



Event-Based Object Detection and Tracking on a Lighter-Than-Air UAV

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Event cameras represent a novel class of bio-inspired vision sensors that offer extremely low latency and high power efficiency by outputting asynchronous changes in light intensity. This paper presents the first application of the lightweight PROPHESSEE GENX320 event camera on a lighter-than-air (LTA) vehicle to perform game ball detection and tracking for the Defend The Republic (DTR) collegiate competition. To address the constraints of edge hardware like the Raspberry Pi 5, a hybrid computer vision pipeline was developed that utilizes a YOLOv26 nano model for initial detection on aggregated event frames followed by a novel Gaussian-weighted mean-shift algorithm for efficient, direct tracking on the event stream. This methodology incorporates event density into pixel brightness, allowing for a robust representation of motion in both bright and dark environments. Flight test results demonstrate that the pipeline is highly robust to lighting variations; specifically, models trained exclusively in one lighting condition successfully detected targets in the opposite condition. By providing a solution that consumes significantly less power than traditional frame-based cameras while maintaining consistent performance in dynamic environments, this work establishes a foundation for fully autonomous balloon capturing and scoring in future DTR competitions.

Introduction

Event cameras are a novel class of bio-inspired vision sensors that are fundamentally different from traditional frame-based cameras. Instead of taking individual frames of data across a whole array of pixels at once, event-based sensors output changes in light asynchronously at any given pixel. The extremely low latency and wide dynamic range of event cameras make them a promising sensor option for autonomous systems where power efficiency, robustness, and consistent object tracking are required. Until recently, event cameras have been relegated to large and heavy sensors and application such as the Triton 2 EVS 0.9MP.¹ This limits their usability in weight-constrained systems such as lighter-than-air vehicles (LTAs). The recently released GENX320 sensor by PROPHESSEE, however, boasts a much smaller, more power efficient, and lightweight package compared to the previously available options. This paper presents the first application of an event camera on an LTA vehicle to perform game ball detection and tracking for future use in the Defend The Republic competition.

Defend The Republic Competition

Defend the Republic (DTR) is a collegiate challenge where teams create lighter-than-air vehicles to capture and score neutrally-buoyant target balloons termed game balls.^{2,3} Each game consists of two 30 minute halves, with each of those halves being split into six five minute intervals. The first 30 seconds of each interval allow teams to manually control vehicles, but the remaining 4.5 minutes require vehicles to act fully autonomously without manual controls by teams. Teams can deploy multiple vehicles at once to capture and score as many neutrally-buoyant game balls as possible in an opposing goal. The DTR competition's emphasis on autonomy makes computer vision-based methods one of the most compelling solutions for vision-based control. A photo of a DTR match is presented in Fig. 1, showing vehicles with captured scoring balloons heading towards the opponent team's goals in a dynamic lighting environment.⁴⁻¹⁸

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Figure 1: LTA vehicles navigating the game space during a DTR match

Event-Based Sensors

One of the major challenges of building an autonomous LTA for the DTR competition is creating a robust computer vision system. Previously, teams have implemented YOLO vision models¹⁹ for detection of scoring balloons and goals, but these models often only work in the specific arena that their training images were taken in. Lighting and environmental conditions change drastically between different arenas, which has a great impact on the effectiveness of the vision model outside of the original intended location. Event cameras, however, do not present this drawback. Since event data is triggered by changes in light intensity, the baseline ambient lighting conditions have a reduced impact on the data when compared with traditional frame cameras. This allows for the development of a robust system capable of performing consistently regardless of lighting conditions. This is an important consideration when traveling to new locations that may not have complete training data recorded or have inconsistent lighting conditions.

Another major advantage of utilizing an event-based sensor for computer vision comes in the form of power consumption. PROPHESSEE claims power consumption metrics of less than 50 milliwatts,²⁰ while a traditional Raspberry Pi camera recording video at 1080p consumes about 680 milliwatts of power.²¹ While this is not a one-to-one comparison due to different aspect ratios, a large portion of that power consumption comes from overhead that would remain constant even if the recording resolution were to be decreased. Furthermore, work by Gehrig et al²² has shown that higher resolution event cameras do not always perform better than lower resolution sensors. This shows that the comparison between the GENX320 and its 320x320 resolution and a Pi Zero Cam recording at 1080p may be more practically appropriate than comparing both sensors at the same resolution.

