A cognitive framework for surgical task automation

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***Abstract*—The use of robots in minimally invasive surgery has improved the quality of standard surgical procedures. So far, only the automation of simple surgical actions, or unreliable black-box models for automation, have been investigated by researchers. In this paper, we propose a novel framework to implement surgical task automation with multiple actions, combining logic-based explainable task planning, adaptive motion planning and semantic interpretation of sensors. The framework is validated on different versions of the standard surgical training ring transfer task.**

***Index Terms*—Autonomous robotic surgery, logic programming, dynamic movement primitives**

I. Introduction

Autonomous robotic surgery can improve the safety and patient recovery time, and reduce hospital costs and surgeon fatigue. Recent research has investigated the automation of basic operations in surgery [1], without however addressing adaptability in dynamic scenarios. Statistical models are also used [2], but they need a huge amount of training data and guarantee poor explainability and reliability. In this paper, we address the problem of the automation of a training surgical task, the ring transfer, with the da Vinci® robot from Intuitive Surgical (setup in Figure 1). The task consists of placing rings on the same-colored pegs, using patient-side manipulators (PSMs) of the da Vinci®. Multiple actions must be coordinated according to dynamic environmental conditions (e.g., reachability regions for PSMs) which mimic variations in the patient's anatomy. We propose a framework which integrates Answer Set Programming (ASP) for explainable logic task planning, and Dynamic Movement Primitives (DMPs) for trajectory learning and obstacle avoidance in real time.

II. The framework

A scheme of our framework is shown in Figure 2. The task reasoner implements an ASP program defining the entities and specifications of the task using Boolean variables (*atoms*) and logical *rules*. For the ring tranfer task, entities are the PSMs, rings and pegs with their color (red, green, blue, yellow and grey), environmental conditions (e.g., status of gripper) and actions (e.g., moving to a ring or grasp). Rules match actions to environmental pre-conditions and effects, and define executability constraints (forbidden operations). Given

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).
The research in this abstract will appear in the Proceedings of the IEEE International Conference on Intelligent Robots and Systems (IROS) 2020, as "Autonomous task planning and situation awareness in robotic surgery".

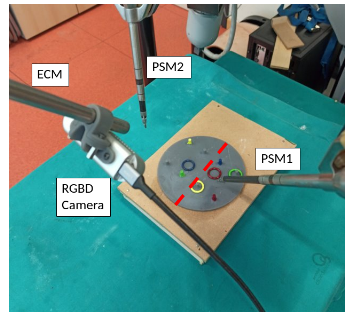


Fig. 1: The setup for the ring transfer task. The red dashed line defines reachability regions for the two arms.

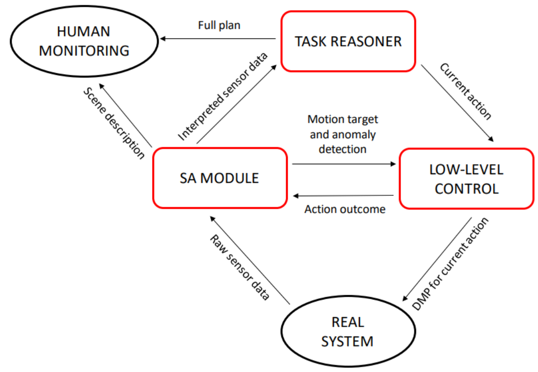


Fig. 2: The proposed framework for surgical task automation. Functional modules of the framework are highlighted in red, while arrows show the stream of information between modules, the real system and an external human observer.

this task description, an ASP solver verifies logical rules and returns the set of actions to the goal (with increasing discrete time step). Actions and ASP encoding are in plain English, hence they can be easily monitored by a human observer.

Each action is described in the low-level control module using DMPs [3]. DMPs model the Cartesian trajectory of the end-effector as:

$$\begin{cases} \tau\dot{\mathbf{v}} = \mathbf{K}(\mathbf{g}-\mathbf{x}) - \mathbf{D}\mathbf{v} - \mathbf{K}(\mathbf{g}-\mathbf{x}_0)s + \mathbf{K}\mathbf{f}(s) \\ \tau\dot{\mathbf{x}} = \mathbf{v}. \end{cases}$$

