A Unified Decision-Theoretic Model for Information Gathering and Communication Planning

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***Abstract*— We consider the problem of communication planning for human-machine cooperation in stochastic and partially observable environments. Partially Observable Markov Decision Processes with Information Rewards (POMDPs-IR) form a powerful framework for information-gathering tasks in such environments. We propose an extension of the POMDP-IR model, called a Communicating POMDP-IR (com-POMDP-IR), that allows an agent to proactively plan its communication actions by using an approximation of the human's beliefs. We experimentally demonstrate the capability of our com-POMDP-IR agent to limit its communication to relevant information and its robustness to lost messages.**

I. Introduction

As artificial agents enter human-inhabited environments, we expect them to be capable of communicating relevant information about their knowledge of environment to us, meaning that they should be capable to proactively select relevant information to report to a teammate. We refer to this process as *Communication Planning* and many applications require such communication. For instance, in assisted surveillance domains as the one described by Witwicki et al. [1], a human operator must monitor many parameters simultaneously (e.g., observe several surveillance cameras for uncommon events) and is at risk of being overwhelmed by the amount of information to process. In such systems, artificial agents can select and communicate about the relevant information to alleviate the operator's workload and improve the efficiency of the surveillance process. Other examples of applications might involve transparency [2] or explainable agency [3] in which the agent should report about its behavior and actions when they might not align with what the user is expecting. Generally speaking, this relates to the problem of Active Situation Reporting [4].

Partially Observable Markov Decision Processes (POMDPs) are suited for these types of problems as they are a well-studied mathematical framework to perform sequential decision making in uncertain environments. POMDPs with Information Rewards [5] are an extension to specifically tackle information-gathering tasks while remaining in the POMDP framework, thus allowing the use of existing POMDP solvers.

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Throughout this paper, we will consider the illustrative example presented in Figure 1 and inspired by Spaan et al. [5]. An exploring agent is located in an environment with an alarm and must perform three tasks in parallel: patrol the environment, observe the current state of the alarm and warn a human operator when the alarm is red. This is an example of a challenging problem where the patrolling agent must reason about its local actions and, simultaneously, decide about the communication to the human operator.

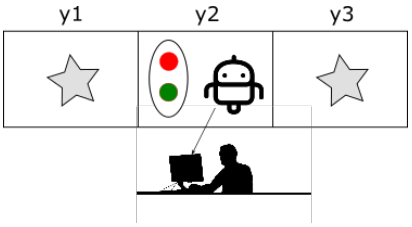


Fig. 1: The surveillance problem. An agent must patrol the environment by traveling between two goals (marked with the stars) while looking at the alarm color and communicating its color to the operator.

Our main contribution is a decision-theoretic framework, called a Communicating POMDP-IR (com-POMDP-IR), which integrates information-gathering tasks and communication planning with more classic goal-oriented tasks. This framework only assumes that the party receiving the communication is using a Bayesian belief update and does not require any other information about its policy or internal model. For this reason, the com-POMDP-IR is well suited for human-machine collaboration. The core idea of this model is that the agent is maintaining its own belief state as well as an estimation of the human's belief over a set of specific features, and that it is rewarded when both are synchronized. To do so, at each time step, the agent selects its primitive and information-reward actions [5], as well as a communication and a *commitSync* action. The communication action only affects the agent's estimation of the human belief, while the *commitSync* action allows the system designer to reward the agent for synchronizing its belief state with the human's. We show experimentally that a com-POMDP-IR agent is capable of restricting its communication to relevant information only and that it adapts its behavior to the reliability of the communication channel.

The remainder of this paper is organized as follows. Section II presents different studies and models similar to our problem. Section III reviews the key aspects of the POMDP-IR on which our work is based and Section IV presents

our contribution: the com-POMDP-IR. Section V evaluates this model on the surveillance problem. Finally, Section VI summarizes our contributions and suggests leads for future work.

II. Related Work

Decision making for Human-Machine Interaction is fundamentally a problem of decision making under uncertainty. Whether it is related to the human's actions, the human's state, or the human's mental state (their beliefs, goals and intentions), some uncertainty is unavoidable. As a very well-studied mathematical framework, Partially Observable Decision Processes (POMDPs) seem to be particularly suitable in this context, and have already been successfully used to facilitate human-machine interaction. For instance, Taha et al. model HRI-related variables such as intention and satisfaction within a POMDP to assist the user more intuitively [6]. More recently, Garcia and Lima model the behavior of a human user in a POMDP-IR to learn latent states of the user [7].