Two predominant methods have been used to see objects in the environment with an event camera. The first type uses initial work on view-based segmentation methods to detect when objects are in motion.^{23–27} The second type uses either learning-based approaches to directly classify an object or classical methods to only see objects of a certain shape.^{27–31} This work initially explored motion segmentation methods to directly see game balls within a DTR game. Following this, additional work was done to explore the classification problem for game balls detection and tracking for a future implementation within an actual game of DTR.

Event-Based Target Detection & Tracking

Inspired by previous iterations of the Maverick platform's vision system, a YOLO model was used to perform initial detection of the game balloon. For initial detection of the game ball balloon, a YOLOv26 nano model was utilized. Raw event stream data was recorded in both bright and dark lighting conditions initially to develop this framework. Unlike traditional frame-based cameras where data labeling is very well understood, an event based data stream required additional considerations to generate the dataset required to train the YOLO models. Each frame produced from the event stream was aggregated from 30 milliseconds of data, similar to a 30Hz frame camera, with positive events (an increase in light) colored as green and negative events (a decrease in light) colored as red. The amount of event activations at each pixel determined their relative brightness in the aggregated frame, where multiple event activations resulted in a brighter lightness in the color representation. This addition of pixel brightness allowed event density to be encoded into the frames fed into the YOLO model.

While YOLO models are generally quite robust, even when operating on aggregated event frames, they still suffer from performance issues on edge hardware. In the case of the Raspberry Pi 5 utilized in this work, it lacked the dedicated hardware to handle running neural networks (such as a TPU or NPU). On top of this, event data turned into a frame and used with traditional vision models does not allow the learning methods to take full advantage of the unique properties of event data. Given this constraint and after the relatively CPU heavy YOLO model makes a detection, the system swaps from using classical detection approaches with it to using a novel tracking algorithm that acts directly on the event data stream. This tracker uses a Gaussian-weighted mean-shift algorithm that acts within a dynamic radius centered around the initial YOLO detection. The tracker shifts its center based on the density of events within its radius, while also calculating its relative velocity in a frame in the case of some of the object is occluded. In order to reduce the risk of the tracker sticking to clusters of events not from game balls and existing indefinitely, a confidence score is also kept. This score decreases whenever too few events trigger within the current radius, but increases if a dense cluster is located within. When the confidence drops to zero, the tracker will reset and detection with the YOLO model resumes until another game ball is detected.

Ground Testing

Before attempting any flight tests with the vehicle, ground testing was performed to evaluate the initial event stream processing methodology and confirm vehicle functionality with the novel GENX320 sensor.

Initial Testing

Before mounting the Raspberry Pi 5 and GENX320 camera onto the vehicle used, tests were conducted on the ground to determine the viability of the visual pipeline for detecting and tracking game balloons. This included initial data recording, labeling, and training of a YOLOv26 nano model. An example of an aggregated frame can be seen below in Fig. 2

