Physiological Assessment of Engagement during Human-Robot Interaction: Impact of Manual versus Automatic Mode

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Context and Goal

Human-machine systems

Increasing use of automated systems

examples: assembly lines, autopilots in aircrafts, autonomous cars, unmanned vehicles (drones/ground robots for military operation or contaminated area ...)

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  technical advances in AI, stat. learning, vision, decision ...

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- **Increasingly decisional autonomy:**
  technical advances in AI, stat. learning, vision, decision ...
- **Human operator still vital:**
  - produces tactical, moral, social and ethical decisions
  - flexible/creative, handles complex/unknown situations
  - complementary strengths (Fitts list [dWD14])
  - need for people for responsibility assessment issues

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- disengagement, lower vigilance
- mind wandering [DDD15]
- over-engagement, attentional tunneling [RDR+14]
- mental confusion... **affect human abilities!**

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Increase in accident risk resulting in mission fails
or sub-optimal achievements

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Improve mixed-initiative missions

Hypothesis on human operators

- not always reliable
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Strategy computation

taking into account the human operator mental state by
→ sending appropriate **information/alarms**
→ **task allocation** between the human and the robot
→ adaption of **machine's behavior**

Approach and theory

Probabilistic planning

non deterministic human behavior + random dynamics of environments
$\rightarrow$ uncertain events $\rightarrow$ **Probabilistic Planning**

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Markov Decision Process

MDP [Put14]

- goal of a mission $\sim$ **rewards** valuating system states
- optimal strategy: **maximizes** the expected sum of rewards

non deterministic human behavior + random dynamics of environments
→ uncertain events → **Probabilistic Planning**

Markov Decision Process

MDP [Put14]

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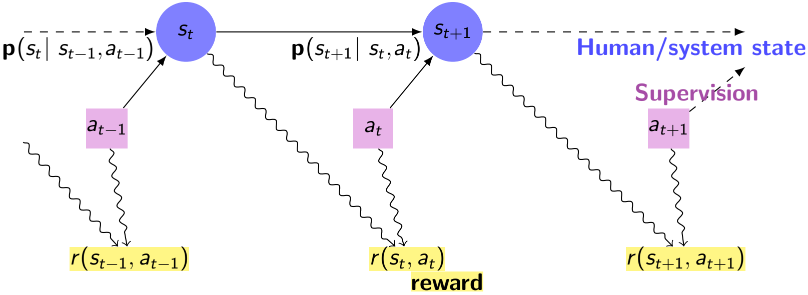
Partially-Observable Markov Decision Process

POMDP [SS73]

- states may be unobservable
- **human mental states not observable!**

Approach and theory

POMDP for driving HMI using human observations



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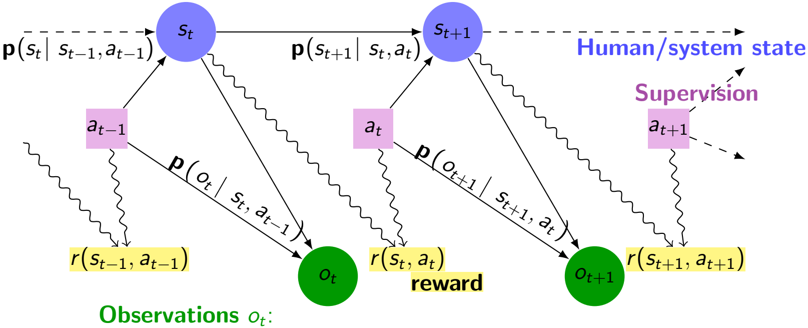

