the computation efficiency against other methods and conducts a separate evaluation for dynamic objects and also studies ablation. This paper proposed pipeline in the dataset compared to MoNet, MoNet (GRU),SPINet, PointINet.

Jiuh-Biing Sheu et. al [13]: addresses the challenges in proposed driver stimulus– response model.it also compares the predicted values with video-based data with respect to average link travel time. Though it is moderately accurate it provides valuable insights about the characterization of behavioral changes in a driver which is useful for autonomous vehicles.

Jinzhao Li a et. al [14]: tackles the challenging Optical Flow (OF), Particle Image Velocimetry (PIV) methods. This paper indicates that the OF method can reasonably capture the primary flow features, as well as obtain the velocity with comparable accuracy of PIV method. Accurately capture primary flow features and provide velocity data similar to PIV specifically in waves.

Doris Hermle et. al [15]: focuses on phase correlation and optical flow. Demonstrates that the dense inverse search (DIS) algorithm was successfully applied to study ground motions in a high-alpine, complex landslide. It finally states the accurate effects of ground motion by the use of optical flow.

Wei Yuan et. al [16]: discusses Pixel-by-pixel digital differential rectification-based automatic DOM generation method and Automatic hole-filling of 3D point clouds using Mosaic line networks. Entire DOMs have saturated color, moderate contrast, and uniform tones, with no obvious noise or geometric distortion. DOM produced by the method proposed in this paper is very accurate.

TABLE I: Different Approaches in Optical Flow

Following table describes year wise publication of paper which describes the method used and accuracy rate

Author	Approaches in optical flow of moving objects using ML techniques		
	Year of publication	**Detection method/ Parameter**	**Accuracy rate**
Di Jia et. al	2021	BRAFT: Recurrent All-Pairs Field Transforms for Optical Flow Based on Correlation Blocks	End point error 1.7% lower than RAFT
Ms. Rajashree Revaji Shinde et. al	2023	Unsupervised recurrent all-pairs field transform of optical Flow unsupervised recurrent all-pairs field transform	Improved accuracy in feature extraction
Maximilian Luz	2022	RAFT meets DICL: combination of RAFT and DICL	Accuracy of Sintel data set improved.
Philippe Weinzaepfel et. al	2013	Deep Matching	Accuracy of 92.07%
Nelson Monzon, et. al	2016	Exponential function together with a TV process. Small constant that ensures a minimum isotropic smoothing.	Moderately accurate on comparison against various datasets.
Philipp Fischer et. al	2015	CNN: FlowNetSimple (top);FlowNetCorr (bottom).	Competitive accuracy at frame rates of 5 to 10 fps.
Xuezhi Xiang et. al	2022	PWC-Net [2]- unsupervised; CNN with transformer architecture; Occlusion compensation loss.	The inference time is increased by 0.058 s
Wei Yuan et. al	2023	Pixel-by-pixel digital differential rectification-based automatic DOM generation method.	DOM produced by the method proposed in this paper is very accurate.

TABLE 2: Different use cases of optical flow

Author	Various Use cases of optical flow		
	Year of publication	**Methods used**	**Remarks**
Karen Simonyan et. al	2014	Deep Convolutional Networks (ConvNets) for action recognition in video. Two-stream ConvNet architecture	Two-stream model (fusion by SVM) with accuracy of 88.0% for UCF-101 and 59.4%, for HMDB-51
Joel Janai et. al	2021	Comparison of datasets such as Geiger, Scharstein & Szeliski, Baker, Everingham, Cordts	Tracked with at least 80% accuracy and loss of trajectories at most 20%
Jun Wu et. al	2023	Field depth estimation method using speckle projection.	The average accuracy error was 0.35 mm
Yahya Moshaei-Nezhad, et. al	2021	Occlusion detection algorithm and then the CNN occlusion masking.	A degree of 28% AAE and 13% RMSE improved results
Zoltan Rozsa et. al	2023	Optical Flow Estimation; MotioninDepth Estimation; Ground Model Estimation; Calculate 3D Scene Flow; Generating Virtual Point Cloud.	Rigid body based up-sampling is the best
Jiuh-Biing Sheu	2011	Proposed driver stimulus– response model.	Moderately Accurate.
Jinzhao Li et. al	2022	Optical Flow (OF), Particle Image Velocimetry (PIV)	Accurately capture primary flow features and provide velocity data similar to PIV specifically in waves.
Doris Hermle et. al	2022	Phase correlation; optical flow.	Accurate effects of ground motion.