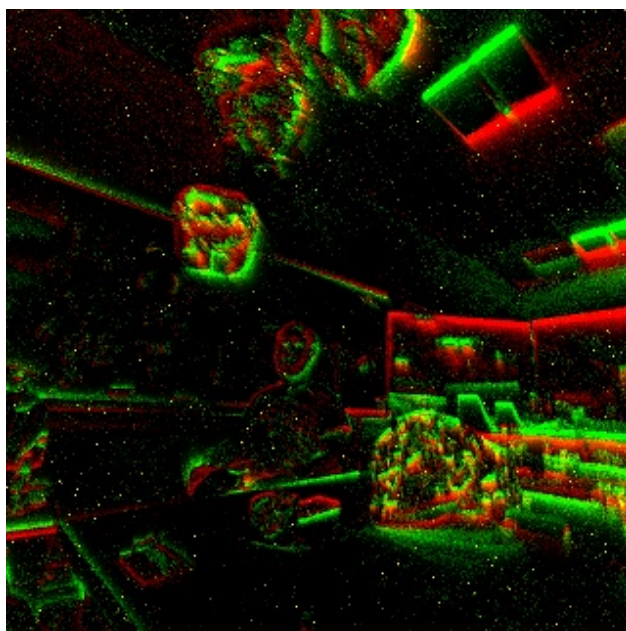


Figure 2: An example of an aggregated frame of event data used to train the initial YOLOv26 nano model.

Initial ground testing facilitated the development and optimization of the tracking algorithm's parameters. Adjusting the system's responsiveness, dynamic radius resizing, and confidence metrics indicated a wide range of configuration options when processing event-based data. Navigating these options required specific design decisions, which informed the architecture detailed in the preceding section. Once the system performed adequately in ground testing, the hardware was integrated into a Maverick Lighter-Than-Air (LTA) vehicle for in-flight data recording and evaluation.

Sensor Integration

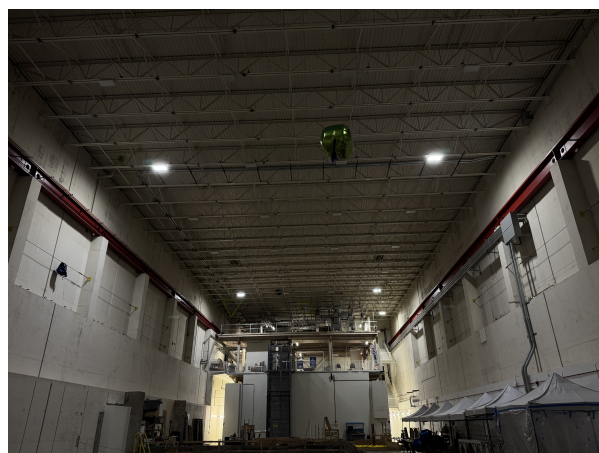
The GENX320 event camera was paired with a Raspberry Pi 5 SBC, which handled the reading in of the event stream, visual processing, and autopilot systems. A BNO055 module was used to measure inertial and altitude data, and a Sreed Studio Xiao ESP32S3 was used to interface between the Raspberry Pi 5, BNO055, and send PWM commands to the motors. The vehicle on which this system was deployed is Maverick, an autonomous lighter-than-air platform built by Indiana University for the DTR competition.³²

Flight Test Results

As mentioned previously, one of the greatest strengths of event cameras are their relative robustness towards changes in ambient lighting conditions. To test this specific attribute of the camera, two separate YOLO models were created: one trained only on data recorded in a bright environment, seen in Fig. 3a, and one trained only data recorded in a dark environment seen in Fig. 3b. To the event camera, these two environments look very similar, as can be seen in Fig. 4a and Fig. 4b when looking at the aggregated event frames discussed the methodology used in this work. For an event camera, the light level itself is the change in light level per pixel, this means that motion, whether it be from the vehicle itself or an object in frame, appears nearly identical in either situation. To demonstrate this, the YOLO model trained on the bright environment data was used on the data taken in the dark, and vice versa to measure relative performance of each in both environments. It was found that the models were still able to accurately detect the game balloon in each case. This was able to show that the tracker was not dependent on ambient lighting as it performed well in both scenarios with few issues. Examples of both can be seen in Fig. 5 and Fig. 6.