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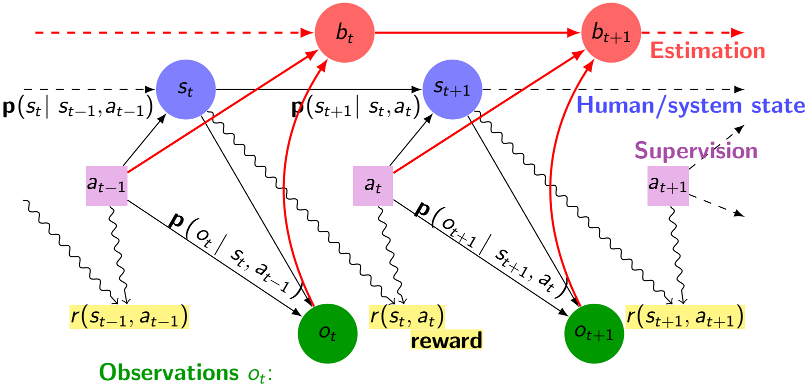

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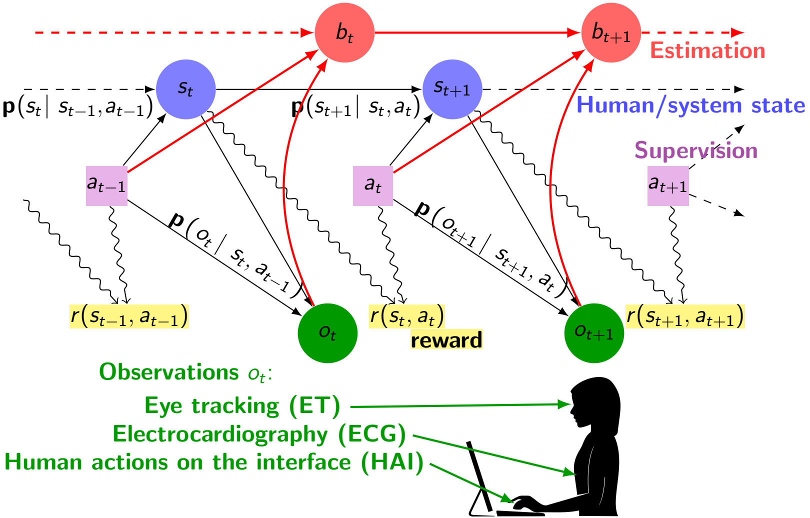

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Probabilistic modeling

precise probability values: transition T, observation O

$\rightarrow$ need for a sufficiently large dataset

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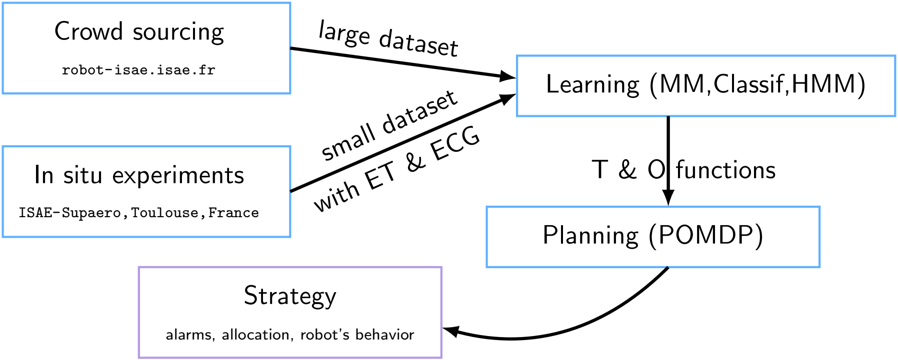
Learning and planning

$\rightarrow$ Markov Chain Model : T learning
$\rightarrow$ Classification : O learning
$\rightarrow$ Hidden Markov Model (HMM): T and O learning
$\rightarrow$ POMDP solver $\rightarrow$ strategy computation (a_t)

Approach and theory

Summary of the approach



Proof of concept mission
Mission and goal

Context:

- A firefighter robot is present in a small area
- with few trees
- which have a weird tendency to self-ignite for some unknown reason...
- Through your graphical interface, you get the position of the robot,
- as well as the video from its camera.
- The battery charge level of the robot decreases with time: when the robot is on the red square, the battery recharges.
- The volume of water contained by the robot is not unlimited: to recharge its water tank, the robot has to be placed on the blue square and the ground tank has to be full enough. For that, you have to fill the ground tank using the buttons on the left-side of the interface.

