# CASAC chair Internship Proposal
# Profile-Based Decision-Making for Mixed-Initiative Interaction

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## Context: human-machine interaction with two-way initiatives

Autonomous systems can be seen as advanced intelligent artifacts from which one may expect a sort of self-directedness (i.e. freedom from outside control) (Bradshaw et al., 2013), as the term *autonomy* would result from delegation of a decision to an authorized entity (e.g. artificial agent into a machine) to take actions within specific boundaries (David and Nielsen, 2016). Autonomous robots are an example of those kind of systems: mobile robots that can be deployed in dirty, dull, or dangerous environments to avoid people to be exposed (Kawatsuma et al., 2012); drones or Unmanned Aerial Vehicles (UAVs) that can be used for persistent surveillance of critical infrastructures or sites (Aiello et al., 2020). In those application, autonomous robots can be see as a support system.

Although for the general public an autonomous system is expected to operate without human intervention, in reality all machines are supervised by humans to some degree (see Figure 1). Therefore, the overall performance of the system would depend on a good coordination and collaboration between humans and machines (Ferrari, 2019; David and Nielsen, 2016) in a human-centered design perspective.

In addition to some level of supervision, autonomous robots still require a human operator to deploy them, to improve their embedded capabilities, or to take over, by teleoperation, when the embedded software/hardware fails. Assuming that the division of tasks between humans and artificial agents is not fixed, the objective is to reach Mixed-Initiative Interaction (MII) level, where autonomous systems collaborate with humans on a peer-to-peer basis (Goodrich et al., 2008), implementing a kind of dynamic, adaptive, or adjustable autonomy (Sheridan, 2011).

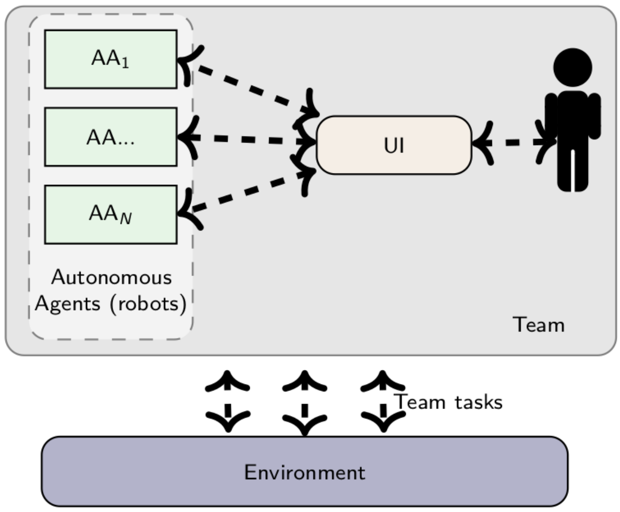



Figure 1: Schematic example of a human is operating autonomous agents (robots) through a User Interface (UI).

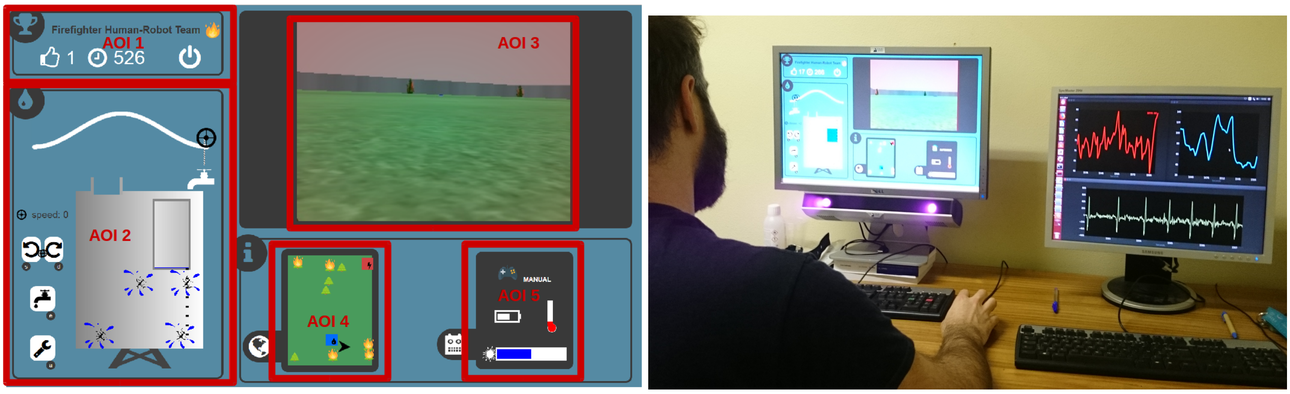
MII defines a flexible interaction framework that allows each agent not only to take charge of the tasks in which they are specialized (Allen et al., 1999), but to dynamically assume the role deemed most relevant given the context. The problem is whether, why, when, and how artificial agents could seize the initiative to perform tasks that, a priori, are expected to be performed by a human agent, as the human operator, which is responsible for the system decision, and preferred for complex tactical, legal or ethical decisions. This problem is known in the literature as the transfer-of-control problem (Scerri et al., 2002), which aims to determine whether and when such a transfer-of-control (in both directions) should occur in adjustable autonomy.