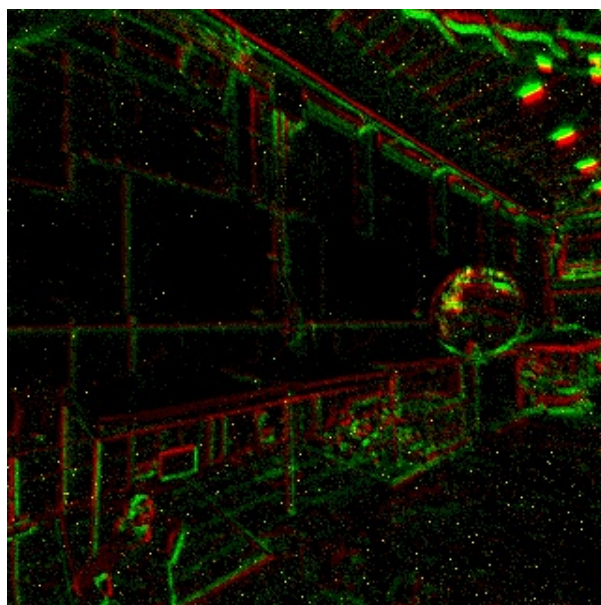


(a) Lights On

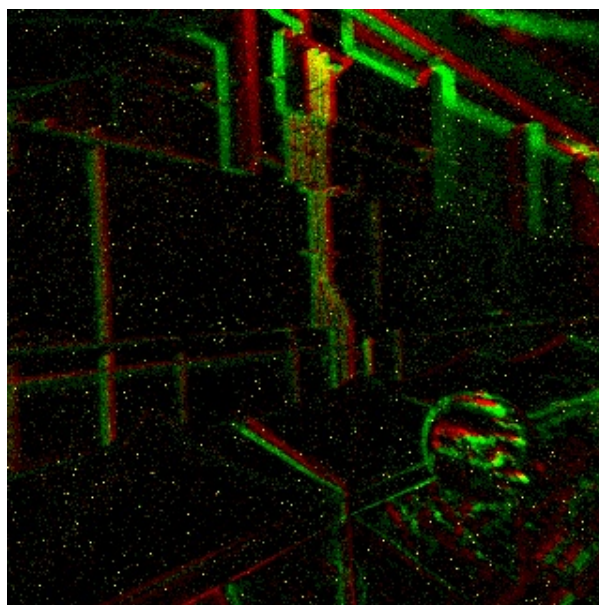


(b) Lights Off

Figure 3: Comparison of lighting conditions with lights turned on and off using a traditional frame camera



(a) Lights On



(b) Lights Off

Figure 4: Comparison of lighting conditions with lights turned on and off using the GENX320 event camera