Goal:

- With the help of this robot, your mission is to fight as much fires as you can.
- The robot can become autonomous at any time.
- Pay attention to the robot's temperature when it is too close of flames!

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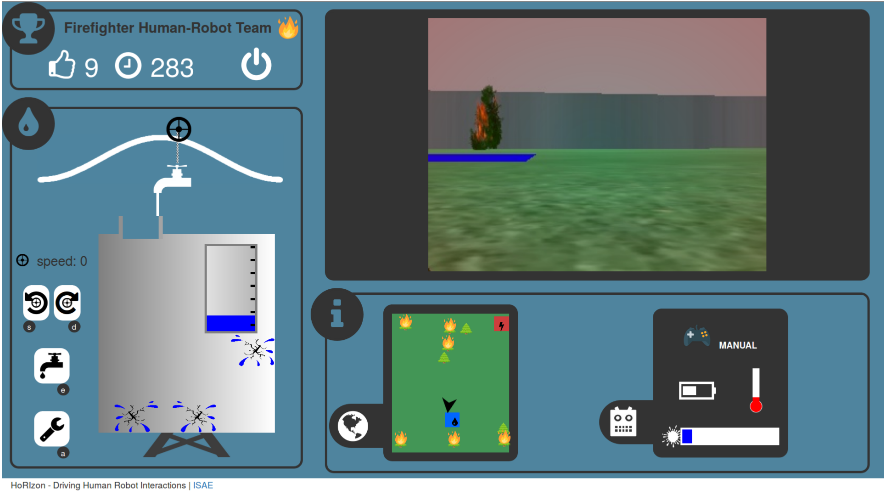
Mission goal: fight fires

- $F_i = \begin{cases} 1 & \text{if target } i \text{ is on fire} \\ 0 & \text{otherwise} \end{cases}$
- reward function: $r(F_1, \ldots, F_N) = \#\{ i \mid F_i = 0 \}$

Proof of concept mission

Graphical user interface (GUI)



Proof of concept mission

Human actions on the interface

Ground tank water management:

	or	s	wheel turns left
	or	d	wheel turns right
	or	e	tap opens few seconds
	or	a	allows to fix leaks

Control of the robot:

	SPACE
	↑
	↓
	←
	→

Proof of concept mission

Displayed alarms

Potential alarms

"low battery", "too-high temperature", "60 seconds before the end of the mission", "robot's tank will soon be empty (2 shoots left)", "robot is in autonomous mode", "robot is in manual mode" and "ground tank's water level is low".

Proof of concept mission

Displayed alarms

$\longrightarrow$ alarms and autonomy are random for learning purpose

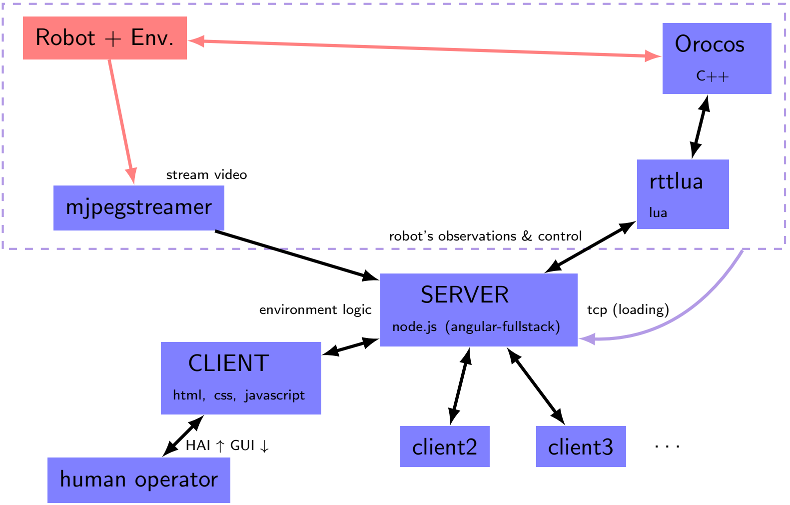
$\longrightarrow$ pre-testing for:

- $\rightarrow$ adaptation to screens/setups (online)
- $\rightarrow$ undesirable mental states emergence :
  - $\rightarrow$ water management + robot's control $\rightarrow$ demanding
  - $\rightarrow$ score/limited time $\rightarrow$ pressure
  - $\rightarrow$ battery empty or too hot robot $\rightarrow$ danger

$\longrightarrow$ interest in the experiment (understandable,feasible, etc.)