Note that a human operator in charge and interacting with several autonomous robots, deployed in a complex environment, can be confronted with task overload and other difficulties. Recent literature has shown examples where artificial (software) agents assist human operators while they operate complex systems in a *man-machine teaming perspective* (Ferrari, 2019): intelligent ground stations for (multi-)robot deployment (Kaufmann et al., 2021), aircraft cockpits (Zhang et al., 2021; Brand and Schulte, 2021), or power or nuclear plants control (Ahn et al., 2022; Marot et al., 2020).

In this context, our goal is to enhance embedded decision-making to favor a peer-to-peer collaboration. We believe that by improving systems abilities to model human's strategies and by adapting machines' decision-making to humans during interaction would push such systems towards a fluent peer-to-peer collaboration. In particular, we are interested on methods that could be applied to model and to translate the human operator behavior and strategies in function of her/his profile and mission context.

## Brief experimental environment description

The Firefighter Robot Game[1] (FRG) (Drougard et al., 2017; Charles et al., 2018) presents a scenario where a human teleoperates a robot to extinguish fires in a bounded area (see Figure 2). The simulated forest has trees that can catch fire, and the human-robot team must extinguish as many fires as possible within 10 minutes. The robot has limited battery power, an embedded water tank for extinguishing fires, and a thermometer enabling the human operator to monitor its temperature. The robot must recharge its battery at an energy supply zone and refill its water tank at a water pool which the level must also be monitored by the human operator. When necessary, the human operator must fill the pool using control commands on a moving valve. The pool's walls are susceptible to leaks and frequently necessitates a manual intervention from the human operator for repairing it using a tool.




(a) AOIs definition following the GUI.

(b) ECG data visualization during experiment.

Figure 2: Figure from (Chanel et al., 2020) showing a screenshot of the Graphical User Interface showing the areas of interest (AOIs) defined for the study; ECG-data acquisition during the experiment.

The human operator can manually operate the robot or can chose to put the robot in automatic navigation mode. In automatic mode, the robot prioritizes battery recharging and embedded water tank refilling (it navigates to the energy supplier or water pool when resources are low). When battery and tank levels are sufficient, the robot finds the shortest path to the nearest burning tree and extinguishes the fire. In manual mode, the human operator remotely controls all robot actions, including navigation, recharging, temperature monitoring, and water dispensing.

This mission scenario was designed to generate deleterious cognitive states in human operators, mainly due to multitasking, uncertainty, and time pressure. Such situations are known to generate stress and cognitive workload, thus impacting human agent performance (Dehais et al., 2020). Deleterious mental states affecting performance can be estimated using physiological computing (Roy et al., 2020; Fairclough, 2009). For instance, metrics such as the Heart Rate (HR) and the Heart Rate Variability (HRV) are known to be impacted by workload (Heard et al., 2018).

[1] http://robot-isae.isae.fr/welcome

In a previous work (Chanel et al., 2020) the two levels of robot operation mode (manual vs. autonomous) were randomly manipulated to assess their impact on the participants' performance across missions. Cardiac activity, eye-tracking, and participants' actions on the user interface were collected. The participants performed differently and we could identify high and low score mission groups that also exhibited different behavioral, cardiac and ocular patterns. Our findings indicated that the higher level of automation could be beneficial to low-scoring participants but detrimental to high-scoring ones, and vice versa. In addition, inter-subject single-trial classification results showed that the behavioral and physiological features were relevant to predict mission performance. Recent results (Angelotti et al., 2023) have shown that the subjective feedback from human operator about the interaction fluency vary when they are facing adaptive interaction policies in the FRG. We noticed that a higher level of automation favored some participants' experience. They reported that they could concentrate on the tank management tasks because they were confident in the robot's behavior. Others participants reported the complete inverse situation preferring a lower level of automation keeping the manual control of the robot.

Based on these results, we believe that exploring human behavioral and physiological features for responding to her/his preferences and for the prediction of human operator actions is a promising venue for the construction MII policies with the aim at maximizing team performance and fluency of the interaction.