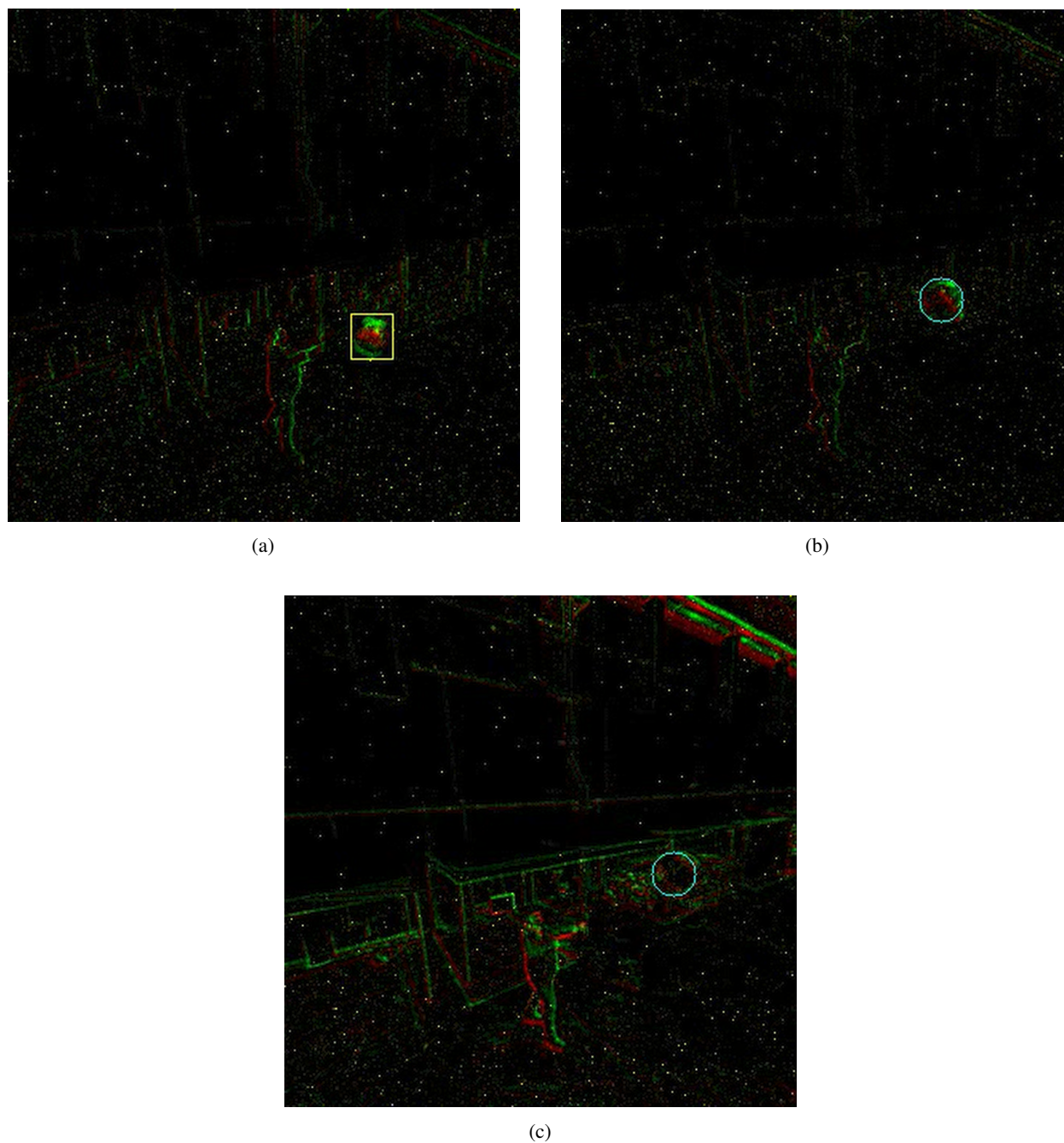


Figure 5: Example of game balloon detection and tracking in bright conditions using the dark YOLO model. The initial detection can be seen in Fig. 5a outlined with the yellow bounding box, whereas Fig. 5b and Fig. 5c show the tracker following the ball (outlined with a cyan bounding circle).