Approach implementation

Mission framework



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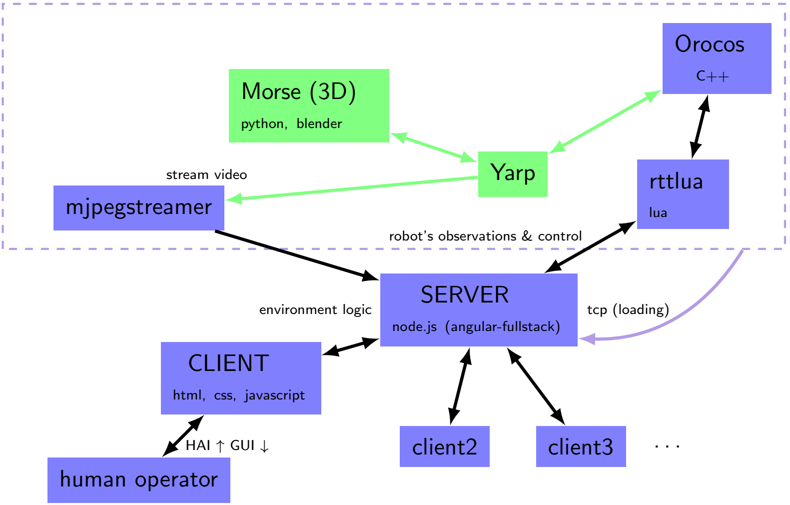
Mission framework



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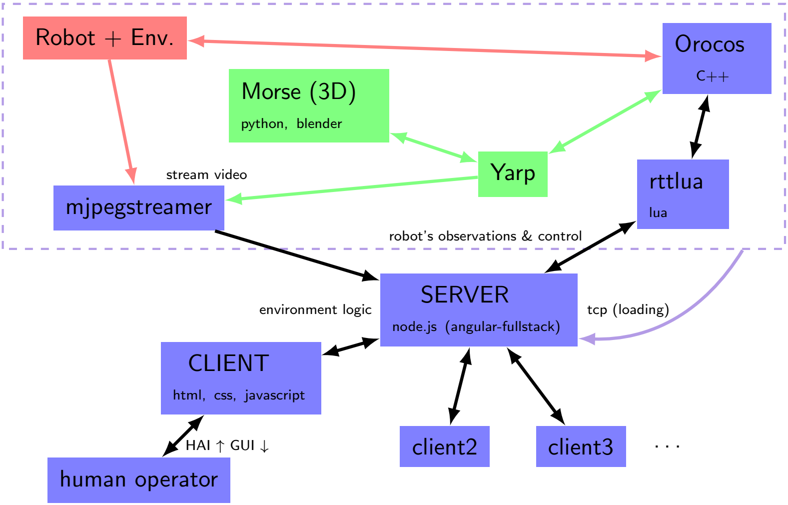
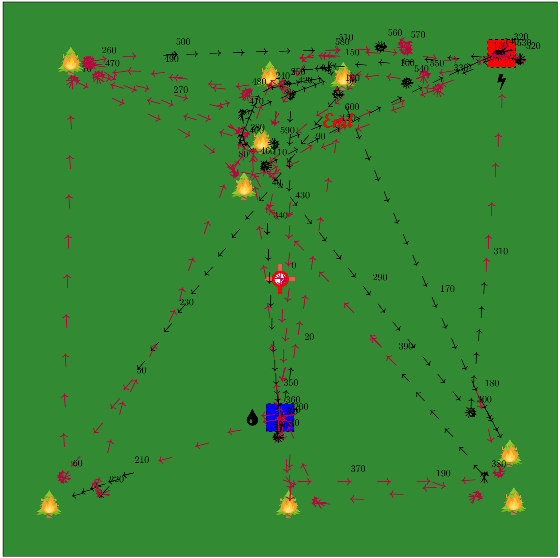


