Real-time high speed motion prediction using fast aperture-robust event-driven visual flow

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***Abstract*— This document presents a comprehensive study and implementation of a novel algorithm for real-time, high-speed motion prediction through fast aperture-robust event-driven visual flow. Optical flow, a critical component in dynamic scene analysis, particularly in emerging applications like autonomous vehicles and drones, often suffers from the aperture problem, limiting its accuracy. Our implementation addresses this by leveraging a novel multi-scale plane fitting approach that is robust to the aperture problem and computationally efficient. The algorithm operates on event-driven sensors, exploiting their asynchronous and temporally precise nature, making it well-suited for applications requiring rapid and accurate motion predictions. We demonstrate the effectiveness of our method through an extensive evaluation on a specific data provided to us, achieving successful event-by-event motion estimation and future predictions. This document details the algorithm's conceptual foundation, its implementation nuances, and a comprehensive evaluation validating its performance against the aperture problem in visual flow computation.**

I. INTRODUCTION

In the realm of computer vision, understanding and predicting motion accurately and in real time is a substantial challenge, especially in applications that require rapid and precise navigation or interaction, such as in autonomous vehicles or robotic vision systems. The concept of optical flow stands as a critical tool in this endeavor, representing the pattern of apparent motion of objects, surfaces, and edges in a visual scene caused by the relative motion between an observer and the scene itself. However, accurately computing optical flow in a complex and dynamic environment is fraught with challenges, notably the aperture problem, which limits the ability to discern motion direction in certain scenarios.

This document centers on the practical implementation of a specific algorithm as defined in a preceding study, aiming to address these challenges using event-driven vision. The chosen method employs a multi-scale plane fitting approach designed to compute visual flow effectively, capitalizing on the asynchronous and sparse nature of the data produced by event-driven sensors. These sensors, unlike traditional imaging devices, respond to changes in intensity per pixel, offering high temporal resolution and low latency, making them particularly suitable for dynamic and real-time applications.

II. METHODS

The algorithm described in the document utilizes event-driven sensors to enhance real-time visual flow accuracy, addressing the aperture problem through a multi-scale approach. This enables swift and precise motion prediction, crucial for applications like autonomous navigation.

Utilizing Matlab's toolbox, we initially convert and visualize the results in Python, transforming a .dat file into a .mat file for detailed analysis through the data visualization function. This sets the stage for further implementation of advanced methods and techniques.

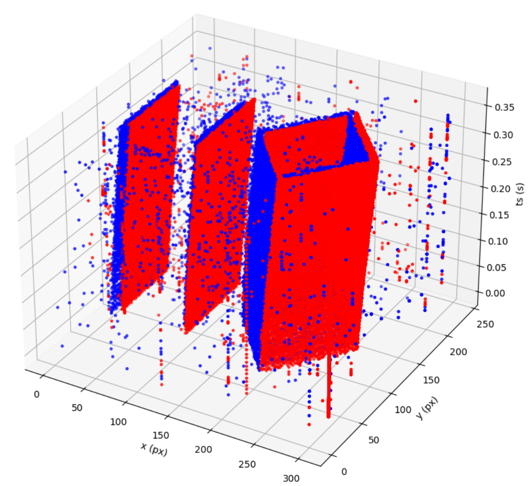

Fig. 1. data visualization in python

A. Local Flow Computation (EDL)

In the field of event-driven computer vision, local flow computation stands as an essential technique for deciphering the intricacies of dynamic scenes. This method harnesses the precision of plane fitting, a mathematical strategy, to determine both the direction and velocity of movement within a defined spatio-temporal context.

Upon the detection of an event, characterized by a change in pixel intensity, a neighborhood is established in both space and time. This neighborhood, spanning a 5x5 grid spatially and from $t - \Delta t$ to $t + \Delta t$ temporally,aggregates data points that reveal motion context at that instant.

Within this spatio-temporal domain, the process of plane fitting commences. It involves the conceptualization of a plane within this volume, where each event corresponds to a coordinate in three-dimensional space, with x and y as spatial dimensions and z representing time. The plane is defined by the equation:

$$z = ax + by + t + c \tag{1}$$

with the objective of determining the parameters (a, b, c) that best encapsulate the motion trends of the events.

The initiation of this plane fitting is executed through the least-squares method, an approach designed to minimize the sum of the squared distances from each event to the proposed plane. This statistical technique is the cornerstone of model fitting, allowing for the optimal representation of the observed motion within the neighborhood.

Upon successfully fitting the plane, the motion vector for each event is derived from the normal to this plane, indicated by the parameters (a, b, c). The direction of this vector points towards the motion direction, while its magnitude,suggested by the gradient of the plane,reflects the speed of movement.