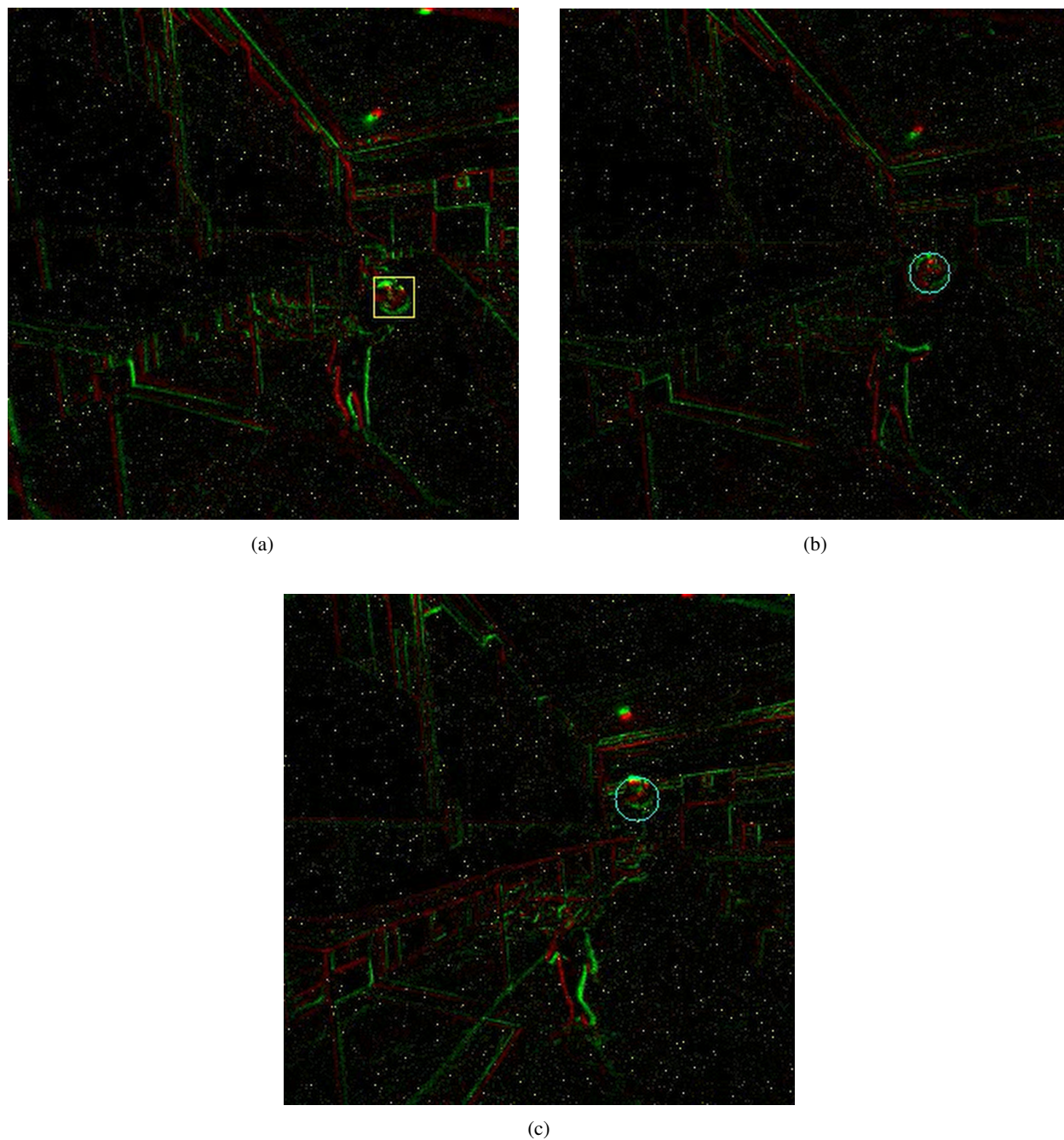


Figure 6: Example of game balloon detection and tracking in dark conditions using the bright YOLO model. The initial detection can be seen in Fig. 6a outlined with the yellow bounding box, whereas Fig. 6b and Fig. 6c show the tracker following the ball (outlined with a cyan bounding circle).

