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# Discussion on event-based cameras for dynamic obstacles recognition and detection for UAVs in outdoor environments

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***Abstract*— To safely navigate and avoid obstacles in a complex dynamic environment, autonomous drones need a reaction time less than 10 milliseconds. Thus, event-based cameras have increasingly become more widespread in the academic research field for dynamic obstacles detection and avoidance for UAV, as their achievements outperform their frame-based counterparts in term of low-latency. Several publications showed significant results using these sensors. However, most of the experiments relied on indoor data. After a short introduction explaining the differences and features of an event-based camera compared to traditional RGB camera, this work explores the limits of the state-of-art event-based algorithms for obstacles recognition and detection by expanding their results from indoor experiments to real-world outdoor experiments. Indeed, this paper shows the inaccuracy of event-based algorithms for recognition due to insufficient amount of events generated and the inefficiency of event-based obstacles detection algorithms due to the high ration of noise.**

***Keywords*— Robotic, Dynamic obstacle, obstacle avoidance, obstacle recognition, Event-based vision, dynamic vision sensor, event reconstruction***

## I. INTRODUCTION

An event camera is a bio-inspired vision sensor that operates in an entirely different way from a conventional camera. Thus, rather than capturing intensity images at a fixed rate as conventional RGB cameras do, event cameras measure the changes of intensity asynchronously at the time they occur. In other words, every pixel will be triggered independently if it witnesses a variation in brightness. This leads to a stream of text called "*events*", which encapsules the time, location and polarity [1]. The latency between events is 0.5 µs. The non-linear dynamic range is valued at 143 dB. The power consumption is assessed with 100k events/sec and measured at 0.25 mW for a supply voltage of 1.2 V[2].

Because of their remarkable characteristics (low latency, high dynamic range, no motion blur), event cameras have the possibility to unlock the potential of UAV to be fully autonomous in cases where traditional cameras are currently unreliable as robust and high-speed perception is required.

## II. RELATED WORK

Currently, research on event cameras is in its infancy. However, several promising event-based algorithms for obstacles detections and recognition have been introduced.

### A. Dynamic obstacles detection for autonomous UAV

In [3], Falanga and Kebler relied on ego-motion for background removal, clustering and optical flow for dynamic obstacles segmentation and detection. The aim of their algorithm is to only compute the position of the moving obstacle without any recognition of the latter's type. They achieved up to 93% accuracy for indoor obstacles detection. However, when the authors tried to reproduce the experiments outdoor, they encountered several problems. In the scenario when the drone is hovering (static environment), the UAV was not able to avoid some obstacles thrown towards it. In a case of dynamic environment (drone flying toward a target), only one attempt was discussed: the drone flying in a cluttered environment at a constant speed of 1.5 m/s was able to avoid the yellow ball thrown toward it. To fully validate the performance outdoor, multiples scenarios for dynamic environment should have been conducted.

### B. Image reconstruction for obstacles recognition

The purpose of image reconstruction from events is to estimate the ego-motion and the brightness gradient map at the same time. As the reconstruction provides grayscale images, standard algorithms for images recognition are used to identify the type of the dynamic obstacle in order to select the right strategy to avoid it. In [4], Scheerlinck and Rebecq used deep learning algorithm with an ReLU architecture for fast video reconstruction from events (less than 10 ms for input of 640 × 480 resolution event-based camera). Their results were only based on data recorded indoor.

## III. MATERIAL AND METHOD

This paper aims to assess the performance of the methods listed above in an outdoor scenario. The algorithms will be tested with an autonomous UAV operating in a dynamic real-world outdoor environment.

### A. Experimental platform

To record the required data needed, a customised quadrotor platform was designed (figure 1). The main frame is a 6″ Lynxmotion and at the end of each arm an energy Propel brushless motor was mounted. The platform is equipped with an autopilot PX4 and an onboard computer NVIDIA Xavier Jetson to run the algorithms. The event camera DAVIS346 was connected to the onboard PC and a depth camera ZED2 was used for state estimation.