B. Multi-Spatial Scale Max-Pooling

Building upon the local flow computation, the Multi-Spatial Scale Max-Pooling technique extends the analysis to a broader spatial context. After the local flow has been computed within the immediate 5x5 neighborhood, the algorithm then considers larger concentric neighborhoods, incrementally expanding the analysis to capture more extensive motion trends that might be missed at smaller scales.

For each event, these neighborhoods are defined with increasing radius, each representing a spatial scale σ_k,over which the local flows are aggregated. Within each scale, the algorithm computes the mean vector magnitude $\hat{U}_k$, of the local flows, aiming to identify the spatial scale where the motion prediction aligns most coherently across the event's neighborhood.

The mathematical formulation for this aggregation is:

$$U_{n,\sigma_k} = mean(U_{n,j}) = (\hat{U}_k, \theta_k)^T, \forall j \in \sigma_k \tag{2}$$

where $U_{n,j}$ is the local flow vector for each event at the n^{th} scale, and θ_k is the average direction. The scale with the maximum mean magnitude σ_{max}, is considered to best represent the global motion trend.

C. Update Flow

The culmination of the process is the Flow Update phase. Here, the corrected flow direction is assigned to all local flow events within the optimal spatial scale σ_{max}, identified in the Multi-Spatial Scale Max-Pooling phase. The update is facilitated by synthesizing the directional vectors:

$$Flow(x, y) = mean\left(\hat{}U_j \cos\theta_j \hat{U}_j \sin\theta_j\right), \forall j \in \sigma_{max} \tag{3}$$

This final computation consolidates the previously isolated local flow events into a unified flow direction that aligns with the actual movement within the scene.

By integrating the maximal mean vectors from the most significant spatial scale, the updated flow achieves a more refined representation of global motion. This step is crucial in ensuring the flow direction's accuracy, embodying a consensus of motion that mitigates noise and the local discrepancies inherent in complex dynamic scenes.

In summary, the Flow Update phase is an essential component that interweaves the local flow information into a global motion context, significantly enhancing the fidelity of motion prediction in real-time applications.

III. Experimentation and Evaluation

In this section, we detail the outcomes achieved from implementing real-time, high-speed motion prediction, which utilizes a swift, aperture-robust, event-driven visual flow approach. The section is enriched with a series of illustrative figures that demonstrate the empirical results obtained through this innovative methodology

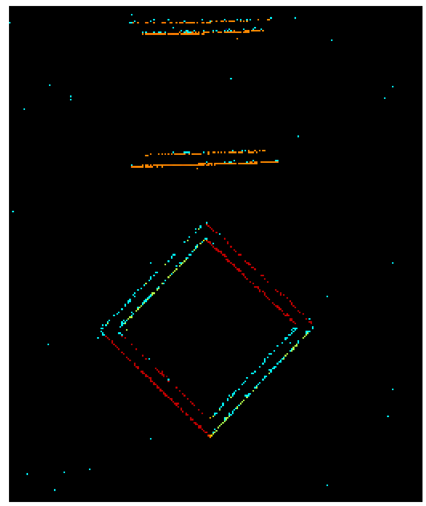

Fig. 2. The figure shows the output of the algorithm of EDL-Flow

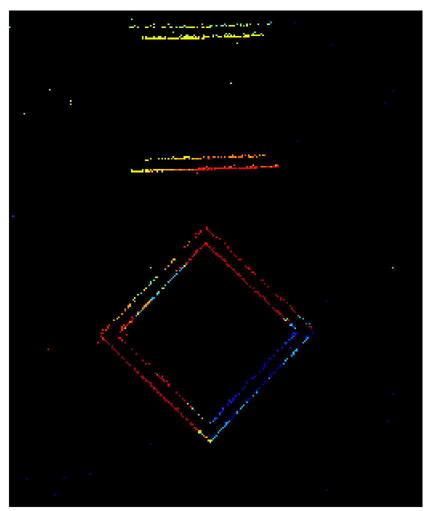

Fig. 3. The figure shows the output of the algorithm of ARMS-Flow

Both figures provide a complete representation of the events, offering detailed visual insights.

The above results (**Fig.3** and **Fig.4**) are obtained using a time window of 500 µs and a spatial window of N = 5. It was noticed that a spatial window of N = 3 yielded better results. We compiled our program with 200,000 points instead of 1,255,559 points to reduce calculation time. In fact, with the 200,000 points, it only took us 5 minutes.