Our work focuses on integrating information-gathering tasks, communication planning and goal-oriented tasks in the context of human-machine cooperation. Information-gathering tasks in decision-theoretic settings have received significant attention in the last decade, especially with the development of the ρ-POMDP [8] and the POMDP-IR [5], which reward agents based on belief states in addition to environmental states. Both models have been later shown to be equivalent [9]. Renoux et al. [10] and Lauri et al. [11] considered information gathering in multi-agent systems, using respectively POMDPs and Dec-POMDPs.

The principle of optimizing communication actions in decision-theoretic multiagent settings has been previously considered, mostly under a request-answer framework (one agent requests information that another agent provides) [12], and with the goal of reducing the complexity of solving large decentralized models by exploiting local interactions, thus assuming that each agent is modeled within the same approach (usually a Dec-POMDP or MTDP) [13], [14], [12]. In the case of a human-machine team, the human's actions cannot be controlled and such modeling is impossible. Recently, Wang et al. [15] consider this specific setup but expect the human's policy and observation model to be known. Their work, similarly to ours, introduces some elements of an Artificial Theory of Mind. The concept of Theory of Mind (ToM), first introduced in the field of Behavioral Sciences [16], describes the ability to dissociate other's mental states (beliefs, intentions and goals) from one's own, and to reason about these mental states. Recently, several studies have been focusing on implementing an Artificial Theory of Mind, either completely or partially. Some models allow to capture the complete model of other agents, such as the Interactive-POMDP (I-POMDP) [17], and its communicating extension, the CIPOMDP [18]. These two models are very expressive, but at the cost of a high complexity and require to maintain possibly infinitely nested beliefs. Various studies focus on the belief aspects of the Theory of Mind [15], [10], in an attempt to reduce the model's complexity. This paper follows the same idea and uses a simple belief-based version of an Artificial Theory of Mind.

III. Background on POMDP-IR

Our work is based on the POMDP with Information Rewards (POMDP-IR) [5]. In this section, we review the key aspects of the POMDP-IR as well as the notation relevant to the rest of the paper.

A POMDP-IR is represented as a tuple $\langle \mathcal{X}, \mathcal{A}, \mathcal{O}, \mathcal{T}, \Omega, R \rangle$ where $\mathcal{X} = \{X_1, \dots, X_{|\mathcal{X}|}\}$ is a set of state factors, $\mathcal{A}$ is a set of actions, and $\mathcal{O} = \{O_1, \dots, O_{|\mathcal{O}|}\}$ is a set of observation factors. We define $S = 2^{\mathcal{X}}$ as the set of all possible states and $Y = 2^{\mathcal{O}}$ as the set of all possible observations. The transition function $\mathcal{T}$ is therefore defined as $\mathcal{T} : S \times \mathcal{A} \times S \to [0, 1]$, and the observation is function is defined as: $\Omega : S \times \mathcal{A} \times Y \to [0, 1]$. $R : S \times \mathcal{A} \to \mathbb{R}$ is the reward function. In a POMDP-IR, the set of state factors $\mathcal{X}$ contains l factors which are called Factors of Interest (FoIs), which are the factors that the agent needs to explore. The POMDP-IR introduces the notion of Information Reward (IR) actions. There are as many IR actions as there are FoIs, and their values are either $commit$ or $null$. At each time step, the agent selects simultaneously a primitive action and l IR actions. In addition to its primitive reward, the agent is also rewarded for each IR action. The IR reward is based on two values: $r_{correct}$ and $r_{incorrect}$. Intuitively, the agent receives $r_{correct}$ when it commits to a correct value for the factor X_i, and $r_{incorrect}$ otherwise. Therefore, the agent should $commit$ to a factor X_i when its belief over X_i's value is high enough. The values of $r_{correct}$ and $r_{incorrect}$ are set depending on the belief threshold β the system designer wishes to enforce before the agent commits. The relation between $r_{correct}$, $r_{incorrect}$ and β is given by $r_{correct} = \frac{1-\beta}{\beta} r_{incorrect}$.

IV. Communicating POMDP-IR

In this section, we present the main contribution of this paper: a decision-theoretic framework rewarding agents for efficient communication planning. This framework is based on three main aspects:

1) an extended set of state factor, which includes not only the state factors for the communicating agent but also duplicated state factors which represent what the communicating agent believes the recipient knows about certain state factors of interest;
2) communication actions that can be chosen simultaneously to other domain-level actions;
3) a reward function that rewards the agent for maintaining synchronized beliefs over its own Factors of Interest and what it believes the recipient knows about these Factors of Interest.

