# An Integrated Approach to Represent and Adapt Human-robot Collaborative Tasks

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*Abstract*—Despite recent developments in perception, processing, and actuation, robots are not able to handle many operations fully autonomously. The presence of human operators becomes necessary to recover from failures and to adapt to novelties. In this paper we propose a novel architecture that manages robot planning while giving the possibility to a human operator to intervene to modify the robot plan using kinesthetic teaching.

Index Terms—Kinesthetic Teaching, AND/OR Graphs, Human-Robot Interaction, Human-Robot Cooperation

## I. INTRODUCTION

Learning from Demonstration (LfD) has been developed to allow novice users to be able to train robots. The most common teaching modalities for providing these demonstrations in robotics context include (i) teleoperation [7], (ii) perception [8], and (iii) kinesthetic teaching (KT) [1]. While using KT human operators physically guide the robot arm/body to demonstrate and teach new skills. KT is helpful to teach low-level motion actions but to extract an high level from a demonstration it is necessary a further processing that could involve manual annotation, the usage of automatic learning policies [6], or the construction of a symbolic representation through learning algorithms [5]. Furthermore, autonomous robots should be able to manage dynamically their task execution plans to efficiently cooperate with human coworkers. To address these challenges, we propose a framework that adopts AND/OR graphs to represent the task execution plan, and manages the human-robot cooperation [3] and we extended it with the possibility for the human operator to modify specific parts of the plan using KT. To preserve a natural human-robot interaction the system is integrated with a simple gesture recognition mechanism that the human can use to notify the system is intention to alter the task execution plan.

## II. METHOD

An AND/OR graph is a graph that represents problem solving processes [2]. The hierarchical structure of AND/OR Graphs, enables to map a complex task into a tree, by segmenting the task into an array of meaningful sub-tasks with logical relationships among them. This feature allows robots to accomplish task execution by traversing through



**Fig. 1:** (left) The normal graph that describes the inspection problem plan, (right) A branched graph that describes the KT procedure.

its representative tree. Therefore, given a structure know in advance, also the KT problem can be modelled into and AND/OR graph. An AND/OR graph G is a directed graph represented by the tuple  $G = \langle N, H \rangle$  where, N is a set of nodes and H is a set of hyper-arcs. For a given AND/OR graph G,  $H = \{h_1, \ldots, h_m\}$ , where  $h_i$  is a many-to-one mapping from a set of child nodes to a parent node. The hyper-arc induces a mapping from the child nodes to the parent node. In that sense, a hyper-arc induces a logical AND relationship between the child nodes/states, i.e., all the child states should be satisfied simultaneously to achieve the parent state. Similarly, a single parent node can be in common for different hyper-arcs  $h_i$ . These hyper-arcs are in logical OR with the parent node. Comprehensive details of AND/OR graphs can be found in [4]. To model a robot task, we break the overall process to many equally structured sub-processes, where every sub-process is mapped into an AND/OR graph.All the graphs are added in a single tree and solved online. In our case the considered task consist in picking an object, inspecting it looking for defects and place it in the appropriate box. This scenario, for a single object, is described by the Normal Graph in Figure 1. In the presented scenario the human can intervene using KT. According to the state in which



**Fig. 2:** System's architecture for an interactive kinesthetic learning for robot manipulation.

the plan execution is the human can update the grasping pose for the object, the inspecting pose, and the positions where the object should be released. The human intervention is activated by a gesture execution and its structure, described by the *Branched Graph* in Figure 1 is pre-defined. Once the execution of the KT graph ends the main plan is updated accordingly and the execution of the *Normal Graph* is restored.

## **III. SYSTEM'S ARCHITECTURE**

Fig. 2 depicts the overall architecture of our framework. The architecture is made up of three layers, including a perception layer in green, a representation layer in blue, and an action layer in red. The perception layer provides information regarding the activities carried out by human operators and product's defect status. The perception layer integrates a Kinect camera used to recognize a specific gesture (see Figure 3). The representation layer forms the alternated manipulation and KT models in the AND/OR Tree module. The *Tree Search* module is responsible for solving the graphs while the Knowledge Base module stores the necessary data to carry on the task, e.g., position of the object. The action layer maps discrete commands into numerical commands that the robot can execute, in particular, the TMP Interface module performs the motion simulation while the Motion Planner module manages the planning and execution. The internal structure of the architecture is presented extensively in our previous work [4].

#### IV. EXPERIMENTAL VALIDATION

To evaluate the adaptability of our approach to real-world robotics problem, we performed the experiments with a dual



**Fig. 3:** Snapshots of the experiment. On the left the human operator teaching a new grasping pose to the robot and on the right the human operator performing the gesture to start the KT procedure.

arm robot and a human operator. Fig. 3 shows some snapshots of the experiment. In this scenario, robot is supposed to pick, inspect, and place them in two distinct boxes, faulty and not faulty. At the beginning the robot has a perfect knowledge of the workspace, object, and boxes positions, and can accurately perform the inspection task. However, the workspace can change, e.g., object displaced or moved box, and the robot would fail the task. At this point the human performs a gesture (see Figure 3) and the robot stops giving the human the possibility to update the robot knowledge. During the KT procedure managed by the Branched Graph the human teaches 3 end-effector poses, namely: pre-grasp, grasp and *post-grasp.* The teaching of each of the 3 poses starts by squeezing the wrist and ends by releasing it. Once the three poses are taught the *Branched Graph* is traversed successfully and the robot switches back to the Normal Graph continuing the task execution from where it had been stopped  $^{1}$ .

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<sup>1</sup>video : https://youtu.be/AeQ0zaPhvNE