Inductive learning of answer set programs for autonomous surgical task planning

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INTRODUCTION

Autonomous robotic surgery requires interpretability for reliability [1], i.e. the input and output to the autonomous system must be clear for a human supervisor. Non-monotonic logic paradigms as **answer set programming (ASP)** guarantee interpretability at action planning level, while allowing online adaptation to dynamic anatomical conditions [2]. However, logic planners require reasoning on exhaustive reliable task knowledge from experts, which is often lacking in the surgical domain due to unforeseen diversity of patients' anatomies. State-of-the-art learning methods in surgery rely on statistical (Markov) models, which however are black box (hence not interpretable) and require many examples, even for simple training tasks [3]. We propose the use of **inductive logic programming to learn and refine interpretable surgical knowledge from few examples**.

METHODS

Goal of ASP task knowledge learning

Given definitions of main ASP variables (robotic agents, objects and properties), the goal is to **learn task specifications**, i.e.:

- Pre-conditions of actions
- Executability constraints
- Effects of actions (with temporal delay) expressed using **event calculus** formulation to reduce negated atoms (safer axioms → faster grounding)

```
occurs(fluent, t) :- initiated(fluent, t).
occurs(fluent, t) :- occurs(fluent, t-1),
    not terminated(fluent, t).
```

Inductive Learning of ASP Programs (ILASP)

Learning task specifications is an instance of inductive learning of ASP programs from context-dependent partial interpretations [4]

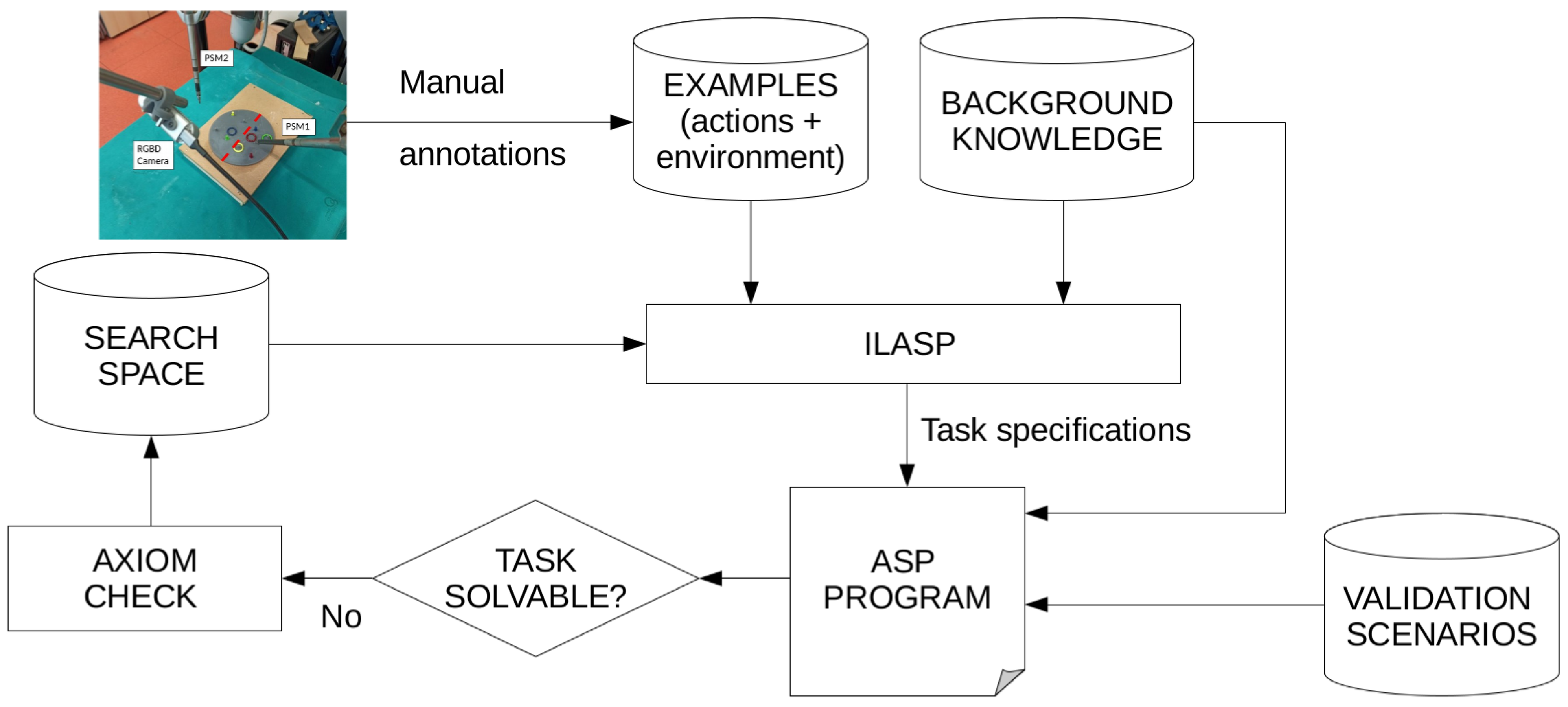
Definition 5 (Context-dependent partial interpretation (CDPI)). A CDPI of an ASP program P with an interpretation I is a tuple $e_c = \langle e, C\rangle$, where e is a partial interpretation, and C is an ASP program called *context*. I is said to extend e_c if $e^{inc} \cup C \subseteq I$ and $(e^{exc} \cup C) \cap I = \emptyset$.

