Active inference-based modeling of human driver collision avoidance behavior

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Contributions

- Extended the active inference model of Engström *et al.*[1] to safety-critical scenarios, reproducing real-life human collision avoidance
- Implemented looming-based perception and evidence accumulation in the active inference framework

Introduction

Active Inference

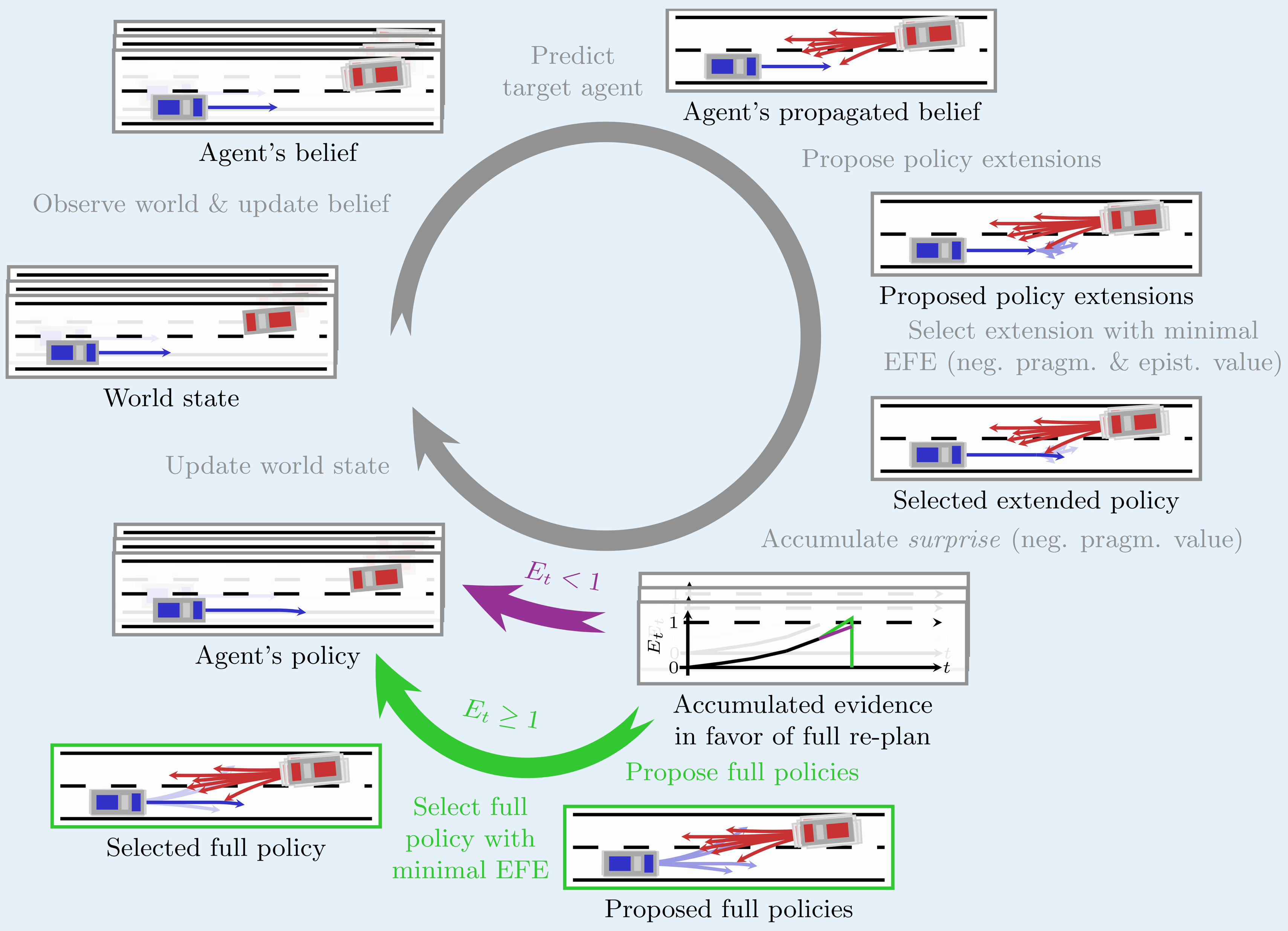
- Humans choose actions which minimize the Expected Free Energy (EFE)[2] by …
  - … maximizing the likelihood of observing a desired state (maximizing the pragmatic value)
  - … minimizing the uncertainty about the state of the world (maximizing the epistemic value)