III. CONCLUSION

This survey paper has delved into the optical flow systematically analyzing a wide range of data, study, and opinions in the field. Our primary goal was to provide a comprehensive overview of the current state of knowledge and identify emerging trends and challenges. Throughout our investigation, several key findings have come to light. It provided insights about our approach to optical flow estimation. RAFT employs new deep network architecture to iteratively refine pixel-wise motion predictions. It excels in handling challenging scenarios like traffic analysis, vehicle tracking, object movement with large displacements and occlusions. Experimental results demonstrate RAFT's superior accuracy and robustness compared to state-of-the-art methods, making it a valuable tool for computer vision applications.

IV. REFERENCES

[1] Di Jia , Kai Wang , ShunLi Luo , TianYu Liu , and Ying Liu "BRAFT: Recurrent All-Pairs Field Transforms for Optical Flow Based on Correlation Blocks." *IEEE* 2021.

[2] Ms. Rajashree Revaji Shinde, Dr. Santosh Pawar "A review on design and analysis of an algorithm for Unsupervised recurrent all-pairs field transform of optical Flow unsupervised recurrent all-pairs field transform." *Semiconductor Optoelectronics, Vol. 42 No. 1 (2023).*

[3] Maximilian Luz – "RAFT meets DICL: A Recurrent All-Pair Transform for Optical Flow Estimation based on Displacement Invariant Cost Volume Learning." *Institute for Visualization and Interactive Systems, May 2, 2022*

[4] Philippe Weinzaepfel Jerome Revaud Zaid Harchaoui Cordelia Schmid: "DeepFlow: Large displacement optical flow with deep matching.", *IEEE Xplore, 2013*

[5] Nelson Monzon, Agustın Salgado and Javier Sanchez - Robust Discontinuity Preserving Optical Flow Methods. *CTIM, University of Las Palmas de Gran Canaria, Spain, 2015*

[6] Philipp Fischer, Alexey Dosovitskiy, Eddy Ilg, Philip Hausser, Caner Hazırbas , Vladimir Golkov- FlowNet: Learning Optical Flow with Convolutional Networks. *arXiv:1504.06852v2 [cs.CV] 4 May 2015*

[7] Xuezhi Xiang • Rokia Abdein • Ning Lv- "Unsupervised optical flow estimation method based on transformer and occlusion compensation." *part of Springer Nature 2022*

[8] Karen Simonyan Andrew Zisserman- Two-Stream Convolutional Networks for Action Recognition in Videos. *Part of Advances in Neural Information Processing Systems 27 (NIPS 2014)*

[9] Joel Janai, Fatma Guney, Aseem Behl, Andreas Geiger- "Computer Vision for Autonomous Vehicles: Problems, Datasets and State of the Art.". *arXiv, Submitted on 18 Apr 2017 (v1), last revised 17 Mar 2021 (this version, v3).*

[10] Jun Wu, Shaoyu Liu, Zirui Wang, Xiaoyu Zhang, Runxia Guo- "Dynamic depth estimation of weakly textured objects based on light field speckle projection and adaptive step length of optical flow method." Elsevier, 30 March 2023.

[11] Yahya Moshaei-Nezhad, Juliane Müller, Christian Schnabel, Matthias Kirsch & Ronald Tetzlaff- "A robust optical flow motion estimation and correction method for IRT imaging in brain surgery". *Taylor and Francis, 22 July 2020*

[12] Zoltan Rozsa and Tamas Sziranyi- "Optical Flow and Expansion Based Deep Temporal Up-Sampling of LIDAR Point Clouds." *MDPI, 9 May 2023*

[13] Jiuh-Biing Sheu- "Characterization of driver behaviour during car following using quantum optical flow theory." *Taylor and Francis, 2011.*

[14] Jinzhao Li a, Xuan Kong a, Yilin Yang b, Zhiwen Yang, Jiexuan Hu a- "Optical flow based measurement of flow field in wave-structure interaction." *Elsevier, 2022*

[15] Doris Hermle , Michele Gaeta, Michael Krautblatter, Paolo Mazzanti and Markus Keuschnig- "Performance Testing of Optical Flow Time Series Analyses Based on a Fast, High-Alpine Landslide" *MDPI, 8 January 2022*

[16] Wei Yuan , Xiuxiao Yuana, Yang Caia and Ryosuke Shibasaki- "Fully automatic DOM generation method based on optical flow field dense image matching" *Taylor and Francis, 13 December 2022*

.