Deep Reinforced Accident Anticipation with Visual Explanation

Wentao Bao, Qi Yu, Yu Kong
Golisano College of Computing and Information Sciences, Rochester Institute of Technology (RIT)

ACTION LAB · Mining LAB · ICCV 2021 OCTOBER 11-17 VIRTUAL

Introduction

➢ Explainable Accident Anticipation

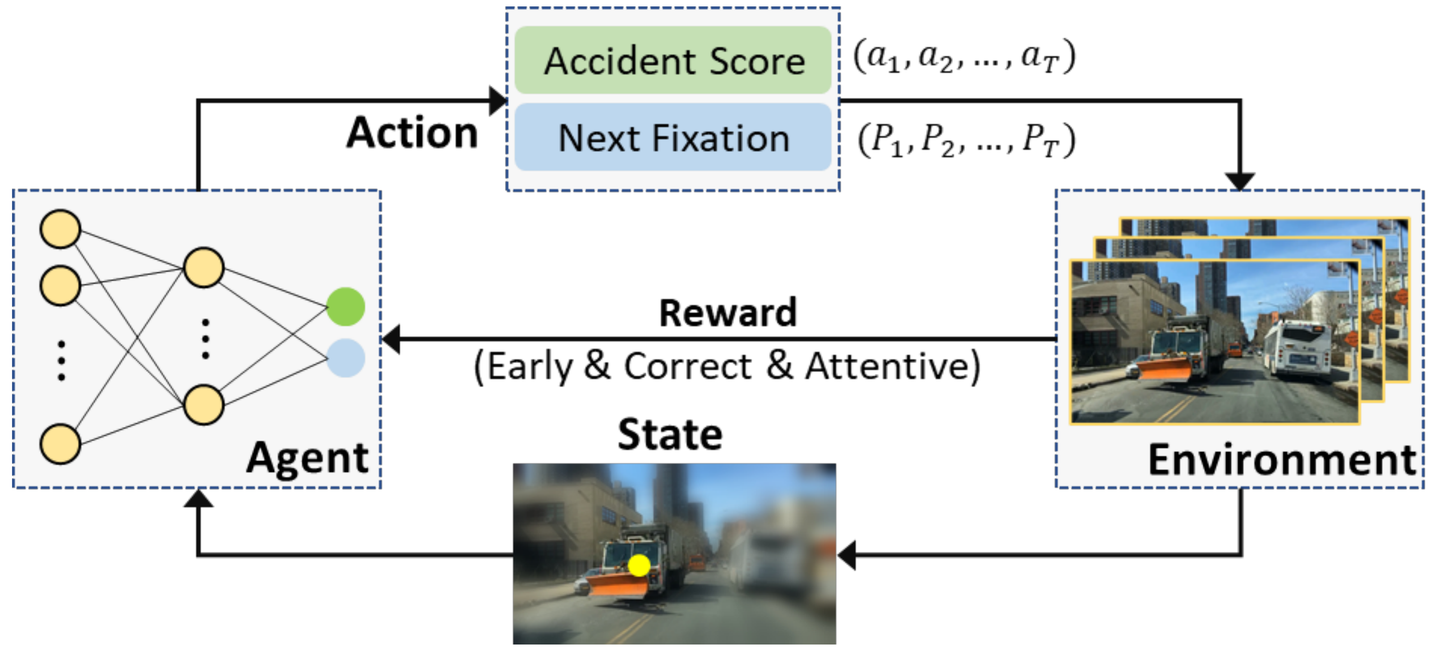
- Predict if an accident will happen.
- Make decision as early as possible.
- Provide visual explanation.

➢ Research Question

*Where do drivers **look** when **predicting** possible future accidents?*

➢ Motivations

- Two interactive processes: **Fixation** ⋈ **Prediction**
- Formulate as one united Markov Decision Process.
- **Causal attention** can be learned from both top-down (task) and bottom-up (env.) mechanisms.



