Mixed-initiative mission planning considering human operator state estimation based on physiological sensors

Nicolas Drougard

Context and Goal

Human-machine systems

Increasing use of automated systems

aircrafts, cars, unmanned vehicles (military operation, contaminated area), ...

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Human factors involved in 80% of AAVs accidents! [Wil]

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Consequences:

- mental confusion
- attentional tunneling
- mind wandering
- lower vigilance
- ...

increase in accident risk resulting in mission fails

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- [GCLD16] search and rescue task (AAVs)
  - **device:** eye tracking
  - **human state:** *current human task* = human gaze
  - **superv. validation:** tested on 10 volunteers

Context and Goal

work on progress

Next stage

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  - type of human behavior

  [NRGS15]

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robot/supervision sequential decisions computation: POMDP

Alternative uncertainty theories

Imprecision modeling

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small number of volunteers?

- poor statistical analysis
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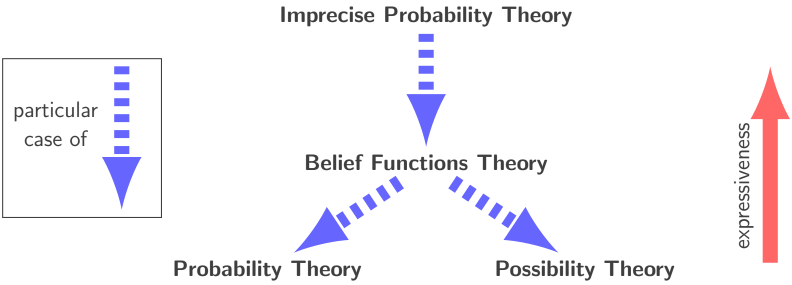
$\rightarrow$ model imprecision using alternative uncertainty theories [DDFT15]



Alternative uncertainty theories

Qualitative Possibility Theory – (max,min) "tropical" algebra

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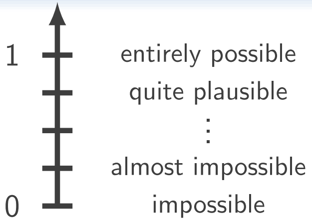
finite scale $\mathcal{L}$

usually $\{0, \frac{1}{k}, \frac{2}{k}, \dots, 1\}$



events $E \subset \Omega$ (universe)

sorted using possibility **degrees** $\Pi(E) \in \mathcal{L}$

$\neq$

quantified with **frequencies** $\mathbb{P}(E) \in [0, 1]$ (probabilities)

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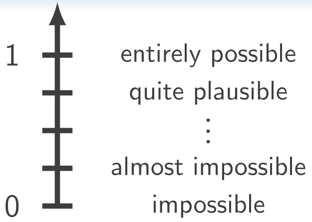

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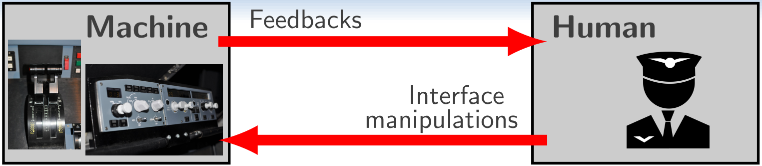
$$\Pi(E) = \max_{e \in E} \Pi(\{ e \}) = \max_{e \in E} \pi(e)$$

Alternative uncertainty theories

joint work with **Sergio Pizziol** – Context



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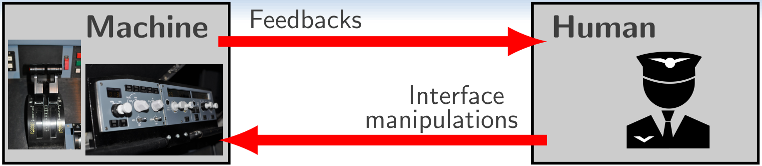

Issue: incorrect human assessment of the machine state
$\rightarrow$ **accident risk**

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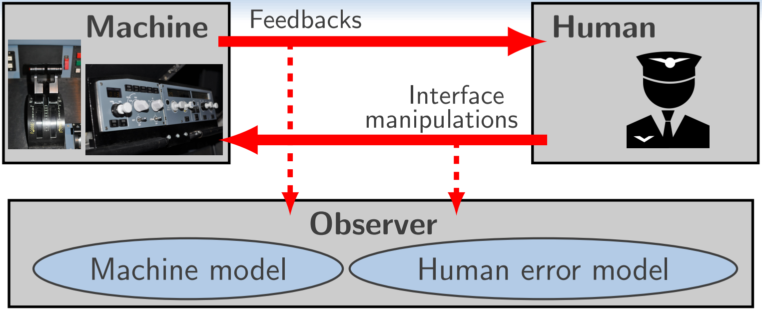