*Figure 1 Experimental platform - customised quadrotor*

### B. *Software*

To assess the performance of event-based algorithms in a dynamic outdoor environment, two state-of-art algorithms were chosen. For obstacle detection, the algorithm BetterFlow [5] to remove the event generated by the ego-motion of the sensor from an event stream, was selected. For the video reconstruction from events the algorithm FireNet [4] was selected.

## IV. Results and discussion

To fully assess the accuracy of the algorithms, three datasets were recorded in a park: (i) flying drone without any dynamic obstacles (ii) hovering drone with obstacles moving toward it (iii) flying drone with obstacles moving toward it. Regarding the maximum length limit, only scenario (iii) for images reconstruction and scenarios (ii) and (iii) for dynamic obstacles detection will be discussed as it covers all the limits and challenges encountered.

### A. *Image reconsutction from events*

*Figure 2: left image: Flying drone with a dynamic obstacle moving toward it (a person running). Right image: Grayscale video reconstructed from events recorded from the same scene*

Figure 2 shows the results of the reconstruction using FireNET [4]. FireNET takes as input variable the number of events per frame and takes as default the total number of pixels (320 x 240) assuming that majority of the pixels will be triggered at the same time. This number was set to the lowest, 1000 events per frame as our dataset was sparse.

As seen in Figure 2 (right image), reconstruction is not realistic compared to the ground truth (Figure 2 – left image). The number of events per window was changed to see if the accuracy could be increased : even with the lowest number of events taken into account per window for the reconstruction, the quality of the video remains the same. To explain the difference of the reconstruction's quality using indoor dataset compared to a real world outdoor environment dataset: we could assume that the reconstruction is accurate when enough events per millisecond were generated. Thus, indoor environments have enough features to generate dense events dataset. However, for an open area, the lack of features generates spare dataset.

### B. *Ego-motion compensation and Noise*

As seen in the left image in Figure 3, the BetterFlow [5] successfully distinguished the static components from the dynamic ones. Indeed, for the situation where the drone is hovering, the background is accurately removed and only the dynamic objects remain. However, as seen on the right image in Figure 3, the same algorithm didn't succeed to remove the events generate from the sensor's ego-motion when the drone is non stationary.

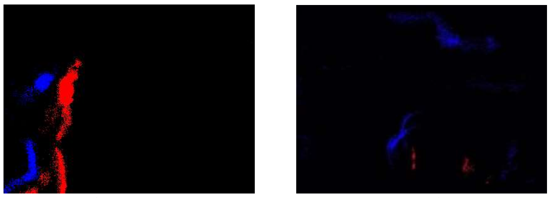

*Figure 3 Left image: Ego-motion compensation for a hovering drone with a dynamic obstacle coming toward it (running person). Right image: Ego-motion compensation for flying drone toward a target while a dynamic obstacle is coming toward it.*

The resolution of the event-based camera and the ratio of the noise could explain the drastic difference of the software's performance in  two scenarios. Indeed, the event-camera DAVIS346 has a resolution of 320 pixels by 240 pixels which is particularly low to have an extensive overview of the surroundings. Moreover, noise remains the biggest challenge for these sensors. These sensors produce more noise outdoor, which can reduce significatively the effectiveness of event-based vision algorithms. Thus, a restricted POV (not enough details captured of the environment) and a high ratio of noise made the events belonging to dynamic objects very hard, if not impossible, to disambiguate among them.

## V. Conclusion

We have presented the limits of the event-based cameras used for dynamic obstacles detection and recognition for autonomous UAV operating in an outdoor environment. We showed that not enough events are generated during the flight for accurate reconstruction. We also showed that denoising and background removal using the state-of-art algorithms are not efficient in the case of a non-hovering UAV.

The majority of state-of-art algorithms for event-based cameras are trying to adapt the existing standard approach for obstacles detection and avoidance using RGB images to "events". Regarding the limits of these software, a new bio-inspired approach for detection should be investigated in order to unlock the full potential of the bio-inspired sensor.

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