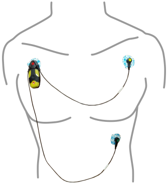
Collected data



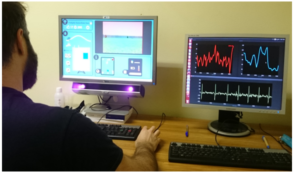
Experimental Protocol

Physiological data acquisition and markers

SMI RED 250Hz



Faros 360^o eMotion



Data streams managed with Lab Streaming Layer (LSL) available at `github.com/sccn`

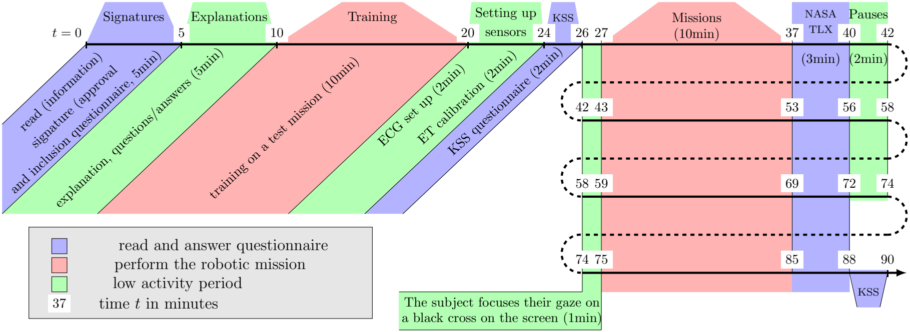
Online markers:

- Eye tracker (ET) features: gaze, number and duration of fixations on areas of interest (AOIs: score, tank, video, map, info)
- Electrocardiograpy (ECG) features: inter-beat intervals and standard deviation
  Instant Heart Rate Variability (**IHRV**) computed with a Exponential Weighted Moving Average (EWMA)

$$IHRV_{t+1} = \frac{SD(\text{last 12 R-R}) + N.IHRV_t}{N+1},$$

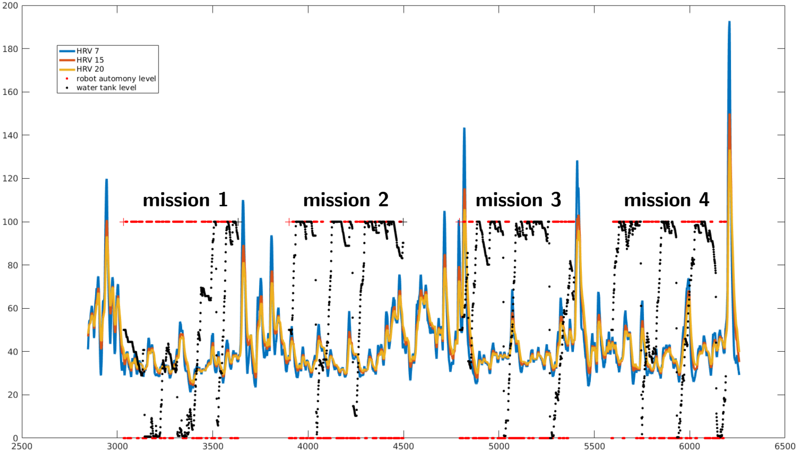
with $N \in \{7, 15, 20\}$

Experimental Protocol



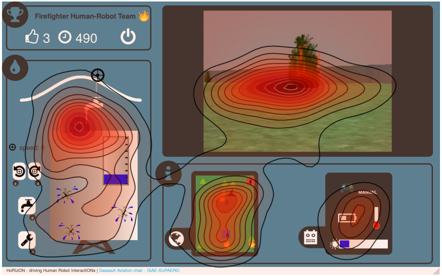
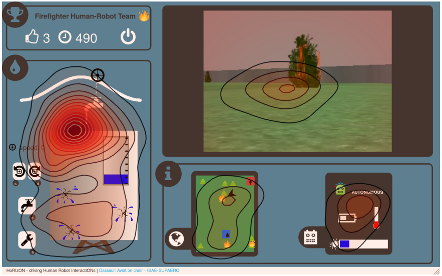
Ethical Agreement CERNI-2018-070