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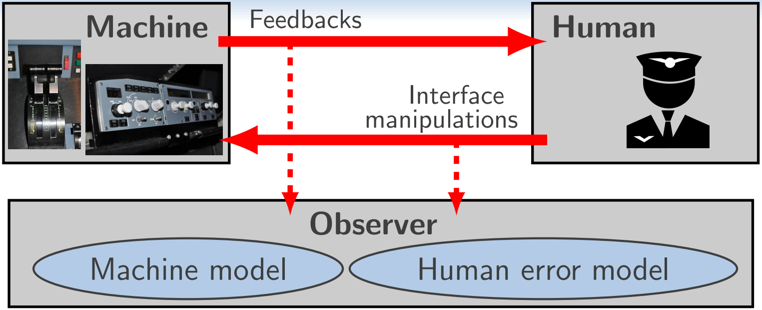

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π-POMDP without actions: π-Hidden Markov Process

- **system space** $\mathcal{S}$: set of human assessments $\rightarrow$ **hidden**
- **observation space** $\mathcal{O}$: feedbacks/human manipulations

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Human error model from expert knowledge

Machine with states A, B, C, ...

state $s_A \in \mathcal{S}$: "human thinks machine state is A"

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$$\text{“human usually aware of feedbacks”} \to \pi\left(s'_B, o'_f \mid s_A\right) = 1$$
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- impossible cases: possibility degree 0

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π-HMP, detection & diagnosis tool for HMI (with **Sergio Pizziol**)

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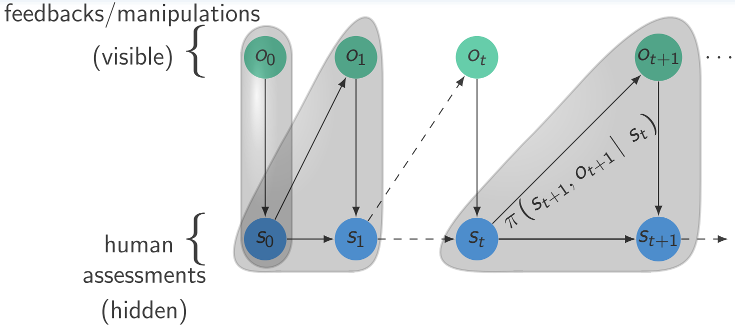

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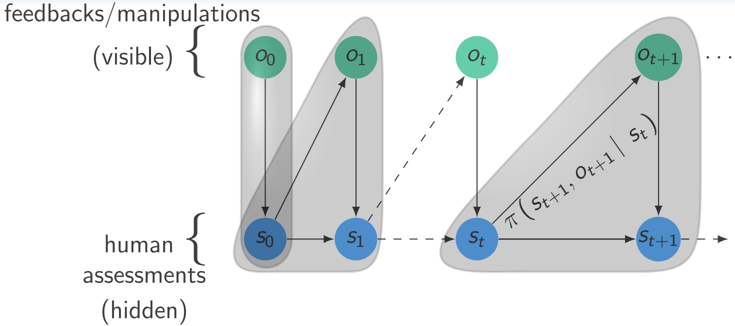

- **estimation** of the human assessment
  $\Leftrightarrow$ **possibilistic belief state**
- **detection** of human assessment errors + **diagnosis**
- validated with pilots on flight simulator missions

Nicolas Drougard, Didier Dubois, Jean-Loup Farges, and Florent Teichteil-Königsbuch.
Planning in partially observable domains with fuzzy epistemic states and probabilistic dynamics.
In *Scalable Uncertainty Management - 9th International Conference, SUM 2015*, 2015.

Thibault Gateau, Caroline Ponzoni Carvalho Chanel, Mai-Huy Le, and Frédéric Dehais.
Considering human's non-deterministic behavior and his availability state when designing a collaborative human-robots system.
In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, IROS '16, 2016.

Stefanos Nikolaidis, Ramya Ramakrishnan, Keren Gu, and Julie Shah.
Efficient model learning from joint-action demonstrations for human-robot collaborative tasks.
In *Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction*, HRI '15, 2015.

Paulo Eduardo Ubaldino de Souza, Caroline Ponzoni Carvalho Chanel, and Frederic Dehais.
Momdp-based target search mission taking into account the human operator's cognitive state.
In *Proceedings of the IEEE International Conference on Tools with Artificial Intelligence*, ICTAI '15, 2015.

Kevin W. Williams.
A summary of unmanned aircraft accident/incident data: Human factors implications.
U.S. Department of Transportation, Federal Aviation Administration, Civil Aerospace Medical Institute.

Thank you!