## Profile-based strategy learning

Human's strategies can be guided by their psychological profiles (Akbari et al., 2021). In particular, some works in entertainment games (Vahlo et al., 2018; Bean and Groth-Marnat, 2016) and in robotics (Nikolaidis et al., 2017) have shown that both level design and system's actions can be adapted to each gamer profile in order to provide an enjoyable experience. In a current study, we are confronting gaming profiles[2], derived from the work of Akbari et al. (2021), with the FRG. We invited participants to play the game and during the 10 minutes mission they were free to control the operation mode of the robot. Our preliminary results with twelve participants suggest differences in behavior and strategies according to different user profiles. For instance, in Figure 3 we detail the percentage of mission time the participants led the robot in manual (resp. autonomous) mode in function of their (gaming) profile. However, at the present moment, we did not yet investigated the impact of profiles on physiological features neither if there are common mission contexts in which operators are more likely to put the robot on manual (resp. autonomous) mode.

Anyway, these preliminary results encourage us to believe that people with different psychological profiles tend to prefer different experiences with intelligent agents, expecting different intervention levels, responsibility and control depending on their own mental state or level of task engagement in a certain activity. However, there are several open questions: How to identify the main mission contexts where participants are more likely to change the robot operation mode? Is this behavior also dependent of the profile? If yes, how to determine the effective number of different profiles? How to set up profiles strategies clustering/classification? Could such a profile-based classification be useful for behavior modeling? Could profile-based learning improve the prediction of operator's actions?

| Profile | Manual Time (%) | Auto Time (%) | Mode Changes (avg) | Final Score (avg) |
|---|---|---|---|---|
| Acrobat | 15.6 | 84.4 | 2 | 25 |
| Skirmisher | 45.7 | 54.3 | 10 | 31.5 |
| Bounty Hunter | 48.3 | 51.7 | 24 | 31 |
| Ninja | 57.4 | 42.6 | 27.5 | 28.5 |
| Gladiator | 52.4 | 47.6 | 10 | 32 |
| Architect | 62.0 | 38.0 | 11 | 31 |
| Gardener | 52.9 | 47.1 | 11 | 28 |
| Bard | 60.6 | 39.4 | 15 | 33 |
| Slayer | 45.9 | 54.1 | 11 | 31 |

Figure 3: Percentage of the mission duration the participants led the robot in manual (resp. autonomous) operation mode in function of their profile.

[2] https://apps.quanticfoundry.com/surveys/start/gamerprofile/

# Internship Objectives

In this internship we want to investigate the use of hybrid AI, in particular Neuro-Fuzzy networks, to model and translate operator's behavior. In Neuro-Fuzzy networks the (to be leaned) weights are mixed variables, i.e. some weights are Boolean - result of logical rules modeling expert knowledge - and other weights are real - rules to be learned during the leaning phase.

Neuro-fuzzy networks can be seen as a hybrid AI model: an artificial neural network which iterativelly adapts the connection weights between neurons via backpropagation of a given loss function, but into which special semantic nodes, representing symbolic descriptors, with an understandable meaning to humans. In addition, expert knowledge can be modeled inside the network by freezing the connection between certain nodes to form logical rules. That kind of model tries to benefit both from the learning capabilities of modern neural networks, and the formal knowledge representation allowed by fuzzy logic, proposing an alternative to build systems able to learn from data but which the learned model can be interpreted and explained at a certain level (de Campos Souza, 2020).

The generation of rules by neuro-fuzzy networks constitutes an interesting approach to produce more refined rules than the strict Boolean ones given by an expert, and those generated by networks integrating no initial knowledge (Mitra and Hayashi, 2000). But there are still several open problems and the possibility of developing new models inspired by the recent deep learning approaches.

In this internship, the idea is to use neural-fuzzy networks with mixed weights (booleans and reals), allowing the incorporation of expert knowledge and the interpretation of the resulting network.

### Scientific challenges and tasks

The chosen candidate will take the continuity of ongoing work both in modeling human profile for the specif game and context described (ISAE-SUPAERO), and a first neural-fuzzy learning algorithm with mixed variables (ONERA). First steps are the discovering and handling the existent work, and reading fundamental papers on the state-of-the-art. Then proceed to the modeling and implementation of an adapted method, and testing it in the experimental scenario.

We strongly believe that such methods would enable to model and predict operator actions (strategies) according to their profile and mission context. This information could be used to anticipate human behavior, identify hies/her preference (profile) and to adapt the system to the user. In fine, we would like to allow the system to take the initiative (i.e. seize the control) when degraded mental states are perceived and in function of human operator preferences.

# Candidate's profile

MSc student or Engineer student with programming skills (Python, C++) and a background in robotics and AI is suitable. The candidate will study/learn machine learning techniques and automated planning theory related to Markov Decision Process and Reinforcement Learning. The student will work with data collected by previous students, and depending on his/her advances, will possibly held new experiments in the lab to validate the proposed model. To that, the student will be located at ISAE-SUPAERO facilities.

- Interns will receive a stipend of 4.05€ net per hour. This gratification gives to approximately 560€ per month.
- **Applications (CV and cover letter) must be send to supervisors** (listed in page 1).

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