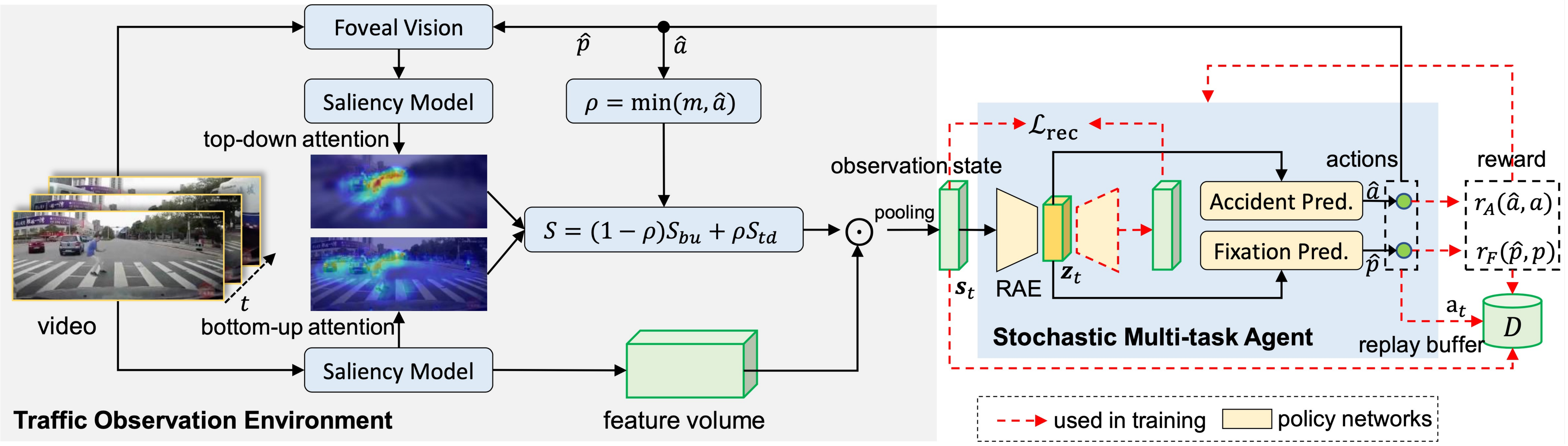
An Illustration of our MDP framework

Contribution

- **DRIVE:** Deep Reinforcement Learning (**DRL**) method for accident anticipation from videos.
- Human visual attention is explicitly simulated such that the anticipation is explainable.

DRIVE Model

➢ Framework Overview



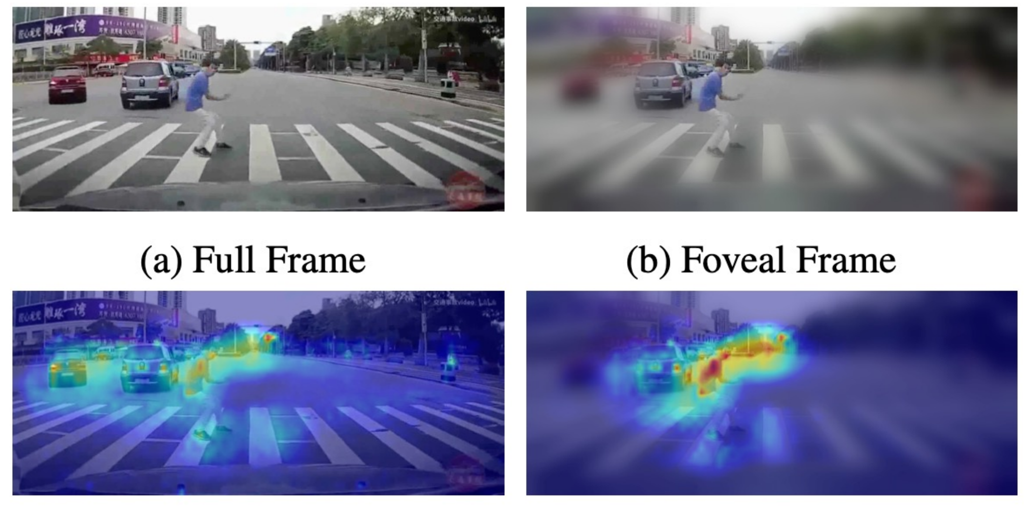
➢ Traffic Observation Environment

- Visual attention modeling

$$S^t = (1-\rho^t)S^t_{bu} + \rho^t S^t_{td}$$

- State Representation

$$\mathbf{s}^i_t = \text{cat}\left(\tilde{f}_{GMP}(S^t \odot V^t_i), \tilde{f}_{GAP}(S^t \odot V^t_i)\right)$$



(a) Full Frame (b) Foveal Frame (c) Bottom-up Attention (d) Top-down Attention

➢ Stochastic Multi-task Agent

- The agent takes actions by:

$$\hat{\mathbf{a}}_t = \text{cat}\left(\phi_A\left(\mathcal{E}(\mathbf{s}_t)\right), \phi_F\left(\mathcal{E}(\mathbf{s}_t)\right)\right)$$

- $\emptyset_A$: **accident score**, $\emptyset_F$: **next time fixation.**

➢ Model Training

- Agent is trained by Soft Actor-Critic DRL

$$\max_{\phi} \sum_{t=1}^{T} \mathbb{E}_{(\mathbf{s}_t, \mathbf{a}_t)\sim\rho_{\pi_\phi}}\left[r(\mathbf{s}_t, \mathbf{a}_t) + \alpha\mathcal{H}(\pi_\phi(\cdot|\mathbf{s}_t))\right]$$