Formally, we consider one artificial agent, denoted by ϕ and a human operator, denoted by ψ. We consider a set $X^{\phi} = \{X_1^{\phi}, \dots, X_n^{\phi}\}$ of state variables, the first l^{ϕ} of them being POMDP-IR Factors of Interest (FoIs). Within these l FoIs, we consider that the first k FoIs are also of interest for the

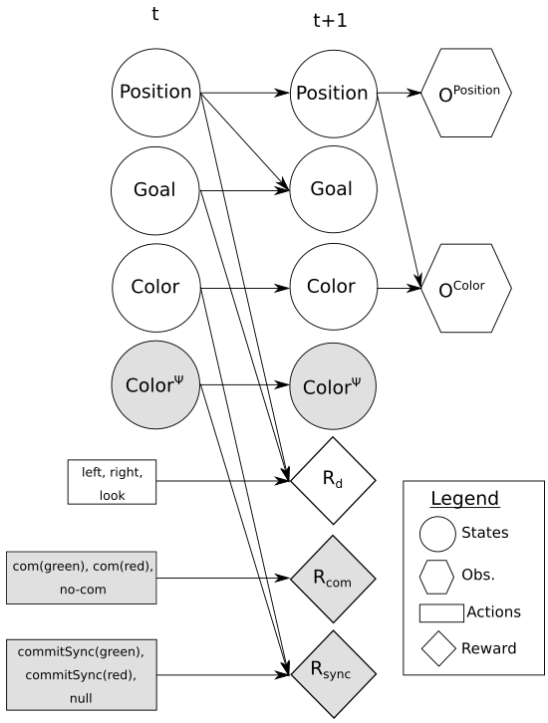


Fig. 2: Dynamic Bayesian Network of the Surveillance Problem model. Grey nodes are specific to the com-POMDP-IR.

human, and that the agent must communicate to the human about them. We call these k FoIs *shared FoIs*.

Our approach is an extension of the POMDP-IR model which integrates communication actions. Figure 2 presents the Dynamic Bayesian Network representation of our model for the surveillance problem.

A. Extended State Space and Observation Factors

To be able to plan for optimal communication, Agent ϕ needs to model the beliefs of the human ψ in its own belief state, hence leading to nested beliefs. In the com-POMDP-IR, we consider only one level of nested beliefs: we only represent what Agent ϕ believes about the human ψ's beliefs. To do so, we extend the belief state of the POMDP by duplicating each of the k shared FoIs. These duplicated factors represent what Agent ϕ believes the human knows about state factors X_i. For improved readability, we use the notation X_i^{ϕ} for the classic state factors for Agent ϕ, $X_i^{\psi/\phi}$ for the duplicated state factors, and X_i for any state factor.

Definition 1 (State Factor Space): The set of state factors $\mathcal{X}$ of a com-POMDP-IR is defined by:

$$\mathcal{X} = \mathcal{X}^{\phi} \cup \mathcal{X}^{\psi/\phi}$$
$$= \{X_1^{\phi}, \dots, X_k^{\phi}, \dots, X_l^{\phi}, \dots, X_n^{\phi}\} \cup \{X_1^{\psi/\phi}, \dots, X_k^{\psi/\phi}\},$$

where $X_1, \dots, X_k$ are the shared Factors of Interest and $X_{k+1}^{\phi}, \dots, X_l^{\phi}$ are the Factors of Interest specific to Agent ϕ. We have $|\mathcal{X}| = 2k + (l-k) + (n-l)$, where n is the number of state factors, $l < n$ the number of FoIs and $k < l$ the number of shared FoIs.

Example 1 (Surveillance Problem - State Factors): In the case of the surveillance problem, the state factors are the following:

$$\mathcal{X} = \{Color^{\phi}, Position^{\phi}, Goal^{\phi}\} \cup \{Color^{\psi/\phi}\}$$

with $Color$ being the color of the alarm (red or $green$), $Position$ being the current position of the robot ($y1$, $y2$ or $y3$) and $Goal$ being the current goal of the robot ($y1$ or $y3$). In this case, only $Color$ is a shared factor of interest.

B. Communication Actions

Agent ϕ should be capable of communicating any possible value for each of the shared FoIs. To do so, we create a $communicate$ action factor, whose possible values are the combination of all the shared FoIs and their respective possible values, plus a $noCom$ action which does not communicate anything. At each time step, the agent must choose a domain-level action and a communication action. Formally, this is described by $\mathcal{A} = A_d \times A_{com}$, where A_d is the set of domain-level actions and A_{com} the communication action, with $DOM(A_{com}) = \bigcup_{i \leq k} DOM(X_i)$. We have $|A_{com}| = 1 + \sum_{i=1}^{k} |X_i|$. We denote by $com(X_i, x_i)$ the action of communicating the value x_i for state factor X_i.