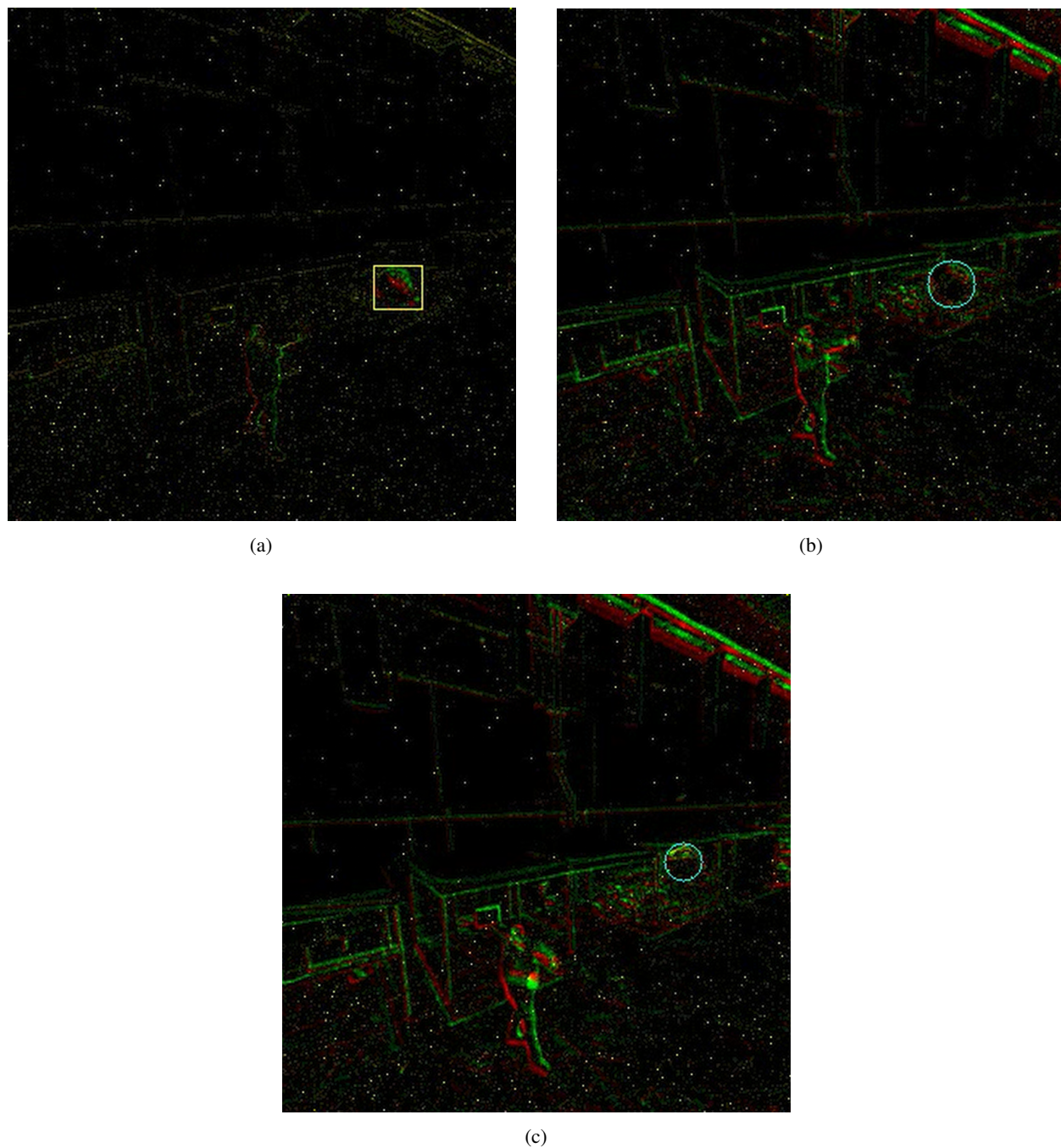


Figure 7: Example of game balloon detection and tracking in bright conditions using the bright YOLO model. The initial detection can be seen in Fig. 7a outlined with the yellow bounding box, whereas Fig. 7b and Fig. 7c show the tracker following the ball (outlined with a cyan bounding circle).

