Live Demonstration: Tangentially Elongated Gaussian Belief Propagation for Event-based Incremental Optical Flow Estimation

Yusuke Sekikawa† and Jun Nagata† DENSO IT LAB., INC., Japan.

Figure 1. Snapshot sequence from our real-time `OpemMP` implementation of TEGBP on MVSEC. Beliefs at each node are updated on an event-by-event basis manner. The estimated flow can be retrieved at an arbitrary timing; for this visualization, we display the estimated full flow at very fine temporal resolution (for every 1,000 events count, which corresponds to 5×10^{-3} [sec] on average). Notice that the estimation is consistent for different timing.

Abstract

Optical flow estimation is a fundamental functionality in computer vision. An event-based camera, which asynchronously detects sparse intensity changes, is an ideal device for realizing low-latency estimation of the optical flow owing to its low-latency sensing mechanism. We developed an efficient full-flow estimation called Tangentially elongated Gaussian belief propagation (TEGBP). TEGBP formulates the full flow estimation as the marginalization of probability using a message-passing based on the BP. The formulation permits event-by-event asynchronous incremental updates of the full flow; i.e., given a normal-flow observation, it updates its belief about full flow by asynchronous local communication. This paper presents a `OpenMP` *based real-time full-flow estimation demo by taking advantage of the asynchronous formulation. Specifically, we parallelize the individual sequence of the message exchange evoked by a single normal-flow observation. Beliefs at each node are updated on an event-by-event basis manner in parallel, realizing the real-time procession on CPUs. Our C++ code is available at* `https://github.com/DensoITLab/tegbp.`

† These authors contributed equally to this work.

1. Introduction

Optical flow estimation, which computes the correspondence of pixels in different time measurements, is a fundamental building block of computer vision. One needs to estimate the flow at low latency in many practical applications, such as autonomous driving cars, unmanned aerial vehicles, and factory automation robots.

The event-based camera is a bio-inspired vision sensor, which asynchronously detects intensity change on each pixel. Thanks to the novel sensing mechanism, the camera equips favorable characteristics for optical flow estimation, such as high dynamic range (HDR), blur-free measurement, and, most importantly, sparse low-latency data acquisition.

However, most of the existing work has not realized the full flow estimation in an incremental manner due to the difficulty of handling the sparse data structure of the event stream. An existing method using local plane fitting of events could utilize the sparsity to realize incremental updates for low-latency estimation; however, its output is merely a normal component of the full optical flow. An alternative approach using a frame-based deep neural network could estimate the full flow; however, its intensive non-incremental dense operation prohibits the low-latency estimation.

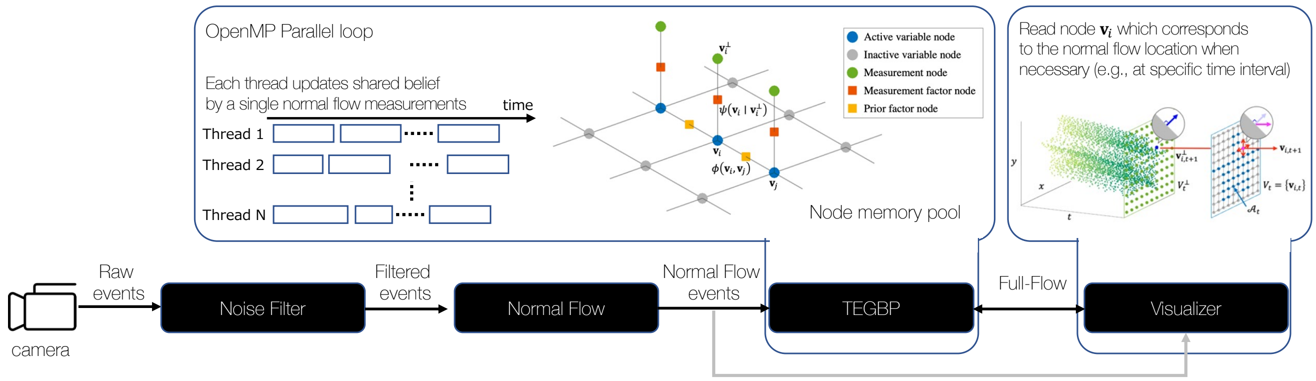

Figure 2. Parallel processing system overview.

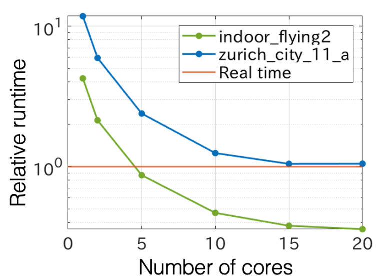

Figure 3. Wall-clock time on Intel Core i9 CPU (9820X,3.30GHz) 10^0 indicates real-time.

2. TEGBP

Tangentially elongated Gaussian belief propagation (TEGBP) [2] realizes incremental full-flow estimation. The TEGBP model the probability of full flow as the joint distribution of TEGs from the normal flow measurements, such that the marginal of this distribution with correct prior equals the full flow. It formulates the marginalization using a message-passing based on the BP to realize efficient incremental updates using sparse measurements. We consider their incremental and asynchronous formulation of TEGBP as a suitable algorithm for realizing the real-time and extremely low latency estimation of full flow on the commercial CPUs, which equips multi-threading architecture.

3. Real-time implementation of TEGBP

TEGBP formulation permits event-by-event asynchronous updates; i.e., given a normal-flow observation, it updates its belief about full flow by asynchronous local communication. We took advantage of the asynchronous formulation and presented a `OpenMP` [1] based real-time full-flow estimation. Specifically, we parallelize the individual sequence of the message exchange evoked by a single normal-flow observation (Fig. 2). Once the message passing procedure for a given normal event has finished, the thread consumes a different normal flow event. In this way, most of the threads could keep running at their full power without waiting for the results of the other threads. Beliefs at each node are updated on an event-by-event basis, and the estimated full flow can be retrieved at an arbitrary timing (e.g., display's refresh timing, such as 30Hz).

Note: We adopted a different algorithm from the original paper [2] for a coarse-to-fine (C2F) mechanism, which was utilized to improve the convergence speed of the BP. Instead of C2F, we only have the finest level belief and connected nodes within a certain range (instead of 1 pixel around). This is much simpler to implement and also suitable for multi-core parallel execution; cores could keep working without waiting for the convergence of the coarser level.

4. Evaluation

Figure 1 display a snapshot from our real-time system on MVSEC [3]. Figure 3 reports the wall-clock time vs the number of cores[1]. Our implementation of TEGBP efficiently utilizes multi-core; the processing speed monotonically increases with respect to the number of cores.

References

[1] Rohit Chandra, Leo Dagum, David Kohr, Ramesh Menon, Dror Maydan, and Jeff McDonald. *Parallel programming in OpenMP*. Morgan kaufmann, 2001. 2

[2] Jun Nagata Yusuke Sekikawa. Tangentially Elongated Gaussian Belief Propagation for Event-based Incremental Optical Flow Estimation. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2023. 2

[3] Alex Zihao Zhu, Dinesh Thakur, Tolga Ozaslan, Bernd Pfrommer, Vijay Kumar, and Kostas Daniilidis. The Multi Vehicle Stereo Event Camera Dataset: An Event Camera Dataset for 3D Perception. *IEEE Robotics and Automation Letters*, 3(3):2032–2039, 2018. 2

[1] compiled with Intel C++ compiler (`https://www.intel.com`)