Depending on the domain, it is also possible to create one communication action factor per FoI. In this case, the domain of each communication action factor corresponds to the domain of the FoI, plus the $noCom$ action. The agent would have to choose one domain-level action and one communication action per FoI at each time step. This would allow the agent to communicate several pieces of information at the same time, at the cost of increasing the number of possible actions and therefore the complexity of the model. We do not consider this option for the remainder of this paper for the sake of simplicity, but all equations and algorithms can be easily adapted to this setup.

As mentioned before, the state factors in $\mathcal{X}^{\psi}$ represent what Agent ϕ believes the human knows. At this point, it is important to note that this might be an approximation of what the human actually knows. Indeed, in some systems, the human will only get information about the shared FoIs through Agent ϕ, but in others it might get some level of information through another channel, for instance by monitoring him or herself. In this case, it is obvious that $B^{\phi}(\mathcal{X}^{\psi/\phi}) \neq B^{\psi}(\mathcal{X}^{\psi})$. In addition, if the communication channel is not perfect, the information might not be received by Agent ψ. All these aspects should be captured in the transition function, as presented in Definition 2.

Definition 2 (Transition Function): The transition function of the com-POMDP-IR related to the communication actions is defined as:

$$T(X_{i,t}^{\psi/\phi}, X_{i,t+1}^{\psi/\phi}, com(X_i, x_i)) = \begin{cases} \theta_1 * \theta_2 \text{ if } X_{i,t+1}^{\psi/\phi} = x_i \\ \frac{1-\theta_1*\theta_2}{|X_i|-1} \text{ otherwise} \end{cases}$$
$$T(X_{i,t}^{\psi/\phi}, X_{i,t+1}^{\psi/\phi}, noCom) = \begin{cases} \theta_2 \text{ if } X_{i,t}^{\psi/\phi} = X_{i,t+1}^{\psi/\phi} \\ \frac{1-\theta_2}{|X_i|-1} \text{ otherwise} \end{cases} \quad (1)$$

where θ_1 represents the probability of the communication to be transmitted successfully and θ_2 represents the probability

that the human's beliefs remain the same in the absence of communication.

If the communication is perfect and the human only receives information about from Agent ϕ, then $\theta_1 = \theta_2 = 1$. If the communication is imperfect, $\theta_1 < 1$. If the human ψ receives information from other sources than Agent ϕ, $\theta_2 < 1$. Capturing the different aspects of the system within θ_1 and θ_2 depends on the domain and should be defined by the system designer.

C. Rewarding Relevant Communication

In the com-POMDP-IR, Agent ϕ should be rewarded for communicating relevant information to the human ψ, which means keeping a belief over $X_i^{\psi/\phi}$ close to the belief over X_i^{ϕ} for all $i \leq k$. To do so, we introduce *commitSync* actions, similar to the *commit* actions of the POMDP-IR [5]. There is one *commitSync* action for each factor $X_i, i \leq k$ and one *commit* action for each factor $X_i, k < i \leq l$. We must then extend the set of actions described in Section IV-B to obtain the complete action space of the com-POMDP-IR, as presented in Definition 3.

Definition 3 (Action Space): The set of action factors of the com-POMDP-IR is defined as follows:

$$\mathcal{A} = A_d \times A_{com} \times A_1 \times \cdots \times A_k \times \cdots \times A_l \tag{2}$$

with A_d being the set of domain-level actions, A_{com} the set of communication actions, $A_1, \ldots, A_k$ the set of *commitSync* actions and $A_{k+1}, \ldots, A_l$ the set of Information Reward actions.

We have for each $X_i, i \leq k$

$$A_i = \{commitSync(x_j), \forall x_j \in DOM(X_i)\} \cup \{null\}$$

At each time step, the agent will choose simultaneously a domain-level action, a communication action, a *commitSync* action for each shared FoI and a *commit* action for each non-shared FoI. The *commitSync* actions only affects the the beliefs of the agent concerning the human's beliefs (i.e. $X_i^{\psi/\phi}$) and are used for rewarding the agent when it communicates. As for the *commit* actions, they are used to avoid belief-dependent rewards. Choosing a *commitSync* action means that the agent commits to a given value for X_i and to a synchronized belief over X_i^{ϕ} and $X_i^{\psi/\phi}$.