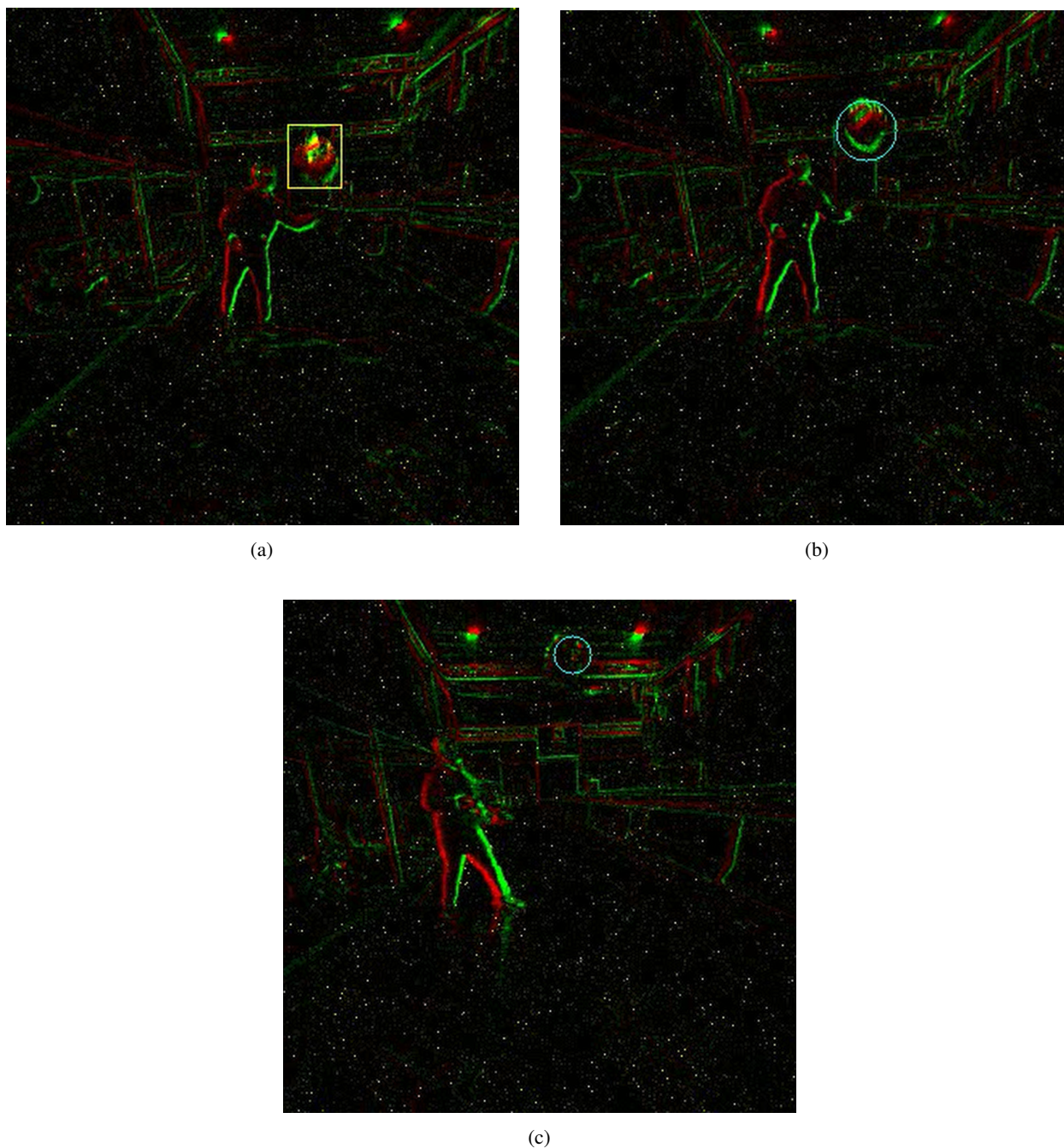


Figure 8: Example of game balloon detection and tracking in dark conditions using the dark YOLO model. The initial detection can be seen in Fig. 8a outlined with the yellow bounding box, whereas Fig. 8b and Fig. 8c show the tracker following the ball (outlined with a cyan bounding circle).

Summary

In this work, a novel detection and tracking pipeline for small helium balloons was developed for the GENX320 event camera for use in the Defend The Republic competition. This pipeline utilizes a YOLOv26 nano model to detect the balloons on aggregated event frames alongside a computationally light mean-shift-based tracking algorithm to follow the target balloon in the frame. Two lighting conditions (bright and dark) were tested in, with two separate YOLO models trained exclusively on data taken in one of two scenarios. These models were then cross-tested on data taken in the opposite lighting conditions. Tests showed that, although using a YOLO model trained in an entirely different lighting environment, the detection and tracking pipeline was able to consistently find and follow target balloons within the frame.

Future Work

In the future, more thorough tests will be conducted in even more extreme lighting environments to evaluate the extent of the robustness of the GENX320 sensor. More thorough comparisons between frame camera and event camera detection and tracking performance will also be conducted. From there, the detection and tracking pipeline outlined in this paper will be integrated into the autonomy systems of the Indiana University DTR vehicles with the intent of fully autonomous balloon capturing and scoring using the GENX320 event camera.

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