A Deep Learning Approach to End-to-end Autonomous Driving Using Event-based Vision

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Mentors: Dr. Igor Gilitschenski, Alexander Amini
Overview

- Motivation
- Brief introduction to event-based vision
- Our goal
- Related works
- Our works
- Experiments
Motivation

Autonomous driving cars need to handle a wide range of scenarios

- Night-time Driving
- No Lane Markings
- Rainy Weather
How do they do it?
Autonomous Driving Pipeline

Separate problem into smaller sub-modules, tackle each independently

Sensor Fusion • What’s happening around me?
Detection • Where are obstacles?
Localization • Where am I relative to the obstacles?
Planning • Where do I go?

[Learning steering bounds for parallel autonomous systems, Amini et al.]
End-to-end Learning

Learn the control directly from raw sensor data

Sensor Fusion
- What's happening around me?

Learned Model
Underlying representation of how humans drive

Actuation
- What control signals to take?

[Learning steering bounds for parallel autonomous systems, Amini et al.]
End-to-end Learning

Learn the steering directly from pixel values

Raw images: a front facing RGB camera

Deep Neural Network

Learned Model
Underlying representation of how humans drive

Actuation
- What control signals to take?

[Learning steering bounds for parallel autonomous systems, Amini et al.]
Problem with RGB cameras

Dynamic Range

Motion blur

Latency
What are event-based cameras

Novel bio-inspired sensors that capture motion in the scene
What are event-based cameras

Novel bio-inspired sensors that capture motion in the scene

[Event-based Cameras: Challenges and Opportunities, Scaramuzza et al.]
What are event-based cameras

Novel bio-inspired sensors that capture motion in the scene

Benefits:
- Low latency (~ 1 microsecond)
- No motion blur
- High dynamic range (140 dB instead of 60dB)
What are event-based cameras

Novel bio-inspired sensors that capture motion in the scene

Benefits:
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Challenges:
• Data format of events
  \[ e_k = (x_k, y_k, t_k, p_k) \]
• Monochromatic
• Low resolution
Our Goal

Use an event camera to drive a car in real time

DAVIS240 from Inivation.com
Related Work: Frame-based models

Event frame
R: positive
G: negative

Network Architecture
Resnet (CNN)  FC

[Event-based Vision meets Deep Learning on Steering Prediction for Self-driving Cars, Manqueda et al.]
If we use frame-based model, why don’t we use RGB cameras instead?
PointNet-based models

- Events = points in (x, y, t, p) dimensions

[PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation, Qi et al.]
[EventNet: Asynchronous Recursive Event Processing, Sekikawa et al.]
PointNet-based models

- Events = points in (x, y, p, t) dimensions
- PointNet is able to process Point Clouds (sets of points):

Input: last N events

[PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation, Qi et al.]
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PointNet-based models

Inspired by EventNet, during inference time:

- Precompute the result of mlp1 into Look Up Table (LUT) of shape $W \times H \times T \times 2$
- Significantly faster than the vanilla PointNet and frame-based models

Input: last N events

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Experiment Metrics

Given ground truth value $\alpha$ and prediction value $\hat{\alpha}$

- Rooted Mean Square Error (RMSE) = $\sqrt{\frac{1}{N} \sum_{j=1}^{N} (\hat{\alpha}_j - \alpha_j)^2}$.

- Expected Variance (EVA) = $1 - \frac{\text{Var}(\hat{\alpha} - \alpha)}{\text{Var}(\alpha)}$. 
Experiment Dataset

2 hours of human driving around Boston on urban roads
Supervise on curvature (1 / radius)
## Experiment Result

Comparison between Frame-based and PointNet-based Models

<table>
<thead>
<tr>
<th></th>
<th>Frame-based</th>
<th>PointNet-based (with fixed N=5000)</th>
</tr>
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<tbody>
<tr>
<td>EVA</td>
<td>0.193</td>
<td>0.144</td>
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EVA result of PointNet-based models trained and validated on different number of points

<table>
<thead>
<tr>
<th>train\valid</th>
<th>N=1000</th>
<th>N=2000</th>
<th>N=4000</th>
<th>N=10000</th>
</tr>
</thead>
<tbody>
<tr>
<td>N=1000</td>
<td>0.104</td>
<td>0.105</td>
<td>0.095</td>
<td>0.054</td>
</tr>
<tr>
<td>N=2000</td>
<td>0.111</td>
<td>0.116</td>
<td>0.113</td>
<td>0.078</td>
</tr>
<tr>
<td>N=4000</td>
<td>0.109</td>
<td>0.125</td>
<td>0.148</td>
<td>0.146</td>
</tr>
<tr>
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<td>0.029</td>
<td>0.039</td>
<td>0.060</td>
<td>0.122</td>
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Our Question

Can these models actually drive a car?
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Can these models actually drive a car?

The model may cheat by predicting the **motion of the car** rather than **learning the steering wheel angle**!
Our Question

Let’s look at our data again

1) Many events are irrelevant
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Region Of Interest (ROI) cropping
Our Question

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2) Event polarity gives away the motion of the car
Our Question

Let’s look at our data again

1) Many events are irrelevant
Region Of Interest (ROI) cropping

2) Event polarity gives away the motion of the car
Ignore the event polarity
Ablation Studies

Ablation studies using Frame-based model in last experiment

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<tr>
<td>Original Data</td>
<td>0.19</td>
</tr>
<tr>
<td>Data with ROI cropping</td>
<td>0.09</td>
</tr>
<tr>
<td>Data with polarity ignored</td>
<td>0.13</td>
</tr>
<tr>
<td>Data with polarity ignored and ROI cropping</td>
<td>0.09</td>
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Our contribution

- Sensor Integration on MIT Autonomous Vehicle
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Thank you! Questions?

- My mentors: Dr. Igor Gilitschenski and Alexander Amini
- Prof Daniela Rus, Distributed Robotics Lab, MIT CSAIL
- MIT PRIMES
- My parents
PointNet-based models

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\[
\begin{align*}
\mathbf{f}(\{x_1, \ldots, x_n\}) & \approx \mathbf{g}(h(x_1), \ldots, h(x_n)), \\
\text{where } f : 2^{\mathbb{R}^N} & \to \mathbb{R}, \ h : \mathbb{R}^N & \to \mathbb{R}^K \text{ and } g : \\
\left( \mathbb{R}^K \times \cdots \times \mathbb{R}^K \right) & \to \mathbb{R} \text{ is a symmetric function.}
\end{align*}
\]

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