Definition 6 (ILASP task with CDPIs). An ILASP learning task with CDPIs is a tuple $\mathcal{T} = \langle B, S_M, E\rangle$, where $E = \langle E^+, E^-\rangle$ is a set of CDPIs with context C. We say that $H \subseteq S_M$ is a solution to $\mathcal{T}$ if the following hold:

$$\forall e \in E^+ \; \exists AS \; s.t. \; B \cup H \cup C \models AS : \; e \text{ is extended by } AS$$
$$\forall e \in E^- \; \nexists AS \; s.t. \; B \cup H \cup C \models AS : \; e \text{ is extended by } AS$$

A framework based on state-of-the-art ILASP tool [5] is proposed, which allows to:

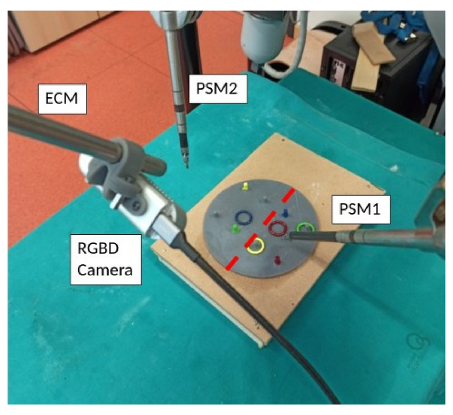
- **Split learning** of pre-conditions, effects and constraints in parallel learning tasks (**smaller search space** → faster learning)
- Systematically **identify problematic axioms** in learned task knowledge in validation, and **refine the corresponding search space to improve knowledge**



The proposed ILP framework to learn, validate and refine task knowledge.

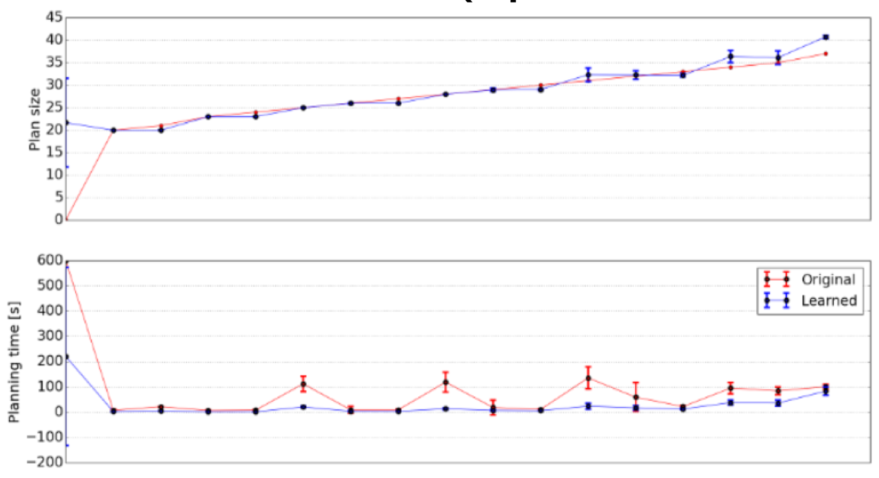
RESULTS

- Experiments on benchmark **ring transfer task** (placing colored rings on same-colored pegs with dual-arm surgical robot), using **only 4 executions as examples**.



The setup for ring transfer task with bi-manual surgical robot..

- **Learning within 178 s** (terminating conditions for effects)
- Learning of **minimum time delay between atoms**
- **Reduced complexity** of axioms leads to **faster planning** in 1000 simulated scenarios (up to **100 s reduction**)



Comparison of planning time and length with original (hand-written) and learned task knowledge. 100 scenarios are clustered according to plan length, mean and standard deviation on planning time are reported.

CONCLUSIONS

Inductive logic programming allows to **fast learn full task knowledge from only 4 executions**, **improving the efficiency of formulation** of specifications and the planning time. Splitting specifications and running parallel learning tasks allows to **systematically refine task knowledge**.

In the future, unsupervised labeling of examples and validation on more complex surgical tasks will be addressed.

REFERENCES

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This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme under grant agreement No. 742671 (ARS).