Collision Avoidance

- Accurately modelling human collision avoidance behavior is critical for the evaluation of autonomous vehicles
- However, common models struggle with such scenarios, which are underrepresented in datasets[3]

→ Active Inference is a promising approach for modeling driver behavior[1] but has not yet been applied to collision avoidance

Methodology



Active inference

- Generative process (world):
  1. Agent's policy $\boldsymbol{\pi}_t = \langle \boldsymbol{a}_t, \dots, \boldsymbol{a}_{t+H-1} \rangle$ is applied
  2. New world state is observed (getting observations $\boldsymbol{o}$)
- Agent's internal generative model:
  1. Update belief q about world state $\boldsymbol{s}$ and (with policy $\boldsymbol{\pi}_t$) its future predicted states $\tilde{\boldsymbol{s}}$ and corresponding observations $\tilde{\boldsymbol{o}}$
  2. Find policy that minimizes EFE

Expected Free Energy (EFE)

$$G(\boldsymbol{\pi}_t) = -\sum_{\tau=t+1}^{t+H} g_{\text{pragm}}(\tilde{\boldsymbol{o}}_\tau) + g_{\text{epist}}(\tilde{\boldsymbol{o}}_\tau, \tilde{\boldsymbol{s}}_\tau)$$

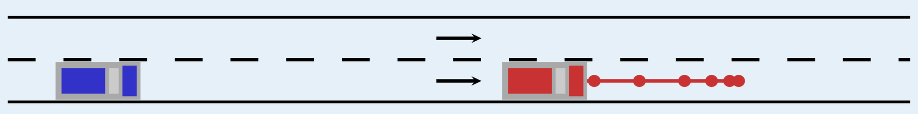
- Epistemic value $g_{\text{epist}}(\tilde{\boldsymbol{o}}_\tau, \boldsymbol{s}_\tau)$ represents the value of observations for resolving uncertainty about the world
- Pragmatic value expresses proximity to desired state:
  $$g_{\text{pragm}}(\tilde{\boldsymbol{o}}_\tau) = \mathbb{E}_{\tilde{\boldsymbol{o}}_\tau} \ln p(\tilde{\boldsymbol{o}}_\tau) - \max_{\boldsymbol{o}} \ln p(\boldsymbol{o})$$
- In our example, we define $p(\tilde{\boldsymbol{o}}_\tau)$ to be maximized by …
  - … avoiding collisions (or minimizing impact velocity)
  - … staying inside the current lane and keeping desired velocity
  - … low absolute control input values

Evidence accumulation

- Used to capture dynamic information processing[4]
- Accumulate *surprise* as evidence
  $$\epsilon_t = -\sum_{\tau=t+1}^{t+H} g_{\text{pragm}}(\tilde{\boldsymbol{o}}_\tau)$$
- Decide whether to replan the policy based on accumulated evidence
  $$E_t = E_{t-1} + \lambda \epsilon_t$$
  - $E_t < 1 \Rightarrow$ No replanning
  - $E_t \geq 1 \Rightarrow$ Replanning & set $E_t = 0$