➢ Reward Functions

- Dense Anticipation Reward:

$$r^t_A = w_t \cdot \text{XNOR}\left[\mathbb{I}[a^t > a_0], y\right]$$

$$w_t = \frac{1}{e^{t_a} - 1}\left(e^{\max(0, t_a - t)} - 1\right)$$

- Sparse Fixation Reward:

$$r^t_F = \mathbb{I}\left[t > t_a\right]\exp\left(-\frac{\|\hat{p}^t - p^t\|^2}{\eta}\right)$$

- Entropy term is decomposed: $-\mathcal{H}(\pi_\phi(\hat{\mathbf{a}}|\mathbf{s})) = \log\left[\pi_{\phi_A}(\hat{a}|\mathbf{s}) \cdot \pi_{\phi_F}(\hat{p}|\mathbf{s})\right]$
- Regularized Auto-Encoder for better sample efficiency.

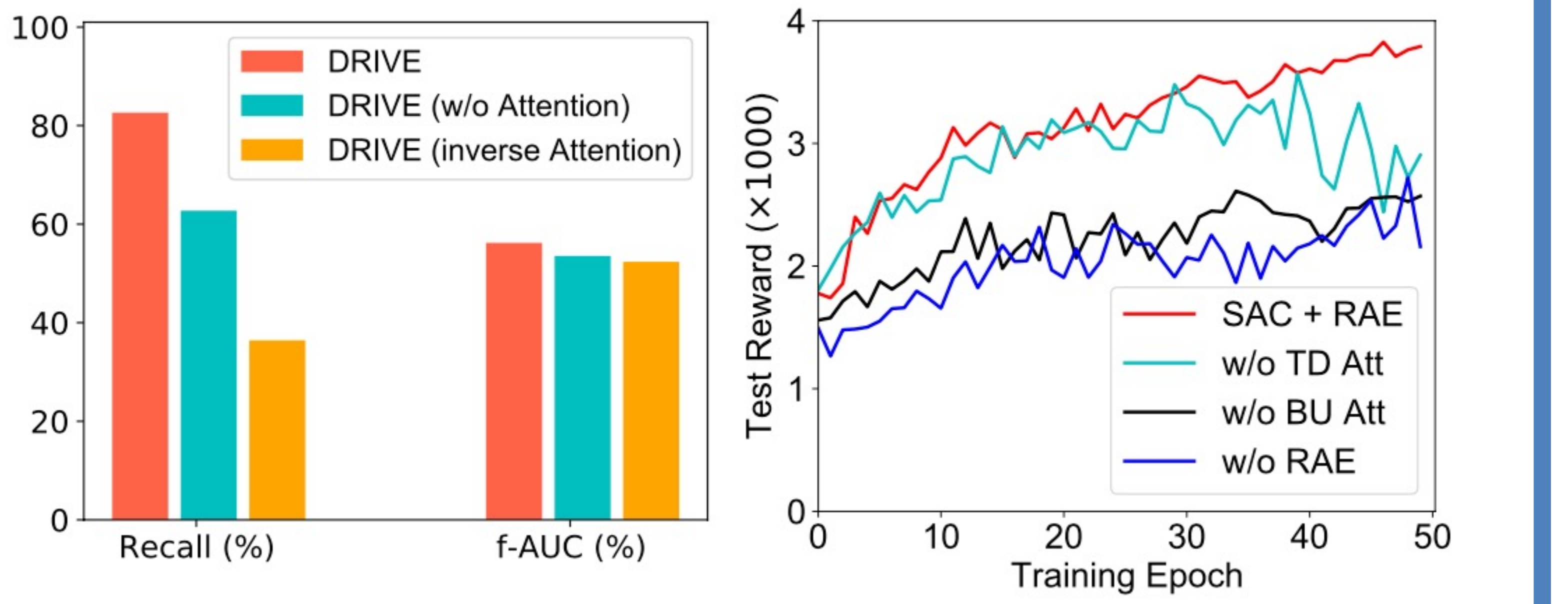
Experimental Results

➢ Main Results

Methods	DADA-2000 [11]		DAD [3]	
	AUC (%)	TTA (s)	AUC (%)	TTA (s)
DSA-RNN [3]	47.19	3.095	71.57	1.169
AdaLEA [40]	55.05	**3.890**	58.06	2.228
UString [2]	60.19	3.849	65.96	0.915
DRIVE (ours)	**72.27**	3.657	**93.82**	**2.781**

- AUC and TTA evaluate accuracy and earliness.

➢ Causal Attention & Ablation Study



- The learned attention plays a causal effect.
- All proposed components are critical to our DRIVE model.

Open Resources

Demo · Code · Project

Feel free to contact **Wentao Bao** via wb6219@rit.edu