Example 2 (Surveillance Problem - Action Space): In the surveillance problem, we have:

$$\begin{aligned} A_d &= \{left, right, look\} \\ A_{com} &= \{com(color, red), com(color, green), noCom\} \\ A_{color} &= \{commitSync(red), commitSync(green), null\} \end{aligned}$$

Using the com-POMDP-IR action space, the agent receives a positive reward when it commits to a correct synchronized belief, as presented in Definition 4.

Definition 4: The com-POMDP-IR reward function is defined as follows:

$$\begin{aligned} R(\mathcal{X}, \mathcal{A}) &= R_d(X, A_d) \\ &\quad + \sum_{i=1}^{k} R_{sync}(X_i, A_i) + \sum_{i=k+1}^{l} R_{commit}(X_i, A_i) \end{aligned} \tag{3}$$

where R_d is the domain-level reward, R_{sync} the reward associated to the *commitSync* actions, and R_{commit} the Information Reward [5].

For each $X_i, i \leq k$, R_{sync} is defined as:

$$\begin{aligned} &R_{sync}(X_i, null) = 0 \\ &R_{sync}(X_i, commitSync(x_j)) = \\ &\begin{cases} r_{sync} \text{ if } X_i^{\phi} = x_j \wedge X_i^{\psi/\phi} = x_j \\ -r_{notSync} \text{ otherwise} \end{cases} \end{aligned} \tag{4}$$

with $r_{sync}, r_{notSync} > 0$.

The values of r_{sync} and $r_{notSync}$ have to be chosen carefully to ensure that the agent only commits when its beliefs over X_i^{ϕ} and X_i^{ψ} are certain enough. It is possible to choose different values of r_{sync} and $r_{notSync}$ for different FoIs and even different values of a single FoI. For instance in the surveillance problem, being certain that the alarm is red might be considered more important than being certain it is green.

D. Choosing the parameters

The com-POMDP-IR reward function depends on 2 additional parameters compared to the POMDP-IR: r_{sync} and $r_{notSync}$. From Equation 4, we can compute the expected reward for *commitSync* actions as follows:

$$\begin{aligned} &R(b^{\phi}, X_i, commitSync(x_j)) \\ &\quad = b^{\phi}(X_i^{\phi} = x_j) \cdot b^{\phi}(X_i^{\psi/\phi} = x_j) \cdot r_{sync} \\ &\quad - (1 - b^{\phi}(X_i^{\phi} = x_j) \cdot b^{\phi}(X_i^{\psi/\phi} = x_j)) \cdot r_{notSync} \end{aligned} \tag{5}$$

We wish the agent to select the *commitSync* action when it is certain enough This translates mathematically to

$$\begin{aligned} &R(b^{\phi}, X_i, commitSync(x_j)) > 0 \\ &\text{iff } b^{\phi}(X_i^{\phi} = x_j) > \beta \text{ and } b^{\phi}(X_i^{\psi/\phi} = x_j) > \beta, \end{aligned} \tag{6}$$

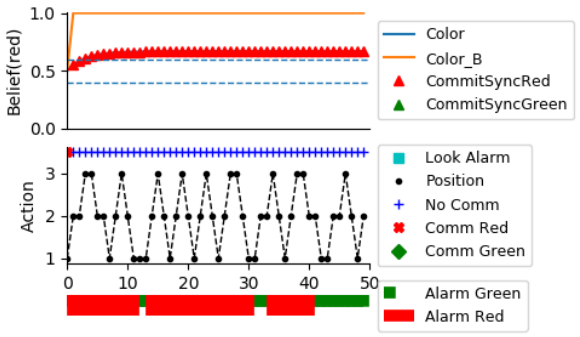
where β is chosen by the system designer. Using this, we can derive the relation between r_{sync} and $r_{notSync}$:

$$\beta^2 r_{sync} - (1 - \beta^2) r_{notSync} = 0 \tag{7}$$

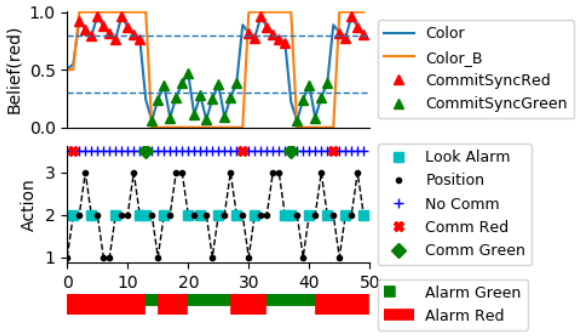
$$\Leftrightarrow r_{sync} = \frac{1 - \beta^2}{\beta^2} r_{notSync}. \tag{8}$$