Results

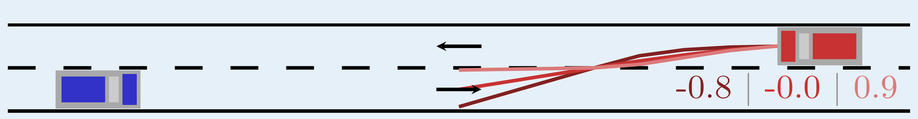
Rear-end scenario



The model reproduces

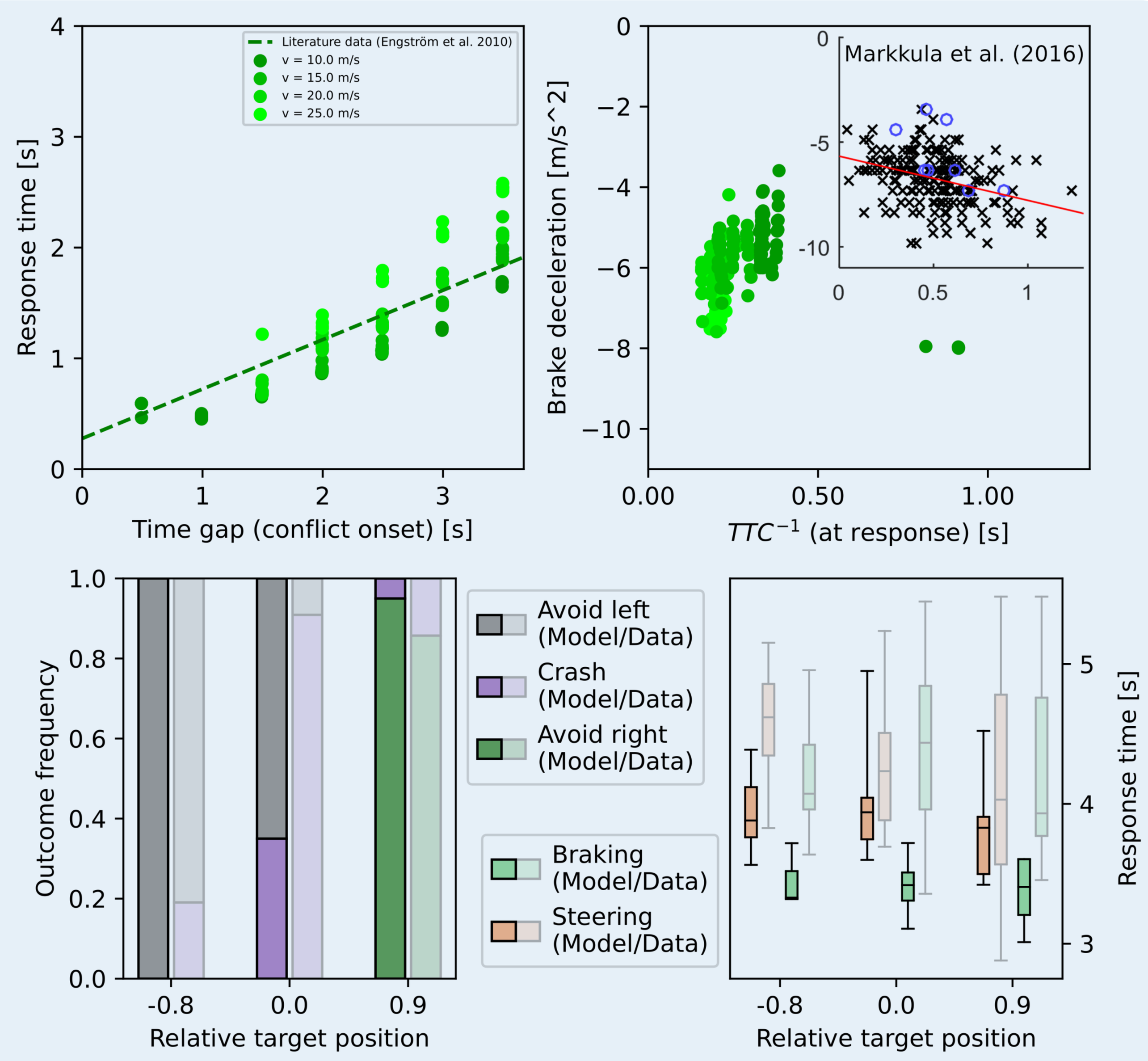
- Human brake reaction times[5]
- Magnitude of braking decelerations[6]

Oncoming scenario



The model reproduces

- Frequency of avoidance maneuvers and crashes[7]
- Response times[7]



Limitations

Even with delayed reaction times, the model still is superhumanly able to avoid collisions

Conclusions

- Our active inference model captures human driver behavior in collision avoidance scenarios
- The model can be easily extended to different scenarios and to multi-agent settings

References

[1]: Engström, J., Wei, R., McDonald, A. D., Garcia, A., O'Kelly, M., Johnson, L. Resolving uncertainty on the fly: modeling adaptive driving behavior as active inference. *Frontiers in Neurorobotics* **18** (2024)
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[4]: Engström, J., Liu, S.-Y., Dinparastdjadid, A. & Simoiu, C. Modeling road user response timing in naturalistic traffic conflicts: A surprise-based framework. *Accident Analysis & Prevention* **198** (2024)
[5]: Engstroem, J. Scenario criticality determines the effect of working memory load on brake response time. *European Conference on Human Centered Design for Intelligent Transport Systems* (2010)
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[7]: Johnson, L., Srinivasan, A., Markkula, G. and Engstrom, J. forthcoming. [preliminary results from Leeds / Waymo driving simulator study]