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Zixun Xiong
Manning College of Information and Computer Sciences, UMASS Amherst
140 Governors Dr, Amherst, MA 01002
zixunxiong@umass.edu

Abstract

This week, I read a paper on dynamic object detection using CNN. At first, I following the whole paper and related materials to get the basic idea. Then, I consider about the limits of the current work while acknowledging the advantages of it. Finding that despite the fact that IMO detector part is quite well defined, the dodging part especially for multi object cases are quite naive, it only solves cases when the IMOs are targeting the drone. However, in real world cases, when facing multiple IMOs this method will fail.

1 EVDodgeNet: Deep Dynamic Obstacle Dodging with Event Cameras

This paper [1] introduces a deep learning-based solution to dynamic object avoidance. By using a series of shallow neural networks, researchers estimate both the ego-motion and the motion of independently moving objects (IMO). This method only needs the algorithm to be trained in simulation and can transfer to the real world without any fine-tuning or retraining. For the evaluation and testing, researchers test this approach in scenes with obstacles that have different shapes and sizes. The proposed method achieves an overall 70% success rate in scenes including objects that are not in the training set and scenes with low light.

1.1 Background and Significance

Independent Motion Detection and Ego-Motion Estimation. In visual Inertial Odometry (IMO), information from Inertial Measurement Units (IMU) is utilized to accomplish tasks like Simultaneous localization and mapping (SLAM). Works have been proposed by introducing event cameras to present a low-latency VIO algorithm to estimate ego-motion [2]. Most works before this paper focused on static scenes, which are rarely met in the real world. [3], however, mentioned that by carefully modeling, one can both estimate ego-motion and IMOs.

Image Stabilization. Recently, image stabilization is the most robust algorithm to make IMO more evident. Works inspired by this idea have been done on event cameras [4].

Obstacle avoidance on aerial robots. Works mentioned above are used to aid obstacle avoidance on aerial robots. Event camera has also been used for dodging high-speed obstacles in [5].

1.2 Challenges and Advantages

Although dynamic object detection using traditional cameras has been studied extensively, they are either of high latency or computationally expensive or don't fit for generalized missions including novel objects. Following [6], this paper applied deep learning to generalize the object detections for novel objects after being trained only on simulation.

EVDeBlurNet The input for event camera-aided VIO systems are event frames, which are generated by projecting event data to 2D arrays. This projection will cause misalignment [7]. Thereby, motion-

compensations are needed. In this part, researchers use a shallow network named **EVDeBlurNet** to complete this task.

First, we get the event frames in equation 1 from a set of event data (shaped like $e = (\mathbf{x}, t, p)$), where $\mathbf{x}$ is the location of the triggered point in raw latent image I of the event camera.

$$\begin{aligned} E(x, \delta t)_+ &= \sum_{t=t_0}^{t_0+\delta t} \mathbb{I}(x, t, p = +1) \\ E(x, \delta t)_- &= \sum_{t=t_0}^{t_0+\delta t} \mathbb{I}(x, t, p = -1) \\ E(x, \delta t)_\tau &= (\sum_{t=t_0}^{t_0+\delta t} \mathbb{I}(x, t, p = \pm 1))^{-1} \mathbb{E}(t - t_0) \end{aligned} \tag{1}$$

These generated event frames of given frequency δt are inputs of the model **EVDeBlurNet**, which is designed as an encode decoder structure. Thus the object model can remove stray events (which are generally noise) while preserving events corresponding to contours. Thereby, the loss function is defined as the equation 2.

$$\underset{E}{\text{argmin}} - C(\overline{E}) + \lambda D(E, \overline{E}) \tag{2}$$

$$C(E) \triangleq \mathbb{E}(||\mathbf{Var}(\nabla E)||) \tag{3}$$

$$D(E_1, E_2) \triangleq \mathbb{E}(||E_1 - E_2||_1) \tag{4}$$

Thus **EVDeBlurNet** can learn to denoise event frames, while images after the deblurring processing are not too far from the origin image by the second term in equation 2.

EVSegFlowNet. This network it aimed at detecting IMOs and dodge them accordingly. It will do do both segmentation and optical flow optimization tasks. For the segmentation network, we use consecutive event frames to train a CNN model (outputting the probability for both background and foreground, which is tag for the IMO), so that it can predict the foreground and the background segmentation. The loss function is defined as in equation 5. It's done on all pixels in even frames.

$$\underset{p_f}{\text{argmin}} \ -\mathbb{E}(\mathbb{I}_f \log(p_f) + \mathbb{I}_b \log(p_b)) \tag{5}$$

After being able to tell the difference between the background and IMOs, the next thing we need to deal with is the optical flow optimization. Considering that any unsupervised or self-supervised method can't predict the non-rigid optical flow (optical flows corresponding to the foreground regions) accurately since the unbalanced data where number of foreground regions are far smaller than the background. However by training on more data will cause the model to overfit, which is against the ideology of unsupervised training. To solve this problem, researchers combined the optical flow optimization with the aforementioned segmentation labels (ground truth) by using a semi-supervised approach. This paper defines $\tilde{p_x}$ as the output of the second networkm, the formulation for this is defined in equation 6. Thus, the loss function thereby defined in equation 7.

$$\tilde{p_x} = \begin{cases} \dot{x}, & \text{if } \mathbb{I}_f(x) = 1 \\ 0, & \text{if } \mathbb{I}_b(x) = 1 \end{cases} \tag{6}$$

$$\begin{aligned} &\underset{\tilde{p_x}}{\text{argmin}}\, \mathbb{E}(D(W(E_t, \tilde{p_x}) \circ \mathbb{I}_f, E_{t+1} \circ \mathbb{I}_f)) + \\ &\lambda_1 \mathbb{E}(||\tilde{p_x} \circ \mathbb{I}_b||_1) + \lambda_2 \mathbb{E}(||\tilde{p_x} \circ \mathbb{I}_b||_2^2) \end{aligned} \tag{7}$$

This netwokr make background flow zero fairly quickly compared to simple l_1 or quadratic penalty. The input to the EVSegFlowNet is $W(E_t, \tilde{H}_{4P_t})$ and E_{t+1}. To be mentioned, the definition of function W can be found in [7].

1.3 Results and Experiments

1.4 Disadvantages of the Paper

I wonder how this algorithm will react when IMOs are not targeting at the drone. Intuitively, this will fail since the naive method mentioned in this paper is all based on the assumption that the IMOs are targeting at the drone.

References

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