where $\mathbf{x}, \mathbf{v} \in \mathbb{R}^3$ are, respectively, position and velocity of the end-effector. $\mathbf{K}, \mathbf{D} \in \mathbb{R}_+^{3\times 3}$ are diagonal matrices guaranteeing critical damping for goal convergence. $\mathbf{g}, \mathbf{x}_0 \in \mathbb{R}^3$ are, respectively, the goal and starting position, and $\tau \in \mathbb{R}_+$ is a parameter to tune the speed of the trajectory. $s \in \mathbb{R}_+$ is a re-parametrization of time governed by $\tau\dot{s} = -\alpha s, \quad \alpha \in \mathbb{R}_+$, with initial condition $s(0) = 1$. Function $\mathbf{f} : \mathbb{R} \to \mathbb{R}^3$ is a perturbation term, approximated as a weighted sum of pre-defined basis functions. Weights are learned with convex optimization from demonstration trajectories, and they preserve the shape of the trajectory when $\mathbf{x}_0$ and $\mathbf{g}$ are changed. Additional perturbation terms are added for obstacle avoidance [4].

The situation awareness (SA) module is in charge of the semantic interpretation of data from sensors (poses of objects from the RGB-D camera and robot kinematics) for monitoring. It computes environmental atoms for ASP, checks failure conditions which trigger re-planning / motion stop, and computes target poses for DMPs.

III. Experiments

The da Vinci Research Kit[1] is used to control the robot. Clingo [5] is used for ASP solving. The communication between modules is implemented with ROS. We use an Intel RealSense d435 camera, which has higher depth range with respect to the standard surgical endoscope with smaller baseline. We perform hand-eye calibration with a custom calibration board as in [6], reaching a state-of-the-art precision of 1.6 mm in pose detection, comparable with the intrinsic accuracy of the da Vinci®. DMPs are learned from 15 human executions of the task with all 4 rings requiring transfer, using the approach presented in [7]. Figure 3 shows the learned Cartesian DMP for the action of moving to ring. We validate our framework in four unconventional scenarios (shown in the attached video) involving failure during transfer and anomalies, such as occupied colored pegs and simultaneous operation with the two PSMs. Figure 4 shows the ASP planning time in 1000 simulated scenarios with four rings on different pegs, guaranteeing computation within 10 s even for longer plans (most complex scenarios).

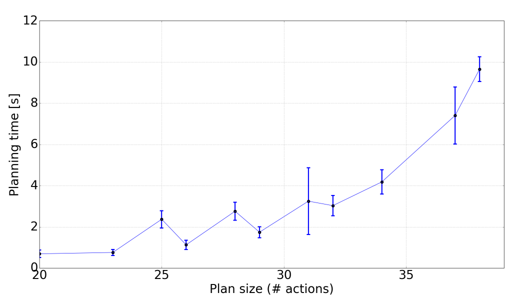
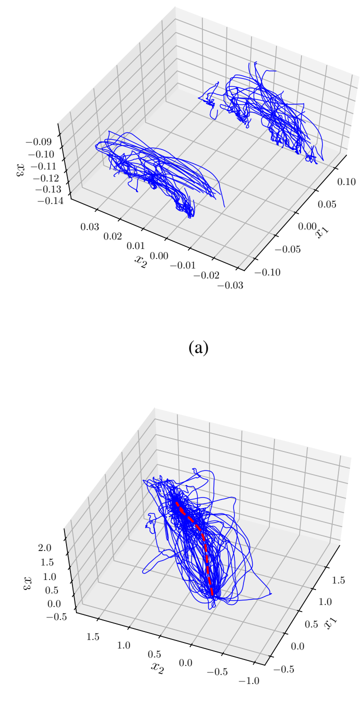


Fig. 4: Plan computation time with ASP in 1000 simulated scenarios. Standard deviation of plan computation time for executions of the same length is also shown.

IV. Conclusion

In this paper, a novel framework for the autonomous execution of surgical tasks was presented, applied to the benchmark training ring transfer task for surgeons. This is the first fundamental step to address issues of autonomous robotic surgery, including failure recovery, motion adaptation and dexterity replication with DMPs, explainable logic plan generation, and situation awareness. In the future, we will test the standard surgical endoscope and we will improve the repeatability of the system implementing visual servoing, for comparison with human execution.

[1] https://github.com/jhu-dvrk/sawIntuitiveResearchKit



(a)

(b)

Fig. 3: a) The set of Cartesian trajectories for the gesture of moving to a ring, for both PSMs; b) trajectories after roto-dilatation, to start at the origin, $\mathbf{x}_0 = \mathbf{0}$ and end at the vector of ones, $\mathbf{g} = \mathbf{1}$ for batch learning. The learned DMP is shown in red dashed line.

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