V. Experiments

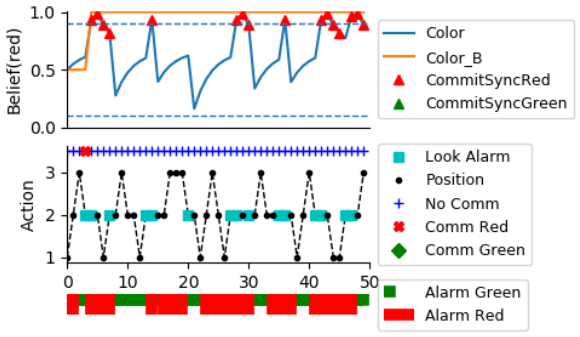
We evaluate our approach in the case of the Surveillance problem described in Section I. Agent ϕ is patrolling the corridor. When performing a movement action, it has a probability of 0.8 to end up in the intended space. When it reaches one goal at the end of the corridor, the goal switches to the other one. The alarm at the center of the



(a) $\beta = 0.6$



(b) $\beta_{red} = 0.8, \beta_{green} = 0.7$

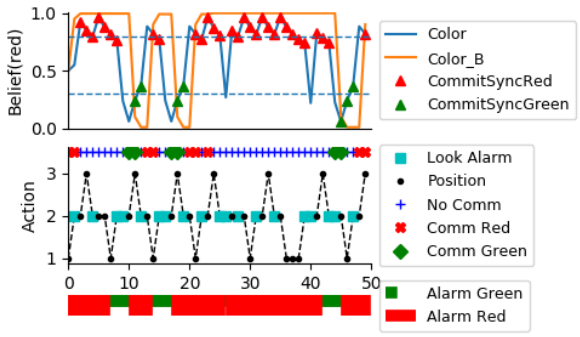


(c) $\beta = 0.9$

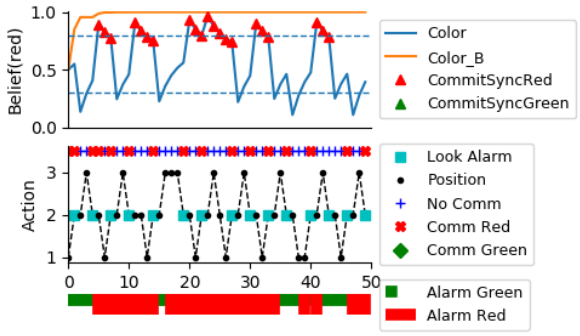
Fig. 3: Surveillance problem results with $\theta_1 = \theta_2 = 1$. Each figure shows the belief evolution over $Color^{\phi}$ (called Color) and $Color^{\psi/\phi}$ (called Color_B) (top row), the communication action and the robot position (middle row), and the actual color of the alarm (bottom row). The dotted lines on the top row indicates the values for β_{red} and $\beta_{green} = 1 - \beta_{red}$.

corridor starts green and will turn red with a probability of 0.8. Once red, it will turn back to green with a probability of 0.1. The reward for reaching a goal is 15. Unless said otherwise, the cost for a communication is 1. The policy has been calculated with the Symbolic Perseus Solver [19], modified for Information-Reward actions [5], with a random sampling of 500 belief points. Each experiment has been run for 500 episodes. During the experiments, we use $r_{sync} = 10$ and calculate $r_{notSync}$ for each β according to Equation 7.

We first evaluate the behavior of the com-POMDP-IR



(a) $\theta_1 = 0.9, \beta_{red} = 0.8, \beta_{green} = 0.7$



(b) $\theta_1 = 0.7, \beta_{red} = 0.8, \beta_{green} = 0.7,$

Fig. 4: Imperfect communication

agent in the case $\theta_1 = \theta_2 = 1$. (Section V-A). This allows us to validate the model by ensuring that the agent is exploring and planning its communication appropriately and to analyze the influence of the threshold β on the behavior of the agent. Next, we study the case where communication can be lost ($\theta_1 < 1$) (Section V-B) and finally the case where the human might receive information from other sources than Agent ϕ ($\theta_2 < 1$) (Section V-C).