Instant HRV timeline



Results over 12 subjects

Eye gaze analysis – number of fixations

fixations' density when robot in **manual mode**	fixations' density when robot in **autonomous mode**
	

Results

Statistical analysis to extract Relevant Physiological Features

Results with 17 subjects (9 females): average age 28.5 (S.D. = 4.52)

HRV & IHRV

During: **mission** < **rest** session

diff = 6 *(Student & Wilcoxon tests* $p < 0.05$*)*

Robot in: **autonomous** mode < **manual** mode

$\rho = 0.03$ (Spearman correlation, $p < 0.05$)

tank filling = hard task

Results

Statistical analysis to extract Relevant Physiological Features

Fixations on AOIs: number & duration

video AOI	**manual** mode	$>$	**autonomous** mode
tank AOI	**manual** mode	$<$	**autonomous** mode

$\rho = 0.22$ (Student, Wilcoxon, Spearman, $p < 0.05$)

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Statistical analysis to extract Relevant Physiological Features

Fixations on AOIs: number & duration

video AOI **manual** mode $>$ **autonomous** mode

tank AOI **manual** mode $<$ **autonomous** mode

$\rho = 0.22$ (Student, Wilcoxon, Spearman, $p < 0.05$)

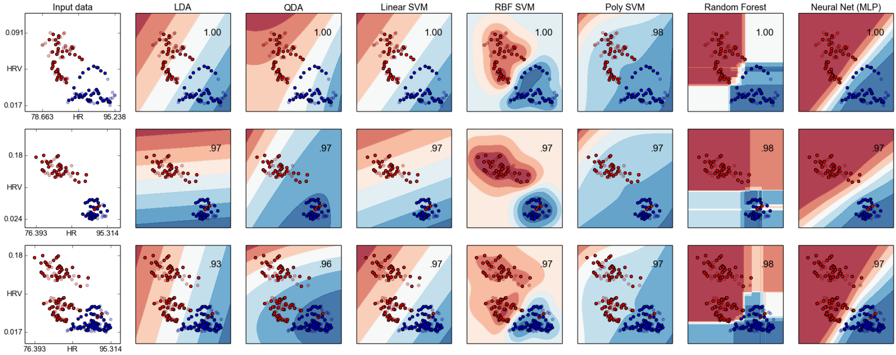
Other significant correlations (Spearman, $p < 0.05$):

-fix. on video AOI	&	on tank AOI		$\rho = -0.6$
-IHRV	&	fix. on AOIs	/	$\rho = -0.06/0.1$
-IHRV	&	remaining time		$\rho = 0.05$
-IHRV	&	performances		

ext. fires: $\rho = -0.07$ tank level: $\rho = -0.14$

Features (HR/HRV) classification

confusion matrix (accuracy details) $\rightarrow$ observation function $\mathbf{p}(o \mid s)$



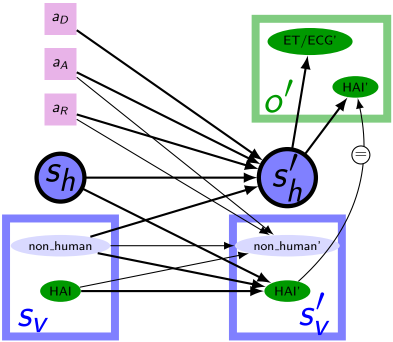
Future work

Closing the loop and Evaluating

- Apply HMM/POMDP solvers with different parameters (*e.g.* number of hidden states)

Last experiment at ISAE-SUPAERO:

- same mission on volunteers equipped with sensors
- compare resulting strategy and others (expert, MDP without physio, ...)
- missions with the real robot



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