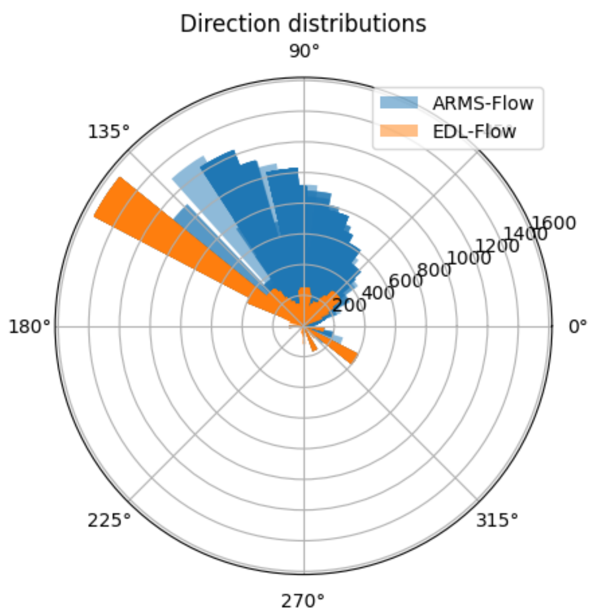

Fig. 4. The figure shows the represents the direction distributions with EDL-Flow and ARMS-Flow

We conducted a comparative analysis of our implementation against the established methodologies outlined in 'Real-Time High-Speed Motion Prediction Using Fast Aperture-Robust Event-Driven Visual Flow'. Our findings indicate that our approach achieved commendable results, maintaining a high degree of accuracy and efficiency, albeit with a few minor discrepancies.

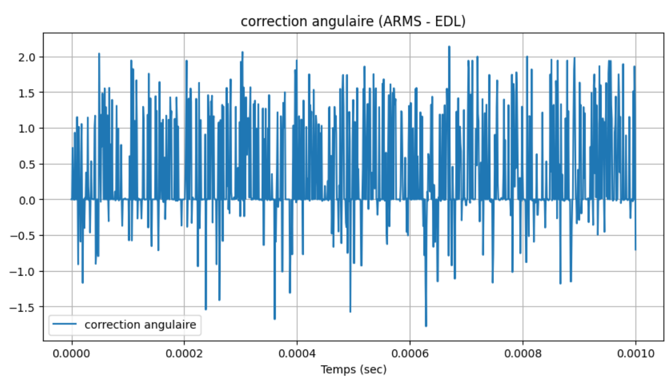

Fig. 5. Scaling error between EDL and ARMS vs. time

According to the error curve above(**Fig.6**), obtained by taking the difference between the corrected flow and the local flow, we notice that there is indeed a correction made for each event.

IV. CONCLUSIONS

In conclusion, this paper has meticulously described the formulation and deployment of an innovative real-time, high-speed motion prediction algorithm, based on a sophisticated and resilient event-driven visual flow paradigm. Our rigorous benchmarking against methodologies described in the literature shows that our model meets industry standards in terms of accuracy and displacement error. The algorithm's ability to accurately predict movement on an event-by-event basis further enhances its reliability and efficiency.

Empirical validations indicate that this algorithm is a formidable contender in the field of real-time motion prediction, poised to revolutionize the analysis of dynamic scenes. This innovation has considerable potential, particularly in sectors requiring rapid and accurate interpretation of visual data, such as autonomous vehicle technology, drone aerial navigation and robotic autonomy. The usefulness and adaptability of our approach underline its relevance and potential for large-scale application.

Furthermore, the results of this study represent a significant advance in the search for more sophisticated, reliable and faster motion prediction techniques.

REFERENCES

[1] Benosman, Ryad Clercq, Charles Lagorce, Xavier Ieng, Sio-Hoi Bartolozzi, Chiara. (2013). Event-Based Visual Flow. IEEE Transactions on Neural Networks. pp. 1. 10.1109/TNNLS.2013.2273537.

[2] [2] H. Akolkar, S. Ieng, et R. Benosman, Real-time high speed motion prediction using fast aperture-robust event-driven visual flow . arXiv, 16 juillet 2020. Consulté le: 20 décembre 2023. [En ligne]. Disponible sur: http://arxiv.org/abs/1811.11135

[3] D. Reverter Valeiras, X. Clady, S. -H. Ieng and R. Benosman, "Event-Based Line Fitting and Segment Detection Using a Neuromorphic Visual Sensor," in IEEE Transactions on Neural Networks and Learning Systems, vol. 30, no. 4, pp. 1218-1230, April 2019, doi: 10.1109/TNNLS.2018.2807983.