A. Perfect Communication

The threshold β for which the com-POMDP-IR agent should choose to commit depends on the problem at hand and must be carefully chosen by the designer. Figure 3 shows some of the possible thresholds and their effect on the agent's behavior. We see that a too low β (Fig. 3a) causes poor communication behavior. Indeed, in the Surveillance problem, the alarm is more likely to turn red and stay red than green. Therefore, the agent can commit to a synchronized belief state without ever looking at the alarm and only communicating *red* once. A too high β (Fig. 3c) also causes undesirable communication patterns as the agent is not capable of reaching such a threshold for one of the values. As the model makes it possible to tailor β for each of the possible values of the factor of interest, we can tune the system for optimal communication (Fig. 3b).

B. Imperfect communication

Figure 4 shows the behavior of the com-POMDP-IR agent when 10% and 30% of the messages are lost. The system is

	$\theta = 1$	$\theta = 0.99$	$\theta = 0.9$	$\theta = 0.8$	$\theta = 0.7$
β_{red}	0.8	0.8	0.8	0.8	0.8
β_{green}	0.8	0.8	0.7	0.7	0.6

TABLE I: Values of β_{red} and β_{green} for each θ_1

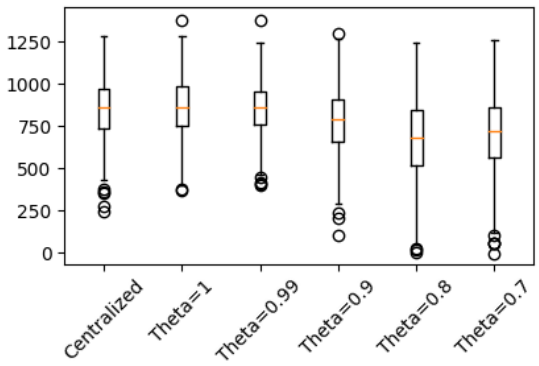


Fig. 5: Accumulated reward for different values of θ_1

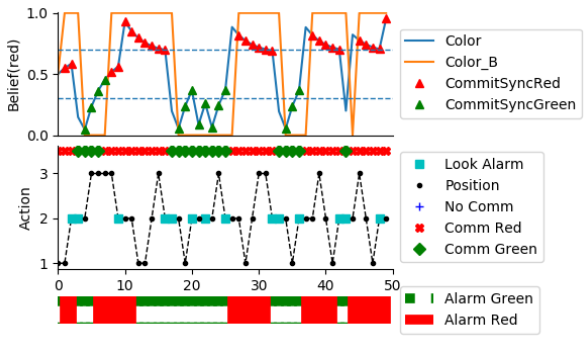
relatively robust to lost messages, provided that β is carefully chosen (Fig. 4a). As expected, when the risk of lost messages is too high, the agent does not communicate anymore about the less probable value of the alarm (green) as it cannot reach the expected belief threshold, even if it is low (Fig. 4b). However, the agent is still capable to communicate about the more probable value.

Next, we consider the case of imperfect communication. To do so, we model the human operator as a purely reactive agent which performs an action *raise-alarm* when it receives a message that the alarm is red. The system receives a positive reward when the alarm is raised appropriately and a negative reward otherwise. This experiment allows us to check that the communication from Agent ϕ is enough to ensure good performance of the system without proactive human behavior. We run this experiment for different values of θ_1. To ensure that a system with perfect communication ($\theta_1 = 1$) is performing optimally, we also computed the value gathered by a centralized POMDP-IR, controlling the agent performing the patrolling and raising the alarm. Since the values of θ_1 and β are linked, the values of β for this experiment have been chosen in order to ensure the best result for each value of θ_1 and are shown in Table I.

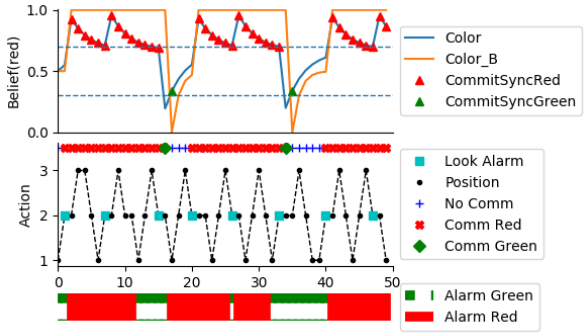
Figure 5 shows the box plots of the value obtained at the end of the simulation for each configuration. The com-POMDP-IR agent performs as well as the centralized POMDP-IR agent when $\theta_1 = \theta_2 = 1$. We also note that a loss of 1% of the messages ($\theta_1 = 0.99$) does not significantly affect the performance of the system and that a loss of 10% of the message still gives good results on average, even though more variability is observed. For configurations where communication is highly unreliable, the need for a confirmation of the value by the human operator is obvious.

C. Varying recipient's beliefs

The parameter θ_2 allows us to model how the beliefs of Agent ψ evolve without communications from Agent ϕ. In this section, we consider a perfect communication ($\theta_1 = 1$) and various values for θ_2. Figure 6 shows the results of the surveillance problem with varying values of θ_2.



(a) $\theta_2 = 0.7$ and $cost = 1$



(b) $\theta_2 = 0.7$, $\beta = 0.7$ and $cost = 3$

Fig. 6: Surveillance problem results with $\theta_1 = 1$, $\beta = 0.7$ and various values of θ_2.

Figure 6a shows that when θ_2 is low, the agent tends to communicate more to maintain a low-uncertainty belief over $\mathcal{X}^{\psi/\phi}$. However, this can be mitigated by introducing a communication cost as part of the domain-level reward, which is given to the agent each time it chooses a communication action (Figure 6b). One could also want to impose a certain number of steps between two successive communications by introducing a bookkeeping variable in the model for instance.

VI. Conclusion and Discussion

In this article, we considered the problem of communication planning for human-machine cooperation. This means that the artificial agent must proactively select relevant pieces of information to communicate to its human teammate at a relevant time. Specifically, we considered that the agent must decide on the timing and the information to send without any request from the human, and that it does not have access to the human's actual beliefs. To tackle this problem, the main contribution of this paper is the Communicating POMDP-IR (com-POMDP-IR), an extension of the Partially Observable Markov Decision Process with Information Rewards (POMDP-IR) model, that allows an artificial agent to (i) maintain an estimate of the human's beliefs regarding a set of features of interest, based on previous communication

actions ; (ii) use this estimate to plan for relevant communication actions ; (iii) integrate this communication mechanism with goal-oriented and information-gathering tasks. This model has been tested in a surveillance problem, in which a robot is patrolling a corridor and must report to a human operator about the state of an alarm. In this scenario, the human operator has no direct access to the alarm and is therefore dependent on the communications from the robot to perform their action. This toy problem demonstrates the importance of reliable communication, especially when the human cannot observe parts of the world. In our experiments, the com-POMDP-IR demonstrated its ability to adjust its communication actions depending on the expected reliability of the communication channel (i.e., rate of lost messages) and the expected evolution of the human's beliefs in the absence of communication.

Currently, our model presents three different limitations that will be considered in future work. The first limitation is an obvious scalability problem, related to the well-known curse of dimensionality, which refers to the fact that solving a POMDP becomes increasingly complex as the number of states and actions increases. In our com-POMDP-IR, the number of actions grows exponentially with the number of features of interest and the number of agents in the system, rendering it intractable for large-scale problems. Two options can be considered to alleviate this issue. First, the actions in the com-POMDP-IR fall under different categories: the primitive actions only impact what the agent itself believes regarding the environment, the communication actions only impact the agent's estimates of the human's belief and the commit actions (*commit* and *commitSync*) do not impact the agent's beliefs but only the reward given to the agent. Satsangi et al. already showed that it was possible to decouple the IR actions from the primitive actions in a POMDP-IR [9] to make the solving more scalable. A similar approach could be possible in the com-POMDP-IR case, using the underlying structure of the action space. Second, another option could be to limit the communications actions to a choice between communicating and not communicating, and deciding on the fly which information to send.

The second limitation resides in the fact that the com-POMDP-IR is a one-way communication model: the artificial agent sends information to the human but cannot integrate information sent by the human. This is due to the fact that the POMDP model requires an observation function to process incoming observations (whether it comes from he environment or from another agent) and that it is hard to model the observation function for human communication. To overcome this limitation, we are considering the use of Reinforcement Learning mechanisms in order to improve a baseline policy, similar to the approach of Bouton et al. [20]. The baseline policy would be the one computed by the com-POMDP-IR, without considering incoming communication, and the improved policy would include such communication by learning the human's communication behavior at run-time.

Finally, the third limitation of our model concerns the parameter θ_2, which models the human's belief evolution in the absence of communication from the agent. In the current model, this parameter is expected to be set by the system designer, which is a challenging task. In addition, representing the whole evolution of the human's belief by a single parameter is rather restrictive. We plan to overcome this in two different ways. First, we can investigate how this parameter could be learned or adapted by the artificial agent during run-time. Second, we intend to use future incoming communication to refine the agent's estimate of the human's beliefs, inspired by Renoux et al. [21]. Indeed, incoming communications provide information to the agent about what the human knows, as we assume that agent and human are cooperative and therefore only share information they believe to be true. Therefore, the artificial agent should be able to use such incoming messages to refine its estimate